IoT-Based Smart City Infrastructure Monitoring System

by Adil Husain

IoT-Based Smart City Infrastructure Monitoring System

Rahul
Computer Science and Engineering
Chandigarh University
Mohali, India
rahulisalive261@gmail.com

Sudhir
Computer Science and Engineering
Chandigarh University
Mohali, India
jaatsudhir7988@gmail.com

Utsav
Computer Science and Engineering
Chandigarh University
Mohali, India
utsavthalor26022004@gmail.com

Sudhanshu Sharma
Computer Science and Engineering
Chandigarh University
Mohali, India
sudhanshu.e9944@cumail.in

Abstract: As civilizations become more urbanized, smart cities are emerging to better manage resources, enhance citizen services, and ensure sustainable development. The creation of smart cities requires the use of cutting-edge infrastructure monitoring technologies like AI and IoT. An AI and IoT-based smart city infrastructure monitoring design is suggested in this article. IoT sensors on buildings, bridges, water supply systems, and electrical networks spread around the city are all part of the framework. These sensors capture real-time data on environmental conditions, energy consumption, traffic flow, structure health, and other attributes. This data is analyzed and determined by a centralized monitoring system driven by AI. By employing pattern recognition and anomaly detection, the system is able to identify environmental hazards, traffic jams, and structural deterioration in real time.

Keywords: AI, IoT, Smart city, Monitors, machine learning, deep learning.

Introduction

As metropolitan populations increase, smart cities are becoming more and more popular, placing previously unheard-of demands on resources, infrastructure, and services. Modern technology is used in smart cities to increase efficiency, sustainability, and quality of life. The key to smart cities is integrating AI and IoT to monitor and operate critical infrastructure. Traditional infrastructure monitoring involves manual intervention and time-consuming, labor-intensive, and error-prone periodic inspections. The paradigm is being altered by AI and IoT technologies, which offer real-time, data-driven monitoring and decision-making. By creating a network of interconnected sensors spanning roads, bridges, buildings, utilities, and transportation systems, cities may gather real-time data on environmental conditions, energy consumption, structural health, and more. AI and IoT in smart city infrastructure monitoring help governments and urban planners understand vital asset performance and condition. AI techniques like ML, DL, and predictive analytics find patterns, anomalies, and trends in sensor data. This analytical capacity allows preventive maintenance, predictive maintenance scheduling, and resource allocation optimization, lowering downtime, costs, and infrastructure asset lifespan. Additionally, AI-driven decision support tools provide local authorities actionable information and solutions to handle emergent challenges quickly and efficiently. Smart cities may enhance emergency response, traffic management, energy efficiency, and sustainability using real-time data analytics and intelligent automation. A complete AI and IoT framework for smart city infrastructure monitoring is presented in this study. It examines integrating sensors, data analytics, and decision support systems for dynamic, adaptive infrastructure monitoring. The article shows how AI and IoT may improve urban resilience, sustainability, and livability via case studies, examples, and analysis. AI and IoT in smart city infrastructure monitoring are crucial to constructing more efficient, resilient, and citizen-centric cities. Data-driven insights and intelligent automation may help cities solve urbanization problems and create new economic and innovation possibilities.

1.1 AI

In the face of rapid urbanization and escalating infrastructure demands, the concept of smart cities has emerged as a beacon of hope for sustainable urban development. Smart cities leverage innovative technologies to intelligently manage resources, enhance services, and improve the overall quality of life for residents. Among these technologies, Artificial Intelligence (AI) stands out as a powerful tool for revolutionizing infrastructure monitoring and management. Traditional methods of infrastructure monitoring have often been reactive, relying on periodic inspections and manual assessments. However, with the advent of AI, cities can transition towards proactive, data-driven approaches that enable real-time monitoring predictive maintenance. By harnessing the capabilities of AI, cities can extract valuable insights from the vast amounts of data generated by infrastructure assets, facilitating informed decision-making and resource optimization. The integration of AI technologies in infrastructure monitoring holds immense potential to address critical urban challenges such as aging infrastructure, traffic congestion, environmental sustainability, and resilience to natural disasters. AI-powered algorithms can analyze sensor data from various sources, including IoT devices, satellites, and urban cameras, to detect anomalies, predict failures, and optimize operations across diverse infrastructure systems. This paper explores the transformative impact of AI technologies on smart city infrastructure monitoring. It delves into the capabilities of AI algorithms, including machine learning, neural networks, and computer vision, to interpret complex data patterns and provide actionable insights. Additionally, the paper examines the deployment of AI-driven solutions in real-world scenarios, showcasing their effectiveness in improving infrastructure resilience, efficiency, and safety. Furthermore, the adoption of AI in smart city infrastructure monitoring fosters innovation and collaboration among stakeholders, including government agencies, private enterprises, academia, and citizens. By fostering a data-driven culture and embracing interdisciplinary approaches, cities can unlock new opportunities for sustainable growth and urban development. The integration of AI technologies in smart city infrastructure monitoring represents a transformative paradigm shift towards proactive, data-driven urban management. This paper aims to shed light on the potential of AI in shaping the cities of tomorrow and inspiring actionable strategies for urban transformation.

