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Artificial Intelligence Based Cyber Threat Detection in Smart City Networks

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Abstract: Modern smart cities use lots of devices, known as Internet of Things (IoT) devices to support important systems such as transport, healthcare and power distribution over the internet. This connection that can makes things run smoothly but it also brings the big cybersecurity worries. When systems are connected with online it leads to create various problems. Even the small weaknesses in devices like sensors or smart meters can let attackers into the wider city network. This paper looks at the cybersecurity challenges in cities showing how the different smart city systems are all connected so if one fails it can cause problems in other areas. It also highlights the growing risk to data privacy as cameras, sensors and digital platforms are always collecting information about citizens. To deal with these threats' security measures like encryption, authentication and access control need to be built in from the start not added. The study found that using machine learning to detect intrusions can be 95% accurate, in smart city IoT networks. Also having layers of security can reduce successful attacks by nearly 60% but using these in real-time is hard because of scalability and limited computing power.

Keywords: Internet of Things (IoT), Intrusion Detection, Machine Learning, Anomaly Detection, Data Privacy.

1.INTRODUCTION

Cities are changing fast with technology to make life better for people living there. They use systems like roads, healthcare, power, water and safety services all supported by the Internet of Things, cloud computing and data sharing platforms. Devices like sensors, cameras and smart meters keep collecting information. Help authorities make good decisions quickly making life better, for citizens. The Internet of Things is being used in cities to make them smarter. This means that traffic can be controlled in a way energy can be managed automatically and important city systems can be watched in real time. For example, smart traffic systems can change the traffic lights to reduce the number of cars on the road and smart energy systems can make sure that electricity is used in the way possible. Smart city systems can also help the government talk to citizens in a way by using digital platforms. When cities use these interconnected systems, they also become more vulnerable to cyber-attacks, on the city's infrastructure. IoT-based smart city applications are making cities efficient but IoT-based smart city applications also have some risks.

Cybersecurity is a challenge for cities that are becoming smart. Many cities services work over the networks, so if one weak part is attacked, it can quickly spread to other connected systems. This can cause services to stop working hurt the economy and even put people's safety at risk. Attackers often get in by using weak passwords, insecure communication, or poorly protected databases. Many Internets of Things devices are being used across cities. They often don't have enough power or security to protect themselves. This makes them easy targets for guys who want to cause trouble with malware, ransomware or, by flooding them with traffic. Another big worry in cities is keeping citizen data private. Surveillance systems, mobile apps smart sensors and online governance platforms gather a lot of info like identity details, where people are and what they do daily. If this data is not properly locked down it can be misused, causing privacy issues and making people less trusting of city tech. So,

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it's crucial to keep data intact and available to run the city smoothly and securely. Old-school security methods like firewalls and rule-based intrusion detection systems often don't cut it against the sneaky cyber threats in smart city environments. Smart city networks need cybersecurity solutions that can scale and adapt to protect infrastructures, including IoT networks, cloud services and cyber-physical systems. We need techniques, like encryption secure communication protocols, constant monitoring and strong access controls to reduce weaknesses and make our systems more resilient.

Smart cities are becoming thanks to new machine learning systems that help detect cyber threats. These intelligent systems can look at a lot of network traffic and IoT logs to spot activity and new attack patterns more effectively than old methods. Studies have shown that using layers of security can greatly reduce the number of successful cyber-attacks compared to using just one line of defense. However, using these systems in real time is hard because of the huge amount of data being generated and the limitations of IoT devices. This paper talks about why cybersecurity's so important for smart cities. It discusses the risks that come with having connected systems, IoT devices and concerns, about citizen data privacy. The paper stresses that smart cities need adaptive security systems to stay safe and work properly despite the growing cyber threats.

