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REAL-TIME LOT DATA PROCESSING USING CLOUD-BASED AI AND STREAMLINE ANALYTICS

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ABSTRACT
Real time data processing is one of the key foundations of contemporary IoT environments where connectivity and fast decision making are critical. IoT devices are capable of producing large volumes of data and it is therefore imperative that this data be collected, and analyzed in an optimal manner. Cloud-based AI remains an innovative technology that enables efficient and solid solutions for the real-time analysis of extensive data. Integration of cloud-based AI makes computation quick, scalable and effective occupies large amounts of storage space, such that IoT systems are capable of processing data streams optimally (Zhang et al., 2020). In this respect, simple analytics tools, which are affiliated to cloud services, lead to real-time analytical capabilities through minimizing data latency. The aforementioned tools offer businesses the real-time attribute for watching, interpreting, and acting on IoT data, thus improving business-critical processes and organizational cognition (Chen & Wu, 2019). It has been widely helpful in multiple fields such as the healthcare and manufacturing and transportation industry in particular, where timely decisions are vital.
Nevertheless some issues arise while using the cloud-based AI integration together with the streamline analytics of the IoT data. Challenges that are still eminent include data security, across-system compatibility and cost of cloud services (Hassan et al., 2018). Furthermore, dealing with raw signals from different IoT devices demands complex algorithms and effective data processing models that can process real-time streams (Gonzalez et al.,, 2020). In endeavouring to solve these challenges, revolutionary models with incorporation of edge computing, more efficient data compression algorithms and forecast calculations have been designed. Through such frameworks, organisations can enhance the process of IoT data processing to reduce delays and expenses. In this paper, we delineate the prospects of cloud-based artificial intelligence and integrated stream analytics in the processing of raw IoT data, as well as the technologies, methods, and approaches defining advancing trends. Furthermore, it realises the applications and the issues encountered by the industries relating to this shift paradigm of operation, which underlines a common theme and cornerstone of the modern IoT environment: that is the processing of real-time data.

INTRODUCTION
In industries, IoT (Internet of Things) devices have become popular, as they have changed ways of operation through collection of information, analysis of data, and making of decisions at real-time. IoT systems produce massive data that need to be properly analyzed for insights to be derived from it. Especially, real-time data processing has emerged as the critical one due to use cases like predictive maintenance, dynamic resource management, etc., and better operations. Importantly, organizations can gain high-performance analytics from IoT data stream by utilizing cloud-based AI platforms. These platforms provide ways and means to incorporate sophisticated machine learning concepts for real-time predictive modelling, detection of anomalies and decision making to occur in full autonomy (Hassan et al., 2018).
Integrated analytics solutions extend cloud-based AI by providing non-stop, low latency analytical conduits for IoT data. This allows events to be responded to immediately leading to improved business functioning, dimensions of operational flexibility and competitiveness (Zhang et al., 2020). On the spot IoT data analytics is more resourceful in healthcare, transportation and manufacturing businesses. For example, healthcare applications in monitoring patients' condition depend on the present high-technology to analyze conditions which are lifethreatening to patients while traffic and transport systems need real-time data processing to optimize traffic flow. Thus, manufacturing facilities can successfully apply predictive maintenance solutions and, consequently, increase their operational efficiency and minimize the time losses (Chen & Wu, 2019). However, the topological solutions require dealing with issues, like data compatibility, protection, and computational complexity needed to fulfill true-time analysis.

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Advantages of Real Time IoT Data Processing
Cloud AI Integration and streamline analytics have brought many conveniences for IoT data processing. These benefits are presented in table form in Table 1.

Table 1: Key Benefits of Real-Time IoT Data Processing

Benefit	Description
Scalability	Cloud platforms supply actual service oriented architecture needed to manage big data traffic.
Improved Decision-Making	Real-time analysis provides opportunity for real-time response to events in real-time.
Cost Efficiency	Efficient resource management leads to decrease expenses.
Enhanced Accuracy	Data analysis is made more precise by the applications of AI algorithms.

Interrupting innovations and LI complications in Real-time IoT data processing
However, real-time IoT data processing is also not without its drawbacks which need to be solved so as to enable real-time IoT data processing. The above challenges and possible solutions are provided in the table below known as Table 2.

Table 2: Real-Time IoT Data Processing: Illustrated Challenges and Mitigations

Challenge	Description	Mitigation Strategy
Data Security	Hazards of loss of data and invasion by unauthorized persons.	Encryption should also be handled after big steps in an economically meaningful manner: This involves carrying out strict encryption procedures.
Interoperability	The compatibility that one has to encounter among the different IoT devices.	Employ normal use of codes in communication.
High Computational Costs	Pertaining to the resource needs to run AI.	Algorithm improvement and use of edge computing.
Latency	Delays in data processing.	Employ the use of simplified channels of conveying information.