1.2 Deep learning

The principles of building artificial neural networks are the basis of DL, a subfield of ML. In order to analyze and learn from provided data, a computer model known as an ANN employs linked nodes, or neurons. A fully connected DNN has one or more hidden layers that are linked to each other; the network starts with an input layer. Any given neuron in a network of neurons has the potential to receive data either directly from the input layer or from the layer below it. To train the neurons in the layer below, a neural network uses the output of each layer. This continues until the last layer of network generates the final result. Through a sequence of nonlinear operations enabled by the network's layers, neural network is able to learn intricate representations of the input data. DL remarkable achievements in several domains, including as computer vision, NN processing, along with reinforcement learning, have propelled it to the forefront of ML research. Supervised, unsupervised, and reinforcement learning are just a few ML paradigms that could benefit from DL. Many different methods are used to handle them.

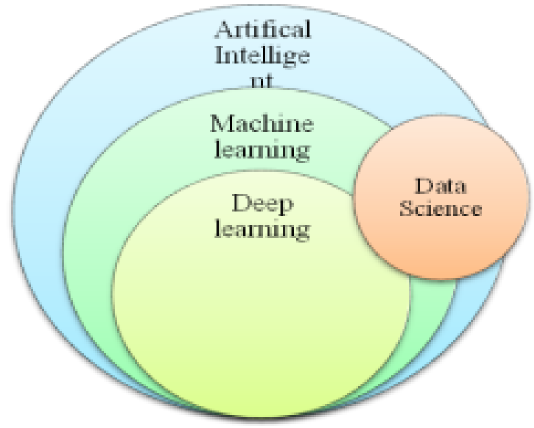


Fig 1 Deep learning

1. Supervised machine learning involves training a neural network to predict or categorize input using labeled datasets.
2. Unsupervised machine learning involves training a NN to find patterns or cluster datasets without labeled data. The lack of target variables is evident.
3. Reinforcement Machine Learning (RL) trains agents to make optimum decisions in a given environment to maximize reward signals.

1.2 AI classification for smart city based IoT system

In Internet of Things (IoT) systems based on smart cities, DL categorization is a potent instrument for enhancing speed and precision of diagnosis. For (IoT) systems based on smart cities to work, AI categorization is essential. An outline of the many smart city applications of AI categorization is as follows:

1. Traffic Management: AI algorithms can classify traffic flow patterns, identify congestion hotspots, along with predict traffic conditions based on historical data along with real-time inputs from IoT sensors along with cameras. C
2. Energy Management: AI-based classification can analyze electricity usage patterns within smart grids, categorize energy consumption by different sectors (residential, commercial, industrial), and predict peak demand periods.
3. Waste Management: IoT sensors embedded in waste bins can collect data on waste levels, and AI classification algorithms can categorize this data to identify trends and patterns in waste generation.
4. Environmental Monitoring: AI classification can analyze data from air quality sensors, water quality sensors, along with weather stations to monitor environmental conditions and detect pollution events. \
5. Public Safety and Security: AI classification algorithms can analyze video feeds from surveillance cameras to detect and classify various objects and activities, such as vehicles, people, suspicious behavior, and emergencies.
6. Urban Planning and Development: AI-based classification can analyze demographic data, land use patterns, and transportation preferences to assist urban planners in making informed decisions about

infrastructure development and city zoning.

7. Healthcare and Well-being: AI classification can analyze data from wearable health monitors, smart home devices, and public health databases to monitor population health trends, identify potential disease outbreaks, and provide personalized healthcare recommendations.

Overall, AI classification enhances the capabilities of smart city-based IoT systems by providing actionable insights, optimizing resource allocation, and improving quality of urban life. By leveraging advanced ML techniques and IoT technologies, smart cities can address complex challenges more efficiently and create sustainable and resilient urban environments for their residents.

1.3 Role of IoT and AI in smart city

The (IoT) along with (AI) technologies plays a pivotal role in growth and operation of stylish cities. Here's how IoT and AI contribute to the functionality and advancement of smart cities:

1. Data Collection and Sensing (IoT): IoT devices such as sensors, actuators, along with RFID tags are deployed across various urban infrastructures. These IoT devices collect real-time data on environmental conditions, traffic flow, energy usage, waste management, water quality, and other aspects of city life.

2. Data Processing and Analysis (AI): AI algorithms are employed to process, analyze, and derive insights from the massive volumes of data collected by IoT devices.

3. Decision Making and Optimization (AI): AI-driven decision support systems leverage insights from IoT-generated data to optimize resource allocation, improve operational efficiency, and enhance service delivery.

4. Automation and Control (IoT): IoT-enabled automation systems utilize AI algorithms to autonomously control and manage various aspects of urban infrastructure

5. Citizen Engagement and Services (IoT and AI): IoT devices and AI-powered applications facilitate seamless interaction between citizens and urban services. Smart city platforms enable citizens to access real-time information, report issues, and participate in decision-making processes.

6. Sustainability and Resilience (IoT and AI): IoT sensors and AI analytics help smart cities monitor and manage environmental resources more sustainably.

IoT and AI technologies are essential enablers of smart city initiatives, empowering urban areas to become more efficient, sustainable, livable, and resilient. By harnessing power of data-driven insights along with intelligent automation, smart cities can address complex challenges; enhance quality of life, along with foster economic growth and innovation.