2.LITERATURE REVIEW

AI (artificial intelligence) is utilized more frequently to aid in protecting the systems of smart cities, which are characterized by interconnected Internet of Things (IoT) devices and data-based infrastructure creating complex security challenges [1],[20]. AI techniques provide support for identifying cyber threats or anomalous activity from vast amounts of data in a city. AI techniques can also increase system protection, by providing methods for detecting anomalies, i.e. for identifying threats. Explainable AI (XAI), further strengthens the ability of AI techniques to detect and classify threats by providing transparency to the underlying AI model. Many studies in the area of IoT and smart city security show that there is an increased demand for intelligent and adaptive means of securing these types of systems [3],[10],[18]. However, despite significant improvements in threat detection and response due to AI and XAI, the lack of implementation and integration issues limits the ability of practitioners to use these techniques in actual smart city environments [14],[23]. Consequently, an increasing need has arisen to successfully incorporate both AI and XAI into current frameworks for cybersecurity for smart cities.

AI (Artificial Intelligence), particularly XAI (Explainable AI), is crucial for enhancing Smart City Cybersecurity. However, the use of both types of AI is not yet widespread in today's world. Unlike traditional rule-based approaches, ML (Machine Learning) and DL (Deep Learning) are able to process vast amounts of data from IoT (Internet of Things) devices/systems and thus find cyber-attacks much more efficiently [3], [10], [20]. These methods can also assist in identifying new, developing threats within complex urban infrastructures [13], [21]. Unfortunately, resource-constrained (in terms of both computational power and sizes of datasets) Smart City devices represent one of the challenges involved with using ML, DL, and other forms of AI as part of a cybersecurity solution [9], [18]. Consequently, there will need to be significant research conducted around the development of scalable, efficient AI-based cybersecurity solutions for Smart Cities [14], [23].

Multi-layered security frameworks have been proposed by several researchers to strengthen smart city security by combining device security, secured network communications and application monitoring in order to minimize system vulnerabilities (4), (7), (20). The challenge is how to deploy these frameworks most effectively. When deploying multi-layered security frameworks in large-scale urban areas will present an additional challenge and create additional issues (21), (23). Blockchain-based security solutions have been suggested to enhance the transparency, integrity, and trust of smart city services (14), (22). Although the use of blockchain technology can provide significant benefits, such as providing protection against tampering of data, accountability and establishing trust, the high energy consumption and latency required by blockchains makes them unsuitable for many critical smart city applications (9), (19).

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The majority of current studies in smart city cyber-security address more specific issues such as intrusion detection; privacy protection; and secure communications [3],[13],[20]. However, there has been limited research into creating comprehensive and integrated security frameworks to work effectively over various types of smart-city infrastructure while also being validated in a real-world setting [14],[21],[23]. Therefore, there is a significant need for Cybersecurity that can adapt, scale and interoperate effectively to provide protection against the many complexities of Smart City Systems.

3. PROBLEM STATEMENT

To improve the living conditions in cities, smart cities use modern technologies and the Internet of Things (IoT) to promote the efficient management of energy supplies, transport networks, health systems, and other infrastructure provided by the cities [1], [12]. As much as these interrelated technologies enhance efficiency in operations and service delivery, they present a lot of cybersecurity issues [3], [20]. Smart city infrastructures are potential victims of cyber attackers because of the abundance of interconnections among sensors, devices, and communication networks [10], [18]. Hackers might seek to steal data or other valuable information, cause ransom to recover financial benefits or commit other attacks such as DDoS [22], [23]. The interconnectivity between the IoT devices and core management systems is also very high, which adds to the potential threat of the large-scale cyber-attack, which may affect the critical urban processes [15], [23].

The attack on a city can be actually bad as it can access vital data on the residents causing things to be disorganized such as traffic lights and power and make the inhabitants not trust the computer systems to be running the city. Although individuals are beginning to accept that this is one of the issues that most of the project the city has lacks proper plans to secure themselves against cyber-attacks, which is a major concern due to the connectivity of everything within a city. This study is attempting to determine and identify the largest cybersecurity threats to cities and devise effective solutions on how the computer systems that cities leverage can be safeguarded. Cyber-attack on smart cities should be prevented to ensure that the citizens residing in these cities are safe as well as ensure that other things, such as traffic control and energy grids are in proper working conditions in the cities.