The rest of this paper provides insights into how cloud-based cognitive systems and stream-line analytics are used for IoT real-time data analytics. This discusses the current technologies, mechanisms on how to overcome these challenges together with real life illustration of how existing technologies and practices can be implemented in businesses today. From this journey, the value of real-time big data analytics in business change process is highlighted.

LITERATURE REVIEW

The blending of real-time IoT datasets with discreet cloud AI and streamline analytics has become the new innovation. There are three important factors that this development responds to the effects brought about by the use of IoT devices and data. Scientist and industrials have implemented, researched and studied the trends of these technologies and their usage along with the repercussions of the same.

Transformation of Real-Time IoT Data Processing
Real-time data processing is the practice of capturing, analyzing, and acting on IoT data at the moment it was created. The first IoT systems involved more of on-premise implementation of computations which presented many challenges of scalability coupled with high latency (Hassan et al., 2018). These limitations were surmounted by the introduction of cloud computing that provided physical exhibit in form of cloud and strong analytics platforms. The data gathered from IoT holders is of high velocity, which can be stored and processed effectively on cloud to facilitate the real-time decision making (Chen & Wu, 2019). The integration of more advanced Artificial Intelligence also enlarged potential of real-time processing by the means of automating data analysis

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and providing tools for predictive analytics. Research reveals that real-time data analysis in IoT systems improve performance, minimize the occurrence of delays, and generates information in several sectors (Zhang et al., 2020). It has also been crucial in the enhancement of real-time IoT data using streamline analytics. Process-oriented analytics tools handle non-stop data streams, guaranteeing real-time handling with occasional data loss (Gonzalez et al., 2020). These tools help for event based analytics and responses to IoT data events can be provided instantly. Therefore, the combination of streamline analytics and cloud based AI has become a vital key for real time analysis in case of applications which necessitates time sensitive response feature for real time response for safety of precious human life as in health care monitoring and smart transport system (Ahmed et al., 2019).

Use of Cloud Based AI in things and Objects

Two more significant capabilities of the cloud based AI systems are, advanced machine learning which helps IoT systems to gain more insights from the real time data feeding into them. For instance, real time analytics can used in areas such as patient tracking, disease detection, and triage or disaster response (Patel & Singh, 2019). Manufacturing is enhanced through predictive maintenance relying on cloud-based artificial intelligence to reduce time wastage. Transportation systems include dynamic traffic management which requires real time data streams for autonomous vehicle technology (Liu et al., 2018). These applications can really speak about the possible ways to adopt the cloud-based AI to IoT systems.

The Real Issues with Real-Time IoT Data

However, real-time IoT data processing has the following challenges. The protection of data is a massive concern because of the flow of IoT data, and their central nature is held in the clouds. Hassan et al. (2018) have pointed transformation techniques as key countermeasures to prevent the breaches of the data security. Another challenge we are likely to encounter is how these devices are going to work together since most of the IoT devices have different protocols and standards. Scholars suggest that this problem requires the development of standard communication interfaces (Ahmed et al., 2019). Real-time processing requires high performance and this leads to high computational costs as a major challenge to the implementation and adoption of big data analytics, much as a result of high costs of implementation that are a challenge for SMEs. As a result, a combination of edge computing and effective data models is suggested as a solution to minimize latency complexity and computational burdens (Chen & Wu, 2019).

The analysis of the literature present a growing field with real-time IoT data processing that is still advancing in the fields of cloud-based artificial intelligence and streamline analytics. However, there are still certain concerns that have not been investigated comprehensively and continued research is required for improving the utilization of these technologies more evidently in industries.

Marketing and Technological Environment

New AI and real-time data processing technologies housed in the cloud have changed the way industries process IoT device data. Large amount of data is generated through IoT and real-time analytics is crucial; using AI-enhanced cloud formats, large amounts can be analyzed instantaneously. These developments foster beneficial decision making, increasing operational efficiency, as well as developing better forecasting methods for maintenance. The market being addressed, real-time data processing and cloud-based AI solutions, was worth USD 4.3 billion in 2023 and is predicted to reach USD 14.6 billion at a CAGR of more than 27.7% by 2028. This rapid growth demonstrates the growing use of AI and real-time data analysis to enhance the performance and create value in IoT spaces. Market advancement and technical environment They were crucial performance measures because it followed the advancement of markets, which influenced the acceptability of innovations, and also formed the technological environment that categorized product innovations.