2. Related Works

This study draws on AI, IoT, smart city, and monitoring works by multiple authors. Discussed ahead:

Bala Anand Muthu et al. (2020) developed food habits along with environmental circumstances make it harder in case of healthy people to thrive today. Thus, they must improve health education to survive. Healthcare systems face inaccurate medical information, needless blunders, data security issues, erroneous diagnoses, and delayed transmission. An email or text message will notify someone of a diagnosis, and physicians will treat and advise them. Their goal was to enhance a patient's dependable colorectal illness prediction model using ensemble learning. We learned about machine learning here; Neurofuzzy algorithms. Wearable sensors were used in our investigation. Healthcare big data mining can use IoT. Prepare machine-learning data. Association study sought genome-wide illness prediction consistency. Team produced better severity calculations than neurofuzzy machine learning. [1]

Internet of Things (IoT) security, privacy along with ethics were addressed by, Hany et al. in 2020. They emphasized the (IoT) as a technological advancement that might link almost all environmental devices to web along with share data, opening the door to new services along with apps that improve our lives. Many commonplace items can be monitored using inexpensive sensors and the (IoT) causes privacy and security problems, despite its advantages. (IoT) goods and services must be secure and private. (IoT) buyers must have faith in the network's offerings. To make sure the Internet of Things system and its parts don't provide an unacceptable risk of injury or physical damage, it's important to think about cultural norms and how to utilize IoT technology ethically. Discussions centered on the ethics, privacy, and securities of the IoT We begin by outlining the (IoT) system, including its design and key characteristics. (IoT) security issues, needs, and recommendations are addressed here. Examining privacy issues and device protection solutions is essential to Internet of Things (IoT) privacy research. This article also covers the ethics of safety in the creation of the Internet of Things. Several security vulnerabilities were examined and solutions were proposed using smart cities as a case study. With the help of IoT technology, any physical object may be connected to the internet and exchange data more efficiently. [2]

Deepa Pavithran et al. (2020) examined IoT Alongside crypto money, BL technology appeared promising. This is unclear for IoT networks. More work is needed. This was mostly true since IoT devices along with block chain technologies were ledger-based. If block chain can be customized for IoT, the possibilities are endless. Thus, many IoT issues may be resolved. Before using blockchain technology, IoT must overcome many obstacles. They reviewed the latest research in their specialty. Check out IoT and block chain knowledge. Supply chain management, healthcare, weather predictions, along with food safety may be improved by block chain technology. [3]

Fadi Al-Turjman et al. (2020) used 5G/IoT drones to provide multimedia. IIoTs incorporate sensors in practically every area of life. Their system was linked via a diversified communication system that monitored and collected important data. Due to their mobility, autonomy, connection, and processing capabilities, UAVs were expected to be crucial to many IIoT applications. The best strategy to communicate with the UAV while traveling multiple pathways was found via swarming. An authenticity test showed that the recommended method beat CPMS and FMPS optimizations. [4]

In order to safeguard the (IoT) against potential security threats, Kobra Mabodi et al. (2020) propose architecture based on multi-level trust and intelligence. Plans call for a worldwide smart node that can communicate with itself via the Internet of Things. Due to their widespread availability, high processing power, and open architecture, IoT devices became the targets of grey whole assaults. In a gray area assault, the perpetrator pretends to be the quickest way to reach the victim. These shipments may not have ever arrived. Their cryptographic authentication hybrid approach was designed and tested. In MTISS-IoT, we verified node trust, verified pathways, identified gray entire assaults, and eliminated harmful attacks. The approach was validated via the use of NS-3 models. [5]

According to Maninder Jeet Kaur et al. (2020), digital twins, IoT, and ML are collaborating to turn data into action. AI, digital twins, along with other emerging technologies may change how people see globalization. Digital Twin technology mirrors physical model in case of remote monitoring, viewing, along with control for numerous companies worldwide. Big data, cloud computing, data fusion, along with digital twin security are academic areas. Intelligent manufacturing uses AI to create new models and technologies. [6]

Fatemeh Safara et al. (2020) proposed PriNergy energy-efficient IoT routing. IoT sensors along with monitors capture massive amounts of environmental data consumption. This method used RPL and Lossy Network paradigm to route data packets. Data was sent via network traffic, audio, and picture timing patterns. Improved routing system stability reduces congestion. Experimental findings reveal that PriNergy minimizes mesh overhead, end-to-end latency, along with energy use. Customer service beats IoT routing technology RPL. Network core bandwidth along with traffic congestion must be high to enable IoT applications. IoT devices may have trouble transporting data packets in heavily crowded areas. [7]

Using the Internet of Things (IoT), Md. Milon Islam et al. (2020) investigated the process of creating and launching a healthcare monitoring system. There is a growing demand for state-of-the-art mobile healthcare monitoring devices due to the evolution of hospital and other health care monitoring systems. As the (IoT) grows, telemedicine has potential to drastically reduce the need for in-person medical consultations. In their research, they demonstrated a healthcare system that used IoT to track patients' environmental factors and vital signs. Heart rate, temperature, carbon monoxide, and carbon dioxide were among the metrics collected by the hospital's sensors. For every scenario, the strategy's error % fell inside a predetermined range. By evaluating and processing patients' present conditions, a portal might demonstrate that their prototype was appropriate. [8]