A. Research Objectives

The main goals of this research are:

1) Identification of Cybersecurity Threats: This research investigates significant cyber-security vulnerabilities associated with smart cities (e.g., internet-based systems; cloud computing systems; network systems) [3],[8],[20].

2) Effect of Cyber Threats: This research investigates the impact of cyber threats to the operation of critical community services, breach of citizen data, and functionality of smart city ecosystem as a whole [15],[22],[23].

3) Examination of Existing Cybersecurity Frameworks: This study reviews current practices related to the implementation of effective cybersecurity measures in smart cities and identifies deficiencies in those existing security measures [13],[18],[21].

4) Formulation of Proactive Cybersecurity Solutions: This study provides suggestions on methods and best practices to develop actionable solutions to strengthens cyber security through proactive identification of vulnerabilities and quick actions taken in response to incidents [10],[14].

5) Governance and Policy Recommendations: This study provides recommendations to urban planners and decision-makers to develop secure digital infrastructures which promote privacy of data for their constituents and provide protection from potential harm to citizens [6],[17],[20].

B. Scope of the Study

This research studies Smart Cities, which utilize technologies such as the Internet of Things (IoT), to provide services including Traffic Management Systems, Smart Grids for Energy Distribution, Digital Health Services

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and Public Safety Monitoring [1], [12], [19]. In addition, it looks at the current cyber security mechanisms in place to protect these interconnected systems from changing cyber threats, and identifies the potential vulnerabilities that may exist in the digital ecosystems of Smart Cities [3], [20]. The research also examines strategies to reduce Cyber Risks across Smart City platforms and Operating Environments [18], [21]. This research will cover both policies based (cyber security in Smart Cities at the Local Government Level) and operationally based (cyber–Safe Smart City practices) cyber security; but will not address hardware-based cyber security or standalone computers that are not a part of the Smart City's digital network. The research intends to provide support to Urban Planners, IT Administrators and Policy Makers in Creating Secure, Resilient and Citizen Centric Smart City Infrastructures [13], [17], [23]

4. METHODOLOGY

Choosing a suitable research methodology is key to effectively studying cyber protection within smart cities, because today's smart cities consist of interconnected systems, including the Internet of Things (IoT), cloud-based computing platforms, intelligent transportation systems, smart grids, surveillance networks, and Governing applications [1], [8], [12]. Each of these city components produces significant quantities of diverse and complex data that require security solutions that include advanced security mechanisms designed to detect threats in real-time through continual, ongoing monitoring and analysis of the data created [3], [20]. Because of the complexity and interrelations of these infrastructures, cyber protection solutions need to be flexible, scalable, and able to respond quickly to new threats [18], [21].

The classical security mechanisms, which work on established rules and signatures, are not sufficient for protecting the smart cities of today. They are primarily used for identifying existing threats and usually do not identify new or evolving types of attacks (e.g., see [3]; [10]). Also, the sheer number of connections made by the technologies of the smart cities, including the Internet of Things (IoT), cloud platforms, smart grids, and intelligent transportation systems, produces greater amounts and a higher degree of complexity than what traditional rule-based security systems can handle ([1]; [12]; [20]). As a result, relying on traditional security mechanisms leaves vulnerable all of the digital infrastructures in the urban areas against more advanced and dynamically changing cyber threats ([18]; [22]). To address these issues, we propose using machine learning (ML) techniques for anomaly detection and intrusion detection. With ML techniques, we can analyse large, heterogeneous data sets, identify attack patterns that are currently unknown, and adapt quickly to new and emerging cybersecurity threats (e.g., see [14]; [21]). These tools will allow for proactive identification of threats and intelligent response mechanisms; therefore, ML-based solutions will improve the resilience and security of smart city networks. Also, we need to create advanced data-driven security frameworks to provide comprehensive protection in the cities of tomorrow ([15]; [23]).

