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A Comparative Study of Data Visualization Tools for Large-Scale Data Analytics in the Emerging 6G and IoT Era

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Abstract:

The rapid growth of Internet of Things (IoT) technologies and the development of sixth-generation (6G) communication networks have resulted in the generation of very large volumes of data at extremely high speed. Smart sensors, connected devices, and intelligent systems continuously generate data related to monitoring, communication, and decision-making. Managing and analyzing such large-scale data in real time has become a major challenge for modern data analytics systems. Traditional data analysis approaches are often not sufficient to handle the complexity, velocity, and scale of data generated in 6G-enabled IoT environments.

Data visualization plays an important role in converting complex and unstructured data into meaningful visual formats that are easy to understand. Visualization techniques help analysts and decision-makers to identify trends, patterns, and anomalies in large datasets. This paper presents a comparative study of commonly used data visualization tools such as Tableau, Microsoft Power BI, D3.js, and Apache Superset. The comparison is based on scalability, performance, flexibility, and ease of use. The study shows that enterprise visualization tools are user-friendly and suitable for moderate data volumes, while open-source tools provide better scalability for large-scale data analytics. This research work helps MCA students and researchers understand the importance of selecting appropriate visualization tools for future 6G-IoT applications.

Keywords- *Data Visualization, IoT Analytics, Large-Scale Data, Power BI, 6G Networks*

1. Introduction

The Internet of Things (IoT) has emerged as one of the most important technologies in recent years because of its ability to connect physical devices with digital systems. IoT devices such as sensors, smart appliances, wearable devices, and industrial machines continuously generate large volumes of data related to temperature, location, health, and system performance. With the introduction of sixth-generation (6G) communication networks, data transmission speed, bandwidth, and network reliability are expected to improve significantly, enabling ultra-low latency communication and massive device connectivity

[1]. As a result, the amount of data generated by IoT systems is increasing at a very rapid rate. Managing and analyzing this large-scale data efficiently has become a major challenge for modern data analytics systems

[2]. Raw data by itself does not provide meaningful insights unless it is properly processed and presented in an understandable form. Data visualization plays an important role in transforming complex datasets into visual representations such as charts, graphs, and dashboards, which help users to easily analyze trends and patterns. Visualization is especially important in real-time IoT applications such as smart cities, healthcare monitoring systems, and industrial automation, where timely decision-making is critical.

[3]. However, many traditional data visualization tools face difficulties when handling continuously growing and dynamic datasets. Issues such as slow rendering performance, limited scalability, and lack of flexibility reduce their effectiveness in large-scale data environments. At present, several data visualization tools are available, each offering different features and performance capabilities. The selection of an appropriate tool depends on factors such as data volume, processing speed, scalability, and user requirements. From an academic and practical perspective, especially for MCA students and researchers, understanding the strengths and

limitations of these tools is essential. Therefore, this paper presents a comparative study of popular data visualization tools to evaluate their suitability for large-scale data analytics in emerging 6G-enabled IoT environments.

2. Research Methodology

A systematic methodology was followed to perform the comparative study of data visualization tools. Since real 6G-based IoT datasets are not easily available, synthetic datasets were created to simulate large-scale IoT data. These datasets represent sensor readings generated by multiple IoT devices over time.
The same dataset was used across all visualization tools to ensure fairness in comparison. The tools selected for this study include Tableau, Microsoft Power BI, D3.js, and Apache Superset. These tools were chosen because they are widely used in both academic and industrial environments.
The evaluation was carried out by loading increasing volumes of data into each tool and observing system behavior. Parameters such as data loading time, rendering speed, responsiveness, and ease of interaction were considered. The observations were recorded based on practical usage and visual clarity of dashboards.