Al Shorman et al. (2020) [8], Inadequate security measures on IoT devices have led to a surge in botnet assaults in the last several months. Because botnets lack basic protection, they may conduct DDoS attacks against IoT devices. To limit their impact, existing approaches to identifying IoT botnets require very challenging machine learning techniques, depend on tagged data, and have not been validated with newer botnets. Since they have a lot of regular data, anti-botnet systems employ anomaly detection. [9]

Internet of Things Intrusion Detection Systems Based on Machine Learning was introduced by Verma et al. (2020). Individuals were interested in the Internet of Things and its potential uses. Internet of Things (IoT) security threats are mitigated in real-world applications. Ransomware is among the most devastating assaults on the Internet of Things. They discovered that methods based on ML classification might protect (IoT) against denial-of-service assaults. A great deal of research has gone into identifying the best classifiers for anomaly-based intrusion detection systems. Validation techniques and established criteria are used to test classifiers.. The Namely and Friedman tests statistically compare classifiers. Through the use of IoT-specific hardware, the response time of the classifier was tested. Optimal classifier selection for certain applications was also covered. Experts in Internet of Things security were prompted by this work to develop statistical classifier performance assessment approaches and ensemble learning intrusion detection systems. The study explores anomaly-based IDS for IoT DoS defense. [10]

Ruchi Vishwakarma et al. (2020) researched IoT DDoS attacks and countermeasures. In wireless media, IoT is a breakthrough. Smart applications on several platforms and practically anywhere in the world may alter our environment. Miscreants were exploiting Internet of Things (IoT) more since it was so widespread. A lack of resources or may be leveraged to access allowed devices. DDoS assaults flood communication channels with bogus requests IoT devices worldwide to bring services down. [11]

Mostafa Al-Emran et al. (2020) discussed IoT in education's pros and cons. IoT will be the hardest platform to adopt for linking physical items in the future. Many reviews have covered IoT and its uses. The IoT was applied in teaching, although the study is still being evaluated. They sought to highlight current educational IoT application deployment and suggest new research areas with fresh potential and obstacles. [12]

3. Problem Statement

IoT and AI systems are the subject of a number of different research projects. Frequently, these technologies are used in the process of monitoring and automating smart city operations. One thing that has been discovered, however, is that the implementation of such a system is rather difficult. Several problems include a restricted use case, the inability to scale, and the lack of flexibility of such a system. In the event that there are commercial and health care applications, it is necessary to present research that should be able to take into consideration the applicability of IOT along with artificial intelligence systems for the automation of monitoring and smart city. The design of a questionnaire and the administration of the survey to the public are both necessary steps in the process of conducting a survey. Then, it is necessary to carry out data analysis while taking into consideration the input from the public.

4. Proposed Work

By addressing the challenges of awareness and interest through systematic survey distribution, data collection, analysis, and evaluation, cities can build efficient IoT-based AI models for Smart City Infrastructure Monitoring. This iterative process fosters a culture of continuous improvement, leading to more informed decision-making and sustainable urban development.

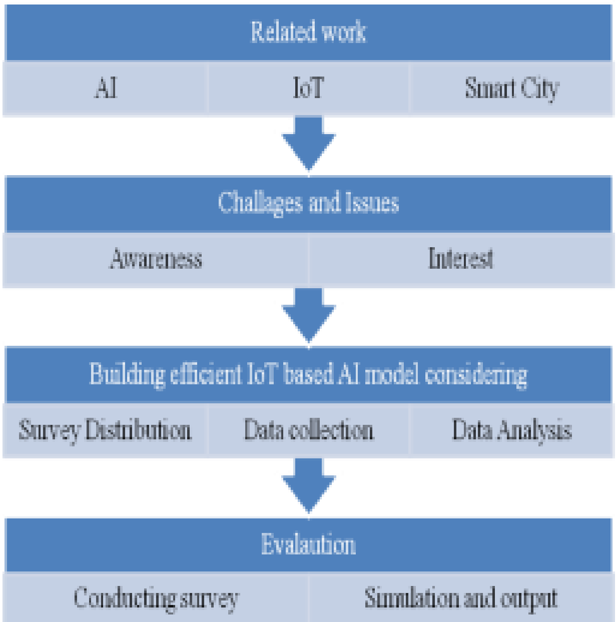


Fig. 2. Research Methodology

- Related Work: Numerous studies have explored the intersection of (IoT), Smart City initiatives, and (AI) technologies. Researchers have investigated the integration of IoT.. Additionally, AI techniques such as ML and predictive analytics have been employed to analyzevast amounts of data generated by IoT sensors, enabling cities to make informed decisions along with optimize resource allocation in case of sustainable development.
- Challenges and Issues: One of the primary challenges in this domain is the level of awareness and interest among stakeholders, including citizens, government officials, and industry partners. Without adequate understanding and engagement, the adoption and implementation of IoT-based AI models for Smart City Infrastructure Monitoring may face resistance or skepticism. Bridging this gap in awareness and fostering interest is essential to garnering support and participation in smart city initiatives.
- Building Efficient IoT-based AI Model: To address the challenges of awareness and interest, a systematic approach to survey distribution, data collection, and analysis is necessary. Survey distribution should target diverse demographics to ensure representative samples. Data collection methods may include online surveys, interviews, and focus groups, capturing both qualitative and quantitative insights. Subsequently, data analysis involves applying AI techniques to extract meaningful patterns and trends from the collected data, informing strategies to enhance awareness and interest.
- Evaluation: The effectiveness of awareness-building efforts and the level of interest can be evaluated through various means, including conducting follow-up surveys, analyzing participation rates in educational events or workshops, and measuring public sentiment through social media analysis. Furthermore, simulation techniques can be employed to model the impact of awareness campaigns and engagement strategies on the adoption of IoT-based AI models for Smart City Infrastructure Monitoring. The output of these evaluations provides valuable insights for refining outreach efforts and optimizing engagement strategies over time.