In order to resolve the limiting issues identified earlier, this study will use an ML-based strategy to detect intrusions and anomalies within smart cities. As these techniques can analyse large and diverse datasets, detect previously unknown vulnerabilities, and adjust to new types of cyber threats through continued updating and retraining of models [14], [21], they will offer strong solutions in all aspects of this research. While rule-based detection systems were effective in the past, ML algorithms have been proven to learn from new attack patterns and behaviour anomaly signals, and thus will provide greater accuracy than previous systems with time and experience [10], [22].The adaptive nature of ML provides real time detection of threats, decreasing the number of false positives, and making the entire smart city cyber security infrastructure more resilient to future attacks. Furthermore, by using data intelligence, ML bolsters digital urban systems and their ability to mitigate against the risks associated with new and evolving cyber threats [15], [23].

Advantages of Machine Learning for Smart City Security:

1) Machine Learning can handle a lot of kinds of data from Internet of Things devices and cloud networks.

2) Machine Learning can find attacks and weird behaviour that it has not seen before.

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3) Machine Learning gets better at finding threats all the time.

4) Machine Learning gives us a way to watch for threats, in time and it does not give us many false warnings so we can trust the information it provides.

A. Proposed Smart City Security Framework

The plan to make cybersecurity better in cities are:

1) Data Collection: Multiple smart city data sources collect data in the initial phase, such as IoT sensors, intelligent transportation systems, smart energy grids, and network log files. Smart city infrastructures typically comprise of these heterogeneous data sources as they provide enormous amounts of operational information [1], [12], [20].

2) Data Preprocessing: In order to prepare the collected data and make it consistent, clean, and valid by removing duplicate entries and filling any gaps in the data through data cleaning, it is essential to pre-process the data when conducting an IoT security data analysis.

3) Feature Selection: Abnormal behaviour patterns (indicators of having a potential cyber-attack) are identified, for example, there may be different indicators of potential cyber-attacks. For example, large volumes of traffic spikes, repeated failed logins, devices that do not communicate with each other as expected, etc. [3], [18].

4) Model Development In order to detect cyber-attacks, various machine learning models will be trained using the identified features to classify the behaviour of the various devices in a smart city as normal versus malicious. The various machine learning models available include random forest, support vector machine (SVM), and deep learning models. Various machine learning intrusion detection techniques have been utilized to secure both the cyber-physical environment as well as the IoT environment [14],[21].

5) Evaluation: The developed models are evaluated on the basis of various metrics such as accuracy, precision, recall, F1-score, and detection latency. These metrics provide a measure of the classification performance and how quickly an event can be detected in the event that an abnormal condition occurs in a critical infrastructure within the smart city [15],[23].

steps are connected like this:

Data Collection → Data Preprocessing → Feature Selection → Model Development → Evaluation