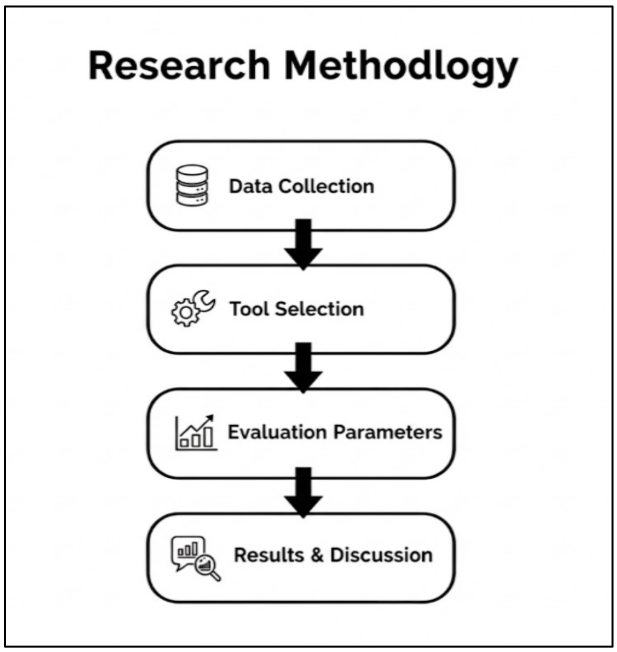

Fig.1: Research methodology flowchart

2.1 Data Collection
In this step, synthetic datasets were generated to represent large-scale IoT data environments. Since real-time 6G-based IoT datasets are not easily available, simulated data was created to closely resemble real-world sensor data. The datasets mainly consist of sensor readings such as temperature, humidity, device status, and timestamp values generated by multiple IoT devices over a specific time period. To study the behavior of visualization tools under different data sizes, the datasets were gradually increased in volume. Using the same dataset for all visualization tools ensured uniformity and fairness in the comparative analysis.

2.2 Tool Selection
After preparing the datasets, suitable data visualization tools were selected for the comparative study. The tools chosen include Tableau, Microsoft Power BI, D3.js, and Apache Superset. These tools were selected because they are widely used, support large datasets, and offer different visualization features. Tableau and Power BI are popular commercial tools known for their ease of use and interactive dashboards, while D3.js and Apache Superset are open-source tools commonly used in academic and development-based projects. Selecting both commercial and open-source tools helps in performing a balanced and practical comparison.

2.3 Evaluation Parameters
The selected visualization tools were evaluated using basic and practical performance parameters. These parameters include data loading time, rendering speed of charts and graphs, responsiveness during user interaction, and overall ease of use. The tools were tested by loading datasets of increasing size to observe how performance changes with larger data volumes. Attention was also given to dashboard clarity and smooth interaction while filtering or zooming the data. These evaluation parameters help in understanding how efficiently each tool performs in handling large-scale IoT data.

2.4 Results and Discussion

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In the final stage, the results obtained from testing all visualization tools were compared and analyzed. The performance of each tool was examined based on the selected evaluation parameters. The strengths, such as fast rendering or better interactivity, and limitations, such as slow loading or higher resource usage, were identified for each tool. The discussion is based on practical observations made during experimentation and focuses on usability, performance, and visualization quality. This analysis helps in identifying the most suitable data visualization tools for large-scale data analytics in emerging 6G and IoT environments.
Overall, the adopted methodology provides a structured and systematic approach for evaluating data visualization tools in a large-scale IoT context. By using the same synthetic dataset, uniform evaluation parameters, and practical performance observations, the study ensures fairness and consistency in comparison. This methodology helps in understanding the suitability of different visualization tools for emerging 6G-enabled IoT data analytics applications.