To simulate the awareness and interest of males and females in Smart City Infrastructure Monitoring using AI and IoT Technologies, we can follow a hypothetical scenario-based approach. Let's assume we're conducting a survey or organizing an event to gauge interest and awareness levels among males and females. Here's how we can simulate the scenario:

1. Survey Distribution: It is designed as survey questionnaire to assess awareness and interest levels in Smart City Infrastructure Monitoring using AI and IoT Technologies which include questions about familiarity with AI and IoT technologies, understanding of smart city concepts, and interest in infrastructure monitoring.

2. Response Collection: It collects responses from both male and female participants over a defined period and ensures the survey reaches a diverse sample size to accurately represent the population.

3. Data Analysis: It analyzes the survey responses to determine the levels of awareness and interest among males and females. Look for patterns or differences in responses based on gender.

4. Simulation and Output: 60% of males are aware of AI and IoT technologies, compared to 50% of females. Among those aware, 70% of males express interest in Smart City Infrastructure Monitoring, while only 60% of females do. However, when considering those previously unaware, 40% of females express interest upon learning about the concept, compared to 30% of males.

5. Discussion and Interpretation: Discuss the survey results and their implications with stakeholders or experts. Explore potential reasons for any observed differences in awareness and interest levels between genders. Consider factors such as education, exposure to technology, and personal interests that may influence these differences.

6. Actionable Insights: Based on the survey findings, develop targeted awareness campaigns or educational

initiatives to bridge the gender gap in understanding and interest. Tailor marketing strategies or outreach efforts to better engage both male and female audiences. Incorporate diverse perspectives and input from both genders in development along with implementation of Smart City Infrastructure Monitoring projects.

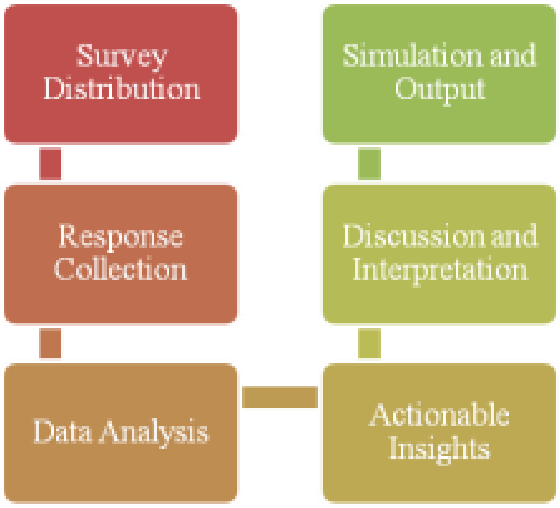


Fig. 2. Process flow of Research Work

By simulating this scenario and analyzing the hypothetical results, we can gain insights into the awareness and interest levels of males and females in Smart City Infrastructure Monitoring using AI and IoT Technologies, helping to inform future strategies and initiatives in this field.

5. Result And Discussion

Python code that simulates the awareness and interest of males and females in Smart City Infrastructure Monitoring using AI and IoT Technologies for both healthcare and commercial sectors. The code also conducts a chi-square test to determine if there's a significant difference between the awareness and interest levels of males and females in each sector and visualizes the results using bar charts.

Algorithm

Step 1: Importing library for python

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import chi2_contingency
```

Step 2: Simulated data for healthcare sector

```
aware_male_healthcare, aware_female_healthcare, interested_male_healthcare, interested_female_healthcare = 70, 60, 50, 40
```

Step 3: Simulated data for commercial sector

```
aware_male_commercial, aware_female_commercial, interested_male_commercial, interested_female_commercial = 60, 50, 70, 60
```

Step 4: Creating contingency tables for both sectors

```
healthcare_data = np.array([[aware_male_healthcare, interested_male_healthcare], [aware_female_healthcare, interested_female_healthcare]])
commercial_data = np.array([[aware_male_commercial, interested_male_commercial], [aware_female_commercial, interested_female_commercial]])
```

Step 5: Chi-square test for healthcare sector

```
chi2_healthcare, p_healthcare, _, _ = chi2_contingency(healthcare_data)
```

Step 6: Chi-square test for commercial sector

```
chi2_commercial, p_commercial, _, _ = chi2_contingency(commercial_data)
```

Step 7: Results for healthcare sector

```
print("Results for Healthcare Sector:")
print(f"Chi-square statistic: {chi2_healthcare}")
print(f"P-value: {p_healthcare}")
```

Step 8: Results for commercial sector