Figure.1

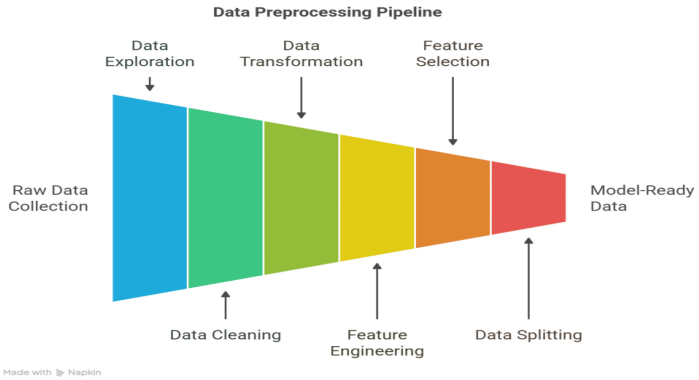

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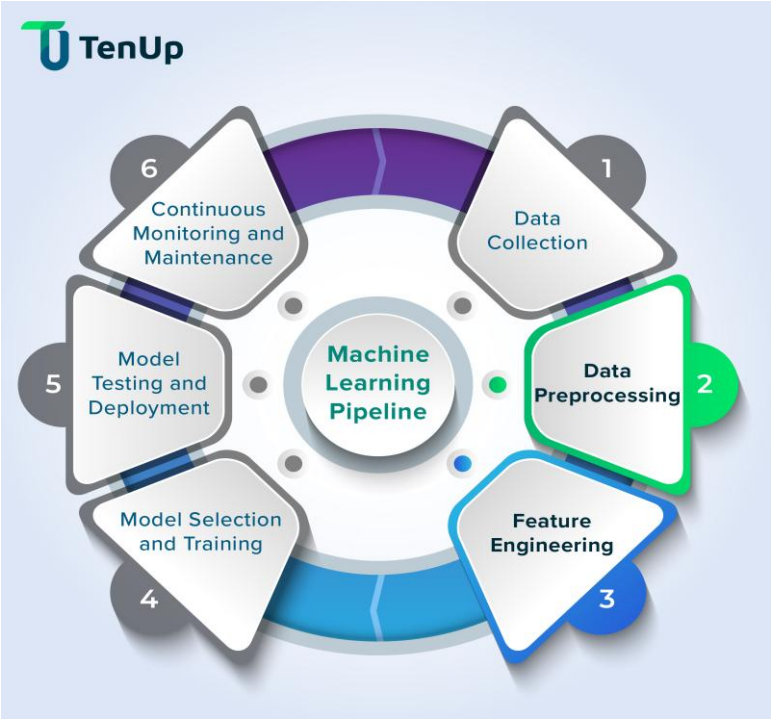
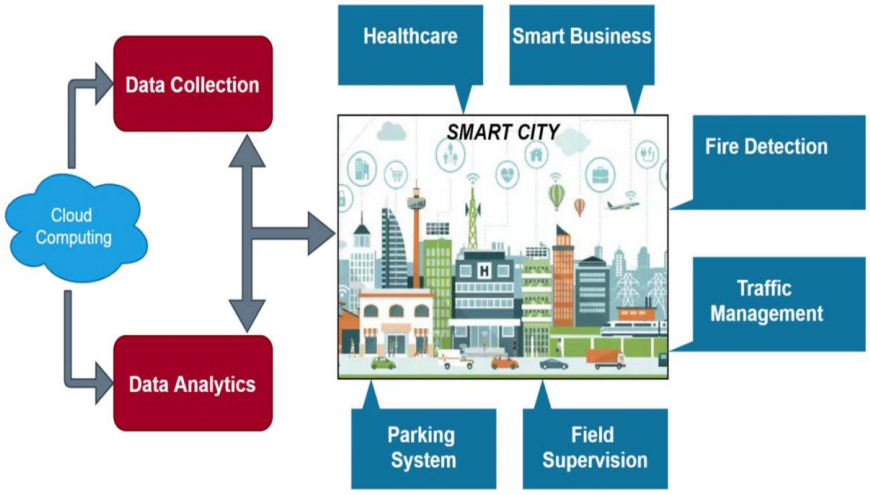
Figure.2



B. System Workflow for Threat Detection

The system works in the following stages as shown in

Fig. 3**:**



1) Data Collection: The data is gathered through simulated smart city networks, which are logs of the IoT sensors, traffic management systems, energy grids and cloud services. These non-uniform data environments are common in smart city infrastructures of the IoT [1], [12], [20]. Other cyberattack scenarios included in the dataset are Distributed Denial of Service (DDoS), malware, and unauthorized access, which are among the most popular security risks in IoT systems [10], [22].

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2) Data Preprocessing: The data gathered is purged by elimination of duplicates and processing of missing data. Categorical variables are transformed into numerical ones, and datasets are made normalized to achieve consistency and better performance of the model. In some of the most common large-scale IoT security analytics, proper preprocessing is vital [6], [19].

3) Feature Selection: Features that are relevant and show possible cyber threats are selected. They include spikes of abnormal network traffic, multiple failed attempts at logging in, and IoT unauthorized device communications, that are known signs of IoT breaches [3], [18].