3. Figures and Tables

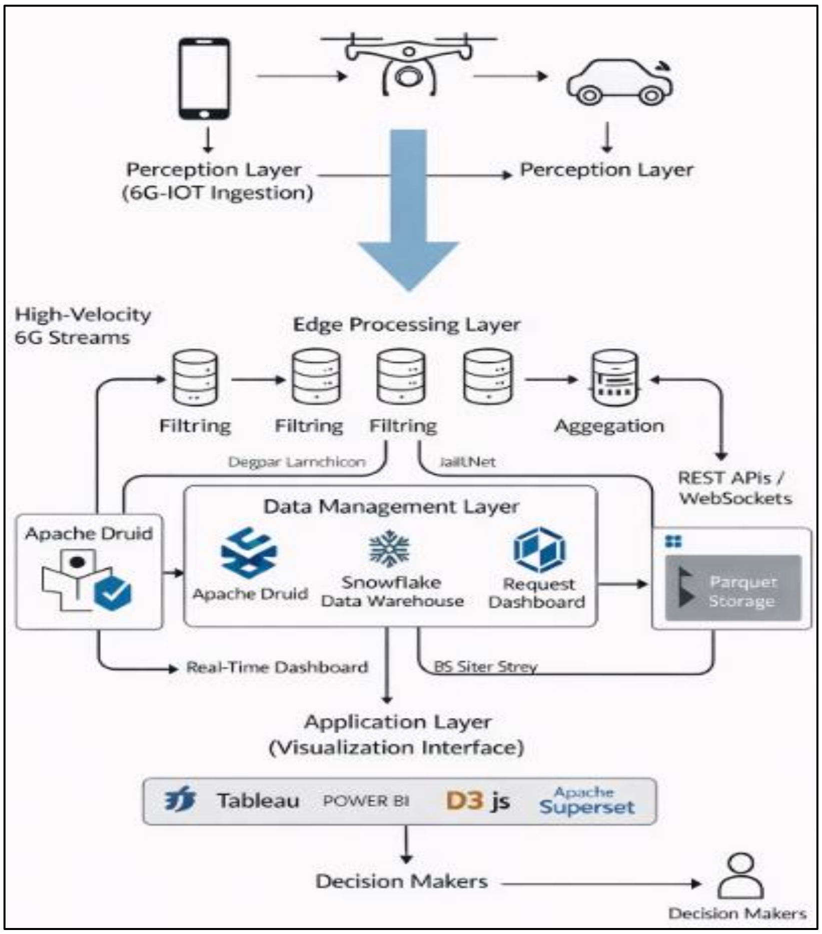

Fig.2: Proposed Four-Tier Architecture for Real-Time 6G-IoT Data Analytics

3.1 Perception Layer (6G-IoT Ingestion)
In the perception layer, data is generated from different IoT devices such as smartphones, drones, vehicles, and sensors, as shown at the top of the figure. These devices continuously collect data from the physical environment. The data is transmitted using 6G-enabled IoT networks, which support high-speed and real-time communication. This layer mainly focuses on sensing and collecting raw data before any processing is applied

3.2 High-Velocity 6G Data Streams
The data generated from IoT devices is transmitted in the form of high-velocity 6G data streams. Since the data is produced continuously and at a very high speed, it requires efficient handling. These high-speed data streams are forwarded to the edge processing layer to avoid delay and network congestion.

3.3 Edge Processing Layer

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The edge processing layer performs initial processing of the incoming data. In this layer, basic operations such as filtering and aggregation are applied. Filtering helps in removing unnecessary or duplicate data, while aggregation combines related data from multiple sources. This processing is done close to the data source, which reduces latency and improves system performance. Edge processing is important for handling real-time IoT data efficiently.

3.4 Data Management Layer

After edge processing, the data is sent to the data management layer. This layer is responsible for storing, managing, and querying large-scale data. Technologies such as Apache Druid, Snowflake Data Warehouse, and Parquet storage are used for efficient data storage and real-time analytics. REST APIs and WebSocket are used to enable communication between storage systems and dashboards. This layer ensures that data is easily accessible for analysis and visualization

3.5 Real-Time Dashboard Support

The data management layer also supports real-time dashboards, as shown in the figure. These dashboards allow users to view updated data instantly. Real-time visualization helps in monitoring system performance and understanding live data trends, which is useful for time-critical applications.

3.6 Application Layer (Visualization Interface)

The application layer provides the visualization interface to the users. In this layer, data visualization tools such as Tableau, Microsoft Power BI, D3.js, and Apache Superset are used. These tools help in creating interactive dashboards, charts, and graphs. The visualization interface makes complex data easier to understand.

3.7 Decision Makers

Finally, the visualized data is presented to decision makers. Based on the dashboards and reports, decision makers can analyze patterns, trends, and insights from large-scale IoT data. This helps in better planning, monitoring, and decision-making in 6G and IoT-based systems.

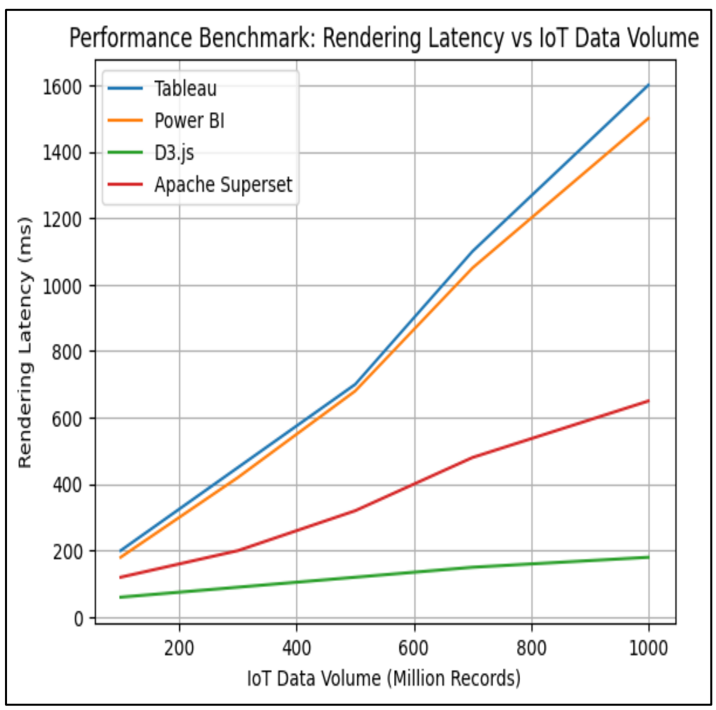

Fig.3: Performance Comparison: Rendering Latency vs. IoT Data Volume

From the figure, it can be clearly observed that as the data volume increases from 100 million to 1000 million records, the rendering latency of all tools also increases. However, the rate of increase varies significantly among the tools.