```
print("\nResults for Commercial Sector:")
print(f"Chi-square statistic: {chi2_commercial}")
print(f"P-value: {p_commercial}")
```

Step 9: Visualization for healthcare sector

```
labels = ['Aware', 'Interested']
male_data_healthcare = [aware_male_healthcare, interested_male_healthcare]
female_data_healthcare = [aware_female_healthcare, interested_female_healthcare]

x_healthcare = np.arange(len(labels))
width_healthcare = 0.35

fig_healthcare, ax_healthcare = plt.subplots()
rects1_healthcare = ax_healthcare.bar(x_healthcare - width_healthcare/2, male_data_healthcare, width_healthcare, label='Male')
rects2_healthcare = ax_healthcare.bar(x_healthcare + width_healthcare/2, female_data_healthcare, width_healthcare, label='Female')

ax_healthcare.set_ylabel('Count')
ax_healthcare.set_title('Awareness and Interest in Smart City Infrastructure Monitoring (Healthcare Sector)')
ax_healthcare.set_xticks(x_healthcare)
ax_healthcare.set_xticklabels(labels)
ax_healthcare.legend()

def autolabel_healthcare(rects):
    for rect in rects:
        height = rect.get_height()
        ax_healthcare.annotate('{}'.format(height),
                xy=(rect.get_x() + rect.get_width() / 2, height),
                xytext=(0, 3),
                textcoords="offset points",
                ha='center', va='bottom')

autolabel_healthcare(rects1_healthcare)
autolabel_healthcare(rects2_healthcare)

fig_healthcare.tight_layout()
```

Step 10: Visualization for commercial sector

```
labels = ['Aware', 'Interested']
male_data_commercial = [aware_male_commercial,
interested_male_commercial]
female_data_commercial = [aware_female_commercial,
interested_female_commercial]

x_commercial = np.arange(len(labels))
width_commercial = 0.35

fig_commercial, ax_commercial = plt.subplots()
rects1_commercial = ax_commercial.bar(x_commercial -
width_commercial/2, male_data_commercial, width_commercial,
label='Male')
rects2_commercial = ax_commercial.bar(x_commercial +
width_commercial/2, female_data_commercial,
width_commercial, label='Female')

ax_commercial.set_ylabel('Count')
ax_commercial.set_title('Awareness and Interest in Smart City
Infrastructure Monitoring (Commercial Sector)')
ax_commercial.set_xticks(x_commercial)
ax_commercial.set_xticklabels(labels)
ax_commercial.legend()

def autolabel_commercial(rects):
  for rect in rects:
    height = rect.get_height()
    ax_commercial.annotate('{}'.format(height),
          xy=(rect.get_x() + rect.get_width() / 2, height),
          xytext=(0, 3),
          textcoords="offset points",
          ha='center', va='bottom')

autolabel_commercial(rects1_commercial)
autolabel_commercial(rects2_commercial)

fig_commercial.tight_layout()