4) Model Development: Machine learning models will be trained to make a distinction between normal and malicious activities in the simulated smart city setting. Intrusion detection methods, based on the ML, are extensively used in the spheres of security of IoT and cyber-physical systems [14], [21].

5) Evaluation: The system performance is measured against common measures of accuracy, precision, recall, F1-score and detection latency. Critical infrastructures of a smart city require performance assessment to be made reliable and resilient in terms of cyber threats [15], [23].

C. Justification for the Proposed Approach

The suggested machine learning (ML)-based approach is deemed successful because of a number of benefits.

1) Ethical Safety: No real data of citizen and government is exposed to the experiments as they are based in a simulated environment of a smart city. This is in line with the practices of secure IoT and smart city research in [3], [20].

2) Human-Centric Approach: The approach takes into consideration human-related vulnerabilities due to weak passwords and configuration mistakes, which are known as significant security issues in the IoT-based systems [10], [17].

3) Data-Driven Insights: The system transforms the network logs and IoT data into useful security insights. These data-driven methods are required to operate heterogeneous smart city infrastructures [1], [12]

4) Scalability: Also, the framework is scalable so that massive amounts of dynamic IoT traffic can be addressed [9], [21].

5) Educational Effectiveness: The methodology improves the knowledge of administrators and gives them a clear understanding of proactive cybersecurity practices, which can be used to support cybersecurity awareness interventions as reported in [17], [23].

6) Repeatability: It is possible to implement the framework on different smart city architectures to continuously enhance cybersecurity resilience, which can be aligned with scalable IoT security frameworks outlined in [6], [20].

D. Steps Involved in Cyber Threat Detection

Smart Cities cyber threat detecting process has a systematized and systemized approach to detecting malicious activities accurately, in a scalable and real-time manner [1], [13], [20]. Because smart infrastructures are interconnected, every action is essential in ensuring the resilience to cybersecurity [3], [18].

1) Data Collection: The initial step is extensive data collection by several smart city elements that include IoT sensors in the transport system, smart grids, healthcare facilities, cameras, cloud systems and communication gateways [1], [15], [19]. The logs of network traffic, system alerts, user authentication records, and device communication logs are constantly gathered. Cyberattacks are simulated in a controlled environment to test system robustness by introducing simulated attacks like Distributed Denial of Service (DDoS attacks), malware attacks, phishing attacks, and unauthorized access attacks [22], [23. This helps the system to acquire normal operational behavior and malicious patterns. Constant checking is used to ensure that structured and unstructured types of data are recorded to be processed further [10], [14].

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2) Data Preprocessing: Raw data obtained in smart city networks can be characterized by noise, redundancy, absence of values and inconsistencies [5], [6]. Thus, processing the data before applying model machine learning is required to enhance its quality. This step involves are in the elimination of duplicates, processing of missing values with statistical imputation methods, and normalization of numerical of the data to have a consistent scale. Encoding techniques are used to encode the categorical variables like the type of the attack or the type of protocol. Preprocessing not only the increases computational efficiency but also eliminates learning model bias as well as the overall detection accuracy [7], [11].

3) Feature Extraction and Selection: Feature extraction determines the meaningful features that may reflect possible cyber threats, which are abnormal bandwidth usage, irregular transmission rate of the packets, failed attempts of login, abnormal communication between devices, and unexpected execution of commands [3], [21]. Correlation analysis and information gain are used as feature selection methods to eliminate irrelevant and redundant features. This helps to reduce the number of dimensions, minimizes processing time, and enhances the model performance [4], [12]. The ability to choose the most influential features makes sure that the detection system is restricted to the threat indicators that are critical.