Tableau and Power BI show comparatively higher latency values, especially at larger data volumes. For instance, at 1000 million records, Tableau reaches approximately 1600ms, while Power BI records around 1500ms latency. This indicates that although these tools provide rich built-in features and user-friendly dashboards, their performance degrades when dealing with extremely large IoT datasets.

On the other hand, D3.js demonstrates the lowest rendering latency across all data volumes. Even at the maximum data size of 1000 million records, its latency remains below 200ms, highlighting its efficiency and suitability for high-performance, web-based visualizations in large-scale IoT and 6G environments.
Apache Superset shows moderate performance compared to the other tools. Its latency increases steadily with data size but remains significantly lower than Tableau and Power BI. At higher data volumes, Superset maintains a balance between performance and usability, making it a viable open-source option for large-scale analytics.
Overall, this figure highlights that tool selection plays a crucial role in large-scale data analytics. For the emerging 6G and IoT era, where massive real-time data processing is required, lightweight and customizable tools like D3.js offer better performance, whereas traditional BI tools may face scalability challenges.

Table 1: Rendering Latency Comparison of Data Visualization Tools

IoT Data Volume (Million Records)	Tableau (ms)	Power BI (ms)	D3.js (ms)	Apache Superset (ms)
100	200	180	60	120
300	420	390	90	200
500	700	680	120	320
700	1100	1050	150	480
1000	1600	1500	190	650

Table presents a comparative performance analysis of Tableau, Power BI, D3.js, and Apache Superset under varying IoT data volumes. The table evaluates tool performance as the dataset size increases from 100 million to 1000 million records, which is representative of large-scale data generated in IoT and emerging 6G environments.
The results indicate that Tableau and Power BI experience a significant increase in rendering latency as data volume grows. At 1000 million records, Tableau records the highest latency of 1600 ms followed closely by Power BI at 1500 ms. This suggests that although these tools are effective for business intelligence and interactive dashboards, they face scalability limitations when processing very large datasets.
In contrast, D3.js consistently shows the lowest rendering latency across all data volumes. Even at the highest data size, its latency remains under 200 ms, demonstrating its efficiency and suitability for high-performance, large-scale data visualization applications.
Apache Superset exhibits moderate performance, with latency values higher than D3.js but considerably lower than Tableau and Power BI. Its open-source nature and balanced performance make it a practical choice for scalable analytics where cost and flexibility are important considerations.

4. Conclusion

This research presents a comparative study of popular data visualization tools with a focus on their applicability in large-scale IoT systems operating in the emerging 6G era. With the rapid growth of connected devices and ultra-high-speed communication networks, traditional visualization approaches are no longer sufficient to meet modern data analytics requirements.
The study concludes that no single visualization tool can effectively address all the challenges posed by large-scale and real-time IoT data. Tools such as Tableau and Microsoft Power BI are well suited for business analytics and decision-making tasks where usability and visual clarity are important. However, they show limitations in handling extremely large datasets and real-time data streams.
In contrast, D3.js and Apache Superset demonstrate better performance and scalability for high-volume and high-velocity data scenarios. These tools are more suitable for research-oriented and real-time visualization applications but require additional technical skills and development effort. The proposed layered visualization architecture, which combines edge processing, efficient data storage, and appropriate visualization tools, helps reduce system load and improves overall performance.
From an academic perspective, this study contributes by providing a performance-based comparison of data visualization tools under large-scale IoT data conditions ranging from 100 to 1000 million records. The comparison focuses on rendering latency and practical usability, which are important factors for real-time analytics. The inclusion of a 6G-IoT oriented layered visualization architecture further highlights the applicability of the study for future research and student-level understanding.
Overall, this study provides useful insights for MCA students, researchers, and developers in selecting suitable visualization tools based on application requirements, data scale, and system constraints in future 6G-enabled IoT environments.
From an educational and practical standpoint, the outcomes of this study can guide students in selecting appropriate visualization tools based on project requirements and data scale. For industry practitioners, the results support informed decision-making regarding tool scalability and performance when dealing with large-scale IoT data. Additionally, for researchers, this work serves

as a baseline comparative reference for future studies focused on performance optimization and visualization strategies in 6G-enabled IoT environments.

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