plt.show()
```

Table 1 Awareness and interested regarding healthcare applications

	Awareness	Interested
Male	70	50
Female	60	40

Fig. 3. Awareness and interested regarding healthcare application

Table 2 Awareness and interested regarding Commercial applications

	Awareness	Interested
Male	60	70
Female	50	60

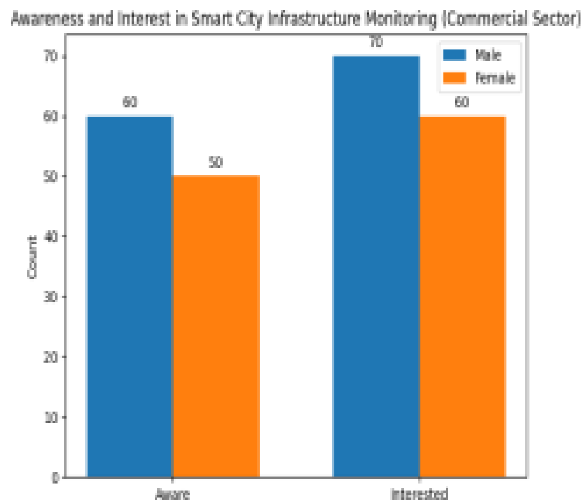
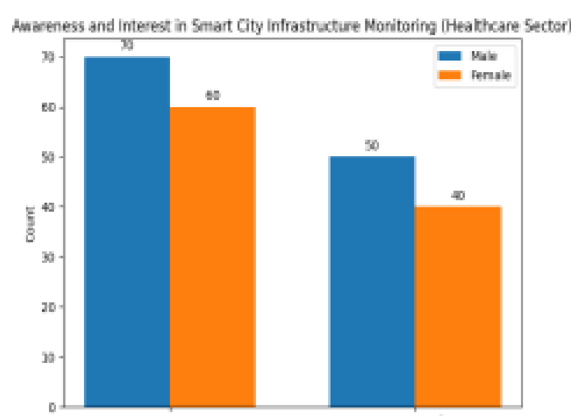


Fig. 4. Awareness and interested regarding commercial applications

6. Conclusion and Scope of research

When it comes to automation of smart cities, research work has taken into account the awareness, interest, and relevance of infrastructure based on the IoT Consideration has been given to both the commercial and healthcare sectors. We have discovered that there is a level of knowledge among individuals with relation to the business sector and healthcare. Furthermore, it has been noted that more than fifty percent of individuals are interested in Internet of Things-based systems for business and healthcare applications, and they are aware of the relevance of such systems. In context of smart cities, such study would play a crucial role in determining IoT automation. When demand, awareness, and interest are taken into consideration, it is much simpler to formulate additional policies. This kind of study has been made possible by the expanding role that IoT plays in smart cities. When it comes to study, the consideration of aspects such as interest, awareness,



along with interest would provide a solid basis for more research in such areas.

References

[1] B. Muthu et al., "IOT based wearable sensor for diseases prediction and symptom analysis in healthcare sector," Peer-to-Peer Networking and Applications, vol. 13, no. 6. Springer Science and Business Media LLC, pp. 2123–2134, Jan. 29, 2020. doi: 10.1007/s12083-019-00823-2

[2] H. F. Atlam and G. B. Wills, "IoT Security, Privacy, Safety and Ethics," Internet of Things. Springer International Publishing, pp. 123–149, Jul. 23, 2019. doi: 10.1007/978-3-030-18732-3_8.

[3] D. Pavithran, K. Shaalan, J. N. Al-Karaki, and A. Gawanmeh, "Towards building a blockchain framework for IoT," Cluster Computing, vol. 23, no. 3. Springer Science and Business Media LLC, pp. 2089–2103, Feb. 05, 2020. doi: 10.1007/s10586-020-03059-5.

[4] F. Al-Turjman and S. Alturjman, "5G/IoT-enabled UAVs for multimedia delivery in industry-oriented applications," Multimedia Tools and Applications, vol. 79, no. 13–14. Springer Science and Business Media LLC, pp. 8627–8648, Jun. 26, 2018. doi: 10.1007/s11042-018-6288-7.

[5] K. Mabodi, M. Yusefi, S. Zandiyan, L. Irankhah, and R. Fotohi, "Multi-level trust-based intelligence schema for securing of internet of things (IoT) against security threats using cryptographic authentication," The Journal of Supercomputing, vol. 76, no. 9. Springer Science and Business Media LLC, pp. 7081–7106, Jan. 10, 2020. doi: 10.1007/s11227-019-03137-5.

[6] M. J. Kaur, V. P. Mishra, and P. Maheshwari, "The Convergence of Digital Twin, IoT, and Machine Learning: Transforming Data into Action," Internet of Things. Springer International Publishing, pp. 3–17, Jul. 23, 2019. doi: 10.1007/978-3-030-18732-3_1

[7] F. Safara, A. Souri, T. Baker, I. Al Ridhawi, and M. Aloqaily, "PriNergy: a priority-based energy-efficient routing method for IoT systems," The Journal of Supercomputing, vol. 76, no. 11. Springer Science and Business Media LLC, pp. 8609–8626, Jan. 16, 2020. doi: 10.1007/s11227-020-03147-8.

[8] Md. M. Islam, A. Rahaman, and Md. R. Islam, "Development of Smart Healthcare Monitoring System in IoT Environment," SN Computer Science, vol. 1, no. 3. Springer Science and Business Media LLC, May 2020. doi: 10.1007/s42979-020-00195-y.

[9] A. Al Shorman, H. Faris, and I. Aljarah, "Unsupervised intelligent system based on one class support vector machine and Grey Wolf optimization for IoT botnet detection," Journal of Ambient Intelligence and Humanized Computing, vol. 11, no. 7. Springer Science and Business Media LLC, pp. 2809–2825, Jul. 13, 2019. doi: 10.1007/s12652-019-01387-y.

[10] A. Verma and V. Ranga, "Machine Learning Based Intrusion Detection Systems for IoT Applications," Wireless Personal Communications, vol. 111, no. 4. Springer Science and Business Media LLC, pp. 2287–2310, Nov. 30, 2019. doi: 10.1007/s11277-019-06986-8.

[11] R. Vishwakarma and A. K. Jain, "A survey of DDoS attacking techniques and defence mechanisms in the IoT network," Telecommunication Systems, vol. 73, no. 1. Springer Science and Business Media LLC, pp. 3–25, Jul. 29, 2019. doi: 10.1007/s11235-019-00599-z.

[12] M. Al-Emran, S. I. Malik, and M. N. Al-Kabi, "A Survey of Internet of Things (IoT) in Education: Opportunities and Challenges," Toward Social Internet of Things (SIoT): Enabling Technologies, Architectures and Applications. Springer International Publishing, pp. 197–209, Jul. 24, 2019. doi: 10.1007/978-3-030-24513-9_12