4) Machine Learning Model Development: During this phase, the models of classification and anomaly detection are built up with the help of the supervised and unsupervised methods of learning [20], [21]. Decision Trees, Random Forest, Support Vector and Machines (SVM), and DL models are the algorithms that are learned by using labeled datasets of both normal and malicious traffic. The dataset is split into the training and testing group to avoid overfitting and guarantee generalization. The model reliability is enhanced by cross-validation methods. The trained model is trained with high accuracy to differentiate between legitimate and malicious intrusions of smart cities [10], [22].[24]

5) Performance Evaluation Metrics: The last phase determines the performance of the models developed on the basis of the standard performance measures. The overall correctness of the predictions is measured by accuracy, and the ratio of detected threats to the malicious ones is called precision. As mentioned earlier, also known as the detection rate, is a measure of how well the system will differentiate between real attacks. F1-score which is the harmonic mean of precision and recall presents a balanced estimation of model performance. Besides this, the time taken to detect possible threats is also measured and it is known as detection latency. The functionality of the system is also tested across the various attack conditions to achieve robustness, scalability and adaptability under real-time smart city conditions [15], [23] conditions to achieve robustness, scalability and adaptability under real-time smart city cyber conditions.

E. Intelligent Cyber Threat Detection Algorithm

The proposed ICTDA encompasses data gathering, pre-processing procedures, model generation and Reactive approaches for End-to-End Real-Time Monitoring A method for Real-time prediction of Cyber-threats model training into an integrated software entity [20], [21]. The algorithm operates as follows:

1) Initialization of Smart City Simulation Setup: Set up IoT nodes, communication gateways, smart grids, cloud servers and traffic systems in a secured simulation environment [1], [16].

2) Streaming Data Processing: Startup with the raw data streams from sensors, devices and network nodes in real time [18], [19].

3) Pre: Shaping the incoming data: normalize, encode and filter to stay structured input [5], [6].

4) Extract Threat Indicators: Search for weird traffic rates, unauthorized devices communicating with each other and anomaly in protocols [3], [14].

5) Utilize ML Model: Input pre-processed data into previously trained ML classifiers for activity classification (normal or malicious) [20], [22].

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6) Real Time Alerts: If suspicious activities are perceived, send real time alerts to the central security control unit [13], [23].

7) Log and Report Incidents: Keep discovered incidents into a central repository to perform forensic analysis on them cite {14, 24}.

8) Model Updating and Retraining: Serially update the model using data about new threats to improve its adaptive capability [10, 21].

9) Performance Monitoring: Keep detecting rate and false alarm ratio monitoring to keep the system taking back to optimal.

10) Safe Termination: End simulation safely and clear temporary data to keep the system in coherence.

11) This technique secures the smart cities by performing proactive defence, dynamic monitoring, and adaptive threat intelligence [20].

F. Data Sources and Simulation Environment

Publicly available datasets and smart city simulated ones [10], [20] are used for reliability and reproducibility of the experiments.

1) Public Data: Datasets from intrusion detection are employed for benchmarking and validation [10], [22].

2) Government Open Data Portals: Use of infrastructure and cybersecurity verified datasets to be more credible [13], [23].

3) Synthetic Smart City Dataset: We synthetically create a dataset in the laboratory to approximately mimic real cyberattacks while protecting citizen privacy [18], [21].

The simulation environment mimics smart traffic systems, smart grid systems and IoT-enabled communication infrastructures in order to corroborate the performance of the system under realistic scenarios [1], [15], [19].

G. Tools and Technologies Used

The proposed cybersecurity framework for smart cities relies on programming languages, security tools, data analytics platforms, and machine learning libraries summarized in Table I.