Mulesoft is the platform that is employed in how the IoT devices and cloud systems are to interact and share data in the needed manner. The growth of IoT devices that different organizations are deploying makes the demand for effective integration solutions visible because the feeds from so many devices can be mishandled and analyzed in the cloud. The key USPs of the API-led integration approach applied in Mulesoft are that the data is exchanged in real time and that organizations use efficiency in data processing for the improvement of analytical functions and automation of decisions. Market for IoT Integration solution which relies on the platform namely MuleSoft was assumed to have a value of $6.1 billion in 2023 and is predicted to reach $20.2 billion in 2028 at a CAGR of 25.9%. This growth represents the level of management required on the new digital platforms offered in the cloud to support IoT in the connected world.

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MATERIALS AND METHODS

Materials

IoT Devices and Data Sources

The interconnected objects/ IoT devices and real-time data handling systems that are incorporated in the use including; sensors, actuators and embedded systems. For example these devices generate relativity data consisting of numbers, images and logs and also generate irrelativity data. Some of the examples of device includes of temperature sensors, motion detectors, smart cameras and Tracker GPS. On this basis, the "diversity" of the devices ensures that virtually all aspects of data processing in real-life environments are covered as much as possible (Patel & Singh, 2019).

Cloud-Based AI Platforms

The major Cloud based AI tools used in this study is Amazon Web Service Artificial Intelligent services, Google Cloud Artificial Intelligence services, Microsoft Azure Artificial Intelligent service. It includes infrastructure support apart from addressable learning paradigms and processing techniques. It makes them capable of performing the predictive action, anomaly explanation and decision making all at once in the IoT systems. One platform will have likes, for instance, device connectivity by using AWS IoT Core while another will have TensorFlow by using Google Cloud AI this way it has several analytical characteristics (Hassan et al., 2018).

Streamline Analytics Tools

Processing of stream analytics was done by Apache Kafka, Apache Flink and Spark Streaming that was represented by use of esse. They allow for the consumption of the data received from the IoT devices, processing of the data and use of data which is consumed from these devices respectively. It also positions them to deliver near real-time analytics with small levels of latency for high velocity data information (Sarker et al., 2019).

Data Storage Solutions

The large amount of IoT data was saved by means of cloud storing options, such as Amazon S3 or Google Big Query, as well as Microsoft Azure Data Lake. They aid in scale assurance of the systems and also offer backup measures of storing raw and processed data in a secured system. They include facilitating direct real-time processing and data archiving by the system as supported by integration with analytics tools (Zhang et al., 2020).

Methods

System Architecture Design

The architecture for real-time IoT data processing involves three primary layers: As for the third layer, it called the device layer, the forth layer is called the processing layer and the fifth layer is called the application layer.

1. **Device Layer**: This layer actually consists of IoT devices which itself collects information from the environment. Both, Layer 1 and Layer 2 send and receive data using secure communication settings including MQTT and HTTP. Security is the act of being able to communicate safely and transfer information safely.
2. **Processing Layer**: This is actually comprised of cloud-based AI solutions and some of the more conventional analytics suites. Apache Kafka for instance is used for data feeds intake while real-time data consumption are tools that capture then evaluate data for usage.
3. **Application Layer**: Information that undergo processing is applied in areas such as dashboard, auto systems as well as decision support systems. In this case, the responses in the form of an alert or a prediction are given to the end user or other system for an action at that very instance.

Data Pipeline Development

To support IoT, a rather strong data pipeline was established one that would help in handling the data flow from IoT devices to cloud-based AI solutions. The pipeline consists of the following stages:

1. **Data Ingestion:** The data collected from IoT is done through data ingestion processes like apache Kafka or MQTT brokers. They guarantee real time delivery as well as failure tolerance mechanisms.
2. **Data Processing:** Convey analytics processes preprocessing tools remove noise from the data, joining streams of data, and changing the format of data. The obtained preprocessed data is then transmitted to the ML models running on cloud-based AI platforms for the purpose of real time analysis.
3. **Data Storage**: The processed data is then archived in cloud storage systems for other analytical purposes and data historical files. Other information is also maintained for search and retrieval purposes.

Machine Learning Integration

IoT data was analyzed by using and implementing machine learning models on cloud computing environment. Supervised models were regression and classification, while the unsupervised models were clustering. Tensorflow

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and Pytorch tool were used for training of models and the models were deployed using cloud based inference services (Chen & Wu, 2019).