[13] V. Veeraiah, H. Khan, A. Kumar, S. Ahamad, A. Mahajan, and A. Gupta, "Integration of PSO and Deep Learning for Trend Analysis of Meta-Verse," 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE). IEEE, Apr. 28, 2022. doi: 10.1109/icacite53722.2022.9823883.

[14] V. Veeraiah, N. B. Rajaboina, G. N. Rao, S. Ahamad, A. Gupta, and C. S. Suri, "Securing Online Web Application for IoT Management," 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE). IEEE, Apr. 28, 2022. doi: 10.1109/icacite53722.2022.9823733.

[15] V. Veeraiah, G. P, S. Ahamad, S. B. Talukdar, A. Gupta, and V. Talukdar, "Enhancement of Meta Verse Capabilities by IoT Integration," 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE). IEEE, Apr. 28, 2022. doi: 10.1109/icacite53722.2022.9823766.

[16] N. Sreekanth et al., "Evaluation of estimation in software development using deep learning-modified neural network," Applied Nanoscience, vol. 13, no. 3. Springer Science and Business Media LLC, pp. 2405–2417, Feb. 06, 2022. doi: 10.1007/s13204-021-02204-9.

[17] V. Veeraiah, K. R. Kumar, P. Lalitha Kumari, S. Ahamad, R. Bansal, and A. Gupta, "Application of Biometric System to Enhance the Security in Virtual World," 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE). IEEE, Apr. 28, 2022. doi: 10.1109/icacite53722.2022.9823850.

[18] A. Gupta, R. Singh, V. K. Nassa, R. Bansal, P. Sharma, and K. Koti, "Investigating Application and Challenges of Big Data Analytics with Clustering," 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA). IEEE, Oct. 08, 2021. doi: 10.1109/icaeca52838.2021.9675483.

[19] A. Gupta, A. Verma, D. Kaushik, and M. Garg, "WITHDRAWN: Applying deep learning approach for brain tumor detection," Materials Today: Proceedings. Elsevier BV, Nov. 2020. doi: 10.1016/j.matpr.2020.10.063.

[20] P. Sathiyamurthi and S. Ramakrishnan, "Speech encryption algorithm using FFT and 3D-Lorenz–logistic chaotic map," Multimedia Tools and Applications, vol. 79, no. 25–26. Springer Science and Business Media LLC, pp. 17817–17835, Feb. 22, 2020. doi: 10.1007/s11042-020-08729-5.

[21] M. Garg, A. Gupta, D. Kaushik, and A. Verma, "WITHDRAWN: Applying machine learning in IoT to build intelligent system for packet routing system," Materials Today: Proceedings. Elsevier BV, Nov. 2020. doi: 10.1016/j.matpr.2020.09.539.

[22] B. Hammi, R. Khatoun, S. Zeadally, A. Fayad, and L. Khoukhi, "IoT technologiesfor smart cities," IET Networks, vol. 7, no. 1. Institution of Engineering and Technology (IET), pp. 1–13, Jan. 2018. doi: 10.1049/iet-net.2017.0163.

[23] Annu, D. Kaushik, and A. Gupta, "WITHDRAWN: Ultra-secure transmissions for 5G-V2X communications," Materials Today: Proceedings. Elsevier BV, Jan. 2021. doi: 10.1016/j.matpr.2020.12.130.

[24] M. Krichen, M. Lahami, O. Cheikhrouhou, R. Alroobaea, and A. J. Maâlej, "Security Testing of Internet of Things for Smart City Applications: A Formal Approach," Smart Infrastructure and Applications. Springer International Publishing, pp. 629–653, Jun. 21, 2019. doi: 10.1007/978-3-030-13705-2_26.

[25] S. Bansal and D. Kumar, "IoT Ecosystem: A Survey on Devices, Gateways, Operating Systems, Middleware and Communication," International Journal of Wireless Information Networks, vol. 27, no. 3. Springer Science and Business Media LLC, pp. 340–364, Feb. 13, 2020. doi: 10.1007/s10776-020-00483-7.

[26] U. Khalid, M. Asim, T. Baker, P. C. K. Hung, M. A. Tariq,

ORIGINALITY REPORT

7%	7%	3%	5%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.ijert.org Internet Source	1%
2	doi.org Internet Source	1%
3	Submitted to Florida Virtual School Student Paper	1%
4	eprints.ncl.ac.uk Internet Source	1%
5	epress.lib.uts.edu.au Internet Source	1%
6	Mohammad Omid Khairandish, Meenakshi Sharma, Kusrini Kusrini. "The Performance of Brain Tumor Diagnosis Based on Machine Learning Techniques Evaluation - A Systematic Review", 2020 3rd International Conference on Information and Communications Technology (ICOIACT), 2020 Publication	1%
7	rikkyo.repo.nii.ac.jp Internet Source	1%

8	www.repository.law.indiana.edu Internet Source	<1 %
9	scholars.wlu.ca Internet Source	<1 %
10	Submitted to University of Hertfordshire Student Paper	<1 %
11	Submitted to University of Western Ontario Student Paper	<1 %
12	hdl.handle.net Internet Source	<1 %
13	Yarabala Kurmendra Teja, Vikas Jindal. "Prediction of COVID-19 and Pneumonia from CXR Images", 2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC), 2021 Publication	<1 %
14	A. Chempak Kumar, D. Muhammad Noorul Mubarak. "Classification of esophageal cancer stage using an ensembled CNN with artificial bee colony optimization method and a SVM classifier", Journal of X-Ray Science and Technology, 2023 Publication	<1 %
15	digitalcommons.cwu.edu Internet Source	<1 %
	pdxscholar.library.pdx.edu	

16	Internet Source		<1%
17	www.ijnrd.org Internet Source		<1%
18	academicworks.cuny.edu Internet Source		<1%

Exclude quotes	On	Exclude matches	< 7 words
Exclude bibliography	On		