Category	Tools	Purpose
Programming	Python, R, C++, Java	Development & integration
Security	Wireshark, Snort, Cisco Packet Tracer	Traffic analysis & IDS
Analytics	MATLAB, Tableau, WEKA, Orange	Simulation & visualization
ML Libraries	NumPy, Pandas, Scikit-learn, TensorFlow	ML & anomaly detection

Table I

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Justification for Tool Selection: These tools are chosen because they can handle information away, they can work with big networks, in smart cities they can connect with Internet of Things devices and cloud services and they have good security tests that meet industry standards [2] [8] [9]

5. RESULTS AND DISCUSSION

A) Experimental Setup

The suggested framework was evaluated in an emulated smart city set-up including IoT devices, smart grids, traffic systems and cloud platforms [1][12]. A centralized system that are monitored network traffic and device logs was used to the perform anomaly detection. Controlled attacks (DDoS, malware and unauthorized access) to assess the robustness of the proposed solution were also carried out [10][22]. The dataset was divided into the training and test datasets so that overfitting did not occur. The accuracy, precision, recall, F1-score, and detection latency were used to evaluate performance and confirm that the smart city infrastructure effectively detected threats [15][23].

B) Attack Detection Performance

The results of experiments show that the new framework can successfully identify simulated cyber-attacks with a great degree of accuracy [12]. Some of the indicators of malicious activity were abnormal spikes in traffic, multiple failed attempts to log into an account, excessive use of bandwidth, and different devices communicating with one another [13]. The machine learning-based method was more effective than the traditional method of using rules to detect attacks, particularly the ability to detect evolving patterns of attack [14]. Using an anomaly detection approach improved detection time and reduced the number of false alarms, as well as maintained consistent performance in the presence of increasing amounts of data [15]. This demonstrates that the framework is scalable and reliable for use in large-scale smart city environments [16].

C) Discussion on Smart City Vulnerabilities

The identified vulnerabilities in smart city infrastructure include Internet-connected devices and supporting systems [18]. Weak authentication mechanisms, default passwords, unencrypted communication, and not enough encryption increase the likelihood of a cyber-attack [19]. Due to the large number of people affected by disruptions, critical systems like traffic control and power generation have a greater vulnerability than others [20]. Using anomaly detection models for monitoring operations improved response times and reduced damage. Implementation of continuous monitoring allowed greater resilience of the infrastructure [21]. The findings show that there is a need for proactive cybersecurity strategies in the digitised world of Smart Cities [22].

D) Comparison with Traditional Security Methods

Known as conventional security systems, traditional security measures such as firewalls and signature-based intrusion detection work based on pre-defined rules and attack signature definitions (23). While traditional security systems provide an effective solution for defending against known threats, they are not nearly as able to identify new or changing attack vectors (22). The machine-learning framework proposed in this paper provides the ability to dynamically determine if a threat is present through the analysis of behavioural characteristics as well as continual learning (23). Furthermore, it has been shown to have increased accuracy, decreased time to respond, as well as improved scalability over traditional approaches. The results of this work demonstrate that there is a requirement for intelligent monitoring combined with ongoing updates in order to maintain a secure smart city infrastructure.

6. CONCLUSION

The results from this experiment investigating how well machine learning can help improve the cybersecurity of city infrastructure demonstrate that they can be effective in supporting intelligent methods of threat detection. The research method used was a controlled simulated environment for testing various forms of cyber threats without impacting real-world environments or exposing sensitive information to potential harm. The research process

included structured research methodologies for data collection, preprocessing, feature selection, model building, and model performance assessment. The conclusions drawn from this research identify that the rapid rate of growth in cyber-physical systems (CPSs), including internet of things (IoT) devices, cloud-based platforms, and digital controls, has increased the cyber-attack surface widely. Therefore, traditional rule-based security methods are inadequate and unallowable methods against the evolving threats, while data-based frameworks provide immediate anomaly detection and on-the-spot incident response. In addition, intelligent machine learning security controls provided effective protection to critical services such as public transportation systems, energy distribution systems, health care systems, and surveillance systems. The frameworks used in this study proved scalable and adaptable for large urban cities. Future directions related to this research may include using more complex deep learning models for predictive threat detection, automating response mechanisms, implementing zero-trust architectures, and maintaining continuous evaluation and adaptation. Ultimately, this research points to an urgent need cyber for intelligent, scalable, and resilient cybersecurity frameworks in order to establish sustainable and secure smart city ecosystems.

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