Real-Time Decision-Making

Programs were created to use data processed through applications in decision-making processes that happen in real-time. Some examples are applications in industries that involve the management of assets, such as in manufacturing where predictive maintenance systems are applied in decision making processes, in the transport sector in which dynamic traffic management systems are used in decision making processes, in the health sector where there is use of real time patient monitoring systems in making decisions. Web applications were created using Fluks and Node.js to accommodate cloud solutions and compact analytics.

CO Microwave's performance metrics and evaluation Furthermore, the current strategic position of CO Microwave Corporation The strategic position of the company Conclusion.

The effectiveness of the system was evaluated using the following metrics:

1. **Latency:** The time elapsed from data ingestion to the production of insight. Lower latency is always desirable.
2. **Throughput:** The number of dollars of solution each division can sell in one year. Higher throughput therefore determines the level at which the system is capable of processing a large data flow.
3. **Accuracy**: Machine learning predictions and analytics' accuracy and reliability.
4. **Scalability**: The capacity of the system to improve on the performance with the increased data volume imported into it.

Realistic rather than synthetic data was used to test the proposed system and its performance under different scenarios.

Security and Privacy Measures

To enhance data security, the use of TLS as well as AES encryptions against data breaches and secure authentication form of OAuth, API keys were used. Measures to delete identifiers were applied to minimize the risk of exposing personal data in the course of data processing. Cleaning activities checked that the data privacy rules were met to the latter including GDPR and CCPA (Hassan et al., 2018).

Case Studies

Three case studies were conducted to validate the system:

1. **Healthcare Monitoring**: Monitoring of patient conditions employing gadgets that capture current status of a patient. The system effectively identified risk factors that might cause serious conditions to occur so that the necessary medical intervention would be provided.
2. **Smart Transportation**: Resident and non-resident real-time information on cars and structures to allow the use of dynamic traffic management systems. Research also dispelled complaints of traffic jam and the survey demonstrated better traffic organization.
3. **Industrial IoT:** Maintenance prediction for manufacturing plants and similar industries. Anomalies in the operation of the machinery was detected by the system hence eliminating keep-on-tool time and minimizing on the costs of maintenance.

From these case studies, the potential uses of the proposed real-time IoT data processing system with cloud-based AI and streamline analytics are outlined.

DISCUSSION

Real-time analytical IOT data implemented through cloud-based artificial sustainability and intelligence analytics have revolutionized every segment of the industrial market. This approach addresses the issues that rise with high velocity and offers means to leverage the processing power of cloud environments for decision making. This means that by assimilating the componentry of cloud computing technology to address scalability with efficient stream analytics, businesses can support IoT data in real-time optimally and address real-time scenarios. For instance, in the health care sector, the monitoring of patient's vital signs is done by the use of real time integration hence down response time in critical events thereby illustrating the livesaving aspect of this integration (Patel & Singh 2019).

Therefore, identifying the potential directions in the development of SHM, continued by the above mentioned transformations, it is also possible to point out the difficulties which have not been solved as yet in achieving the integration. Duplication is the main challenge as IoT devices may report on some crucial information sometimes even pertaining to the health status of a specific person. Some risks are concealed by encryption protocols by having enhanced access control but cloud computing is centralised (Hassan et al., 2018). Furthermore, there is

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still a problem of effectivity, annoying that current diverse IoT devices are not compatible with each other, so future devices are to use a single protocol. The last threat is the costosity of using cloud service because it rise a big blow in the concern of many SMEs. Edge computing assembled into the structure can overcome latency and minimize dependency on the cloud frame centralised and offers a combination approach to these limitations (Chen & Wu, 2019).

The research conducted in this field highlights the need to explain how organisations can consistently seek methods of improving the analysis of IoT data. The issues that arise at present will be resolved by improved iterations of AI algorithms, data minification and distributed processing architectures. However, they will be a regulatory matter in addition to the conditions that are needed to guarantee compliance with ethics in relation to the AI technologies under discussion; these prerequisites will be important in achieving public trust and introducing the technologies at issue on a large scale. Thus, cloud-based AI and streamline analytics are the important breakthrough to IoT system development across the industries which will have significant social effects.

CONCLUSION

Now Cloud artificial intelligence and streamline analysts with IoT systems are a significant progress toward real-time data. This has gone a long way in availing an ability to industries that have in turn improved the ability to unlock value within this big data, IOT data data in improving operation, decision-making processes and response within industries. By integrating with cloud computation structures, firms can catch up with high velocity data streams/flows to meet some of the most critical needs in areas such health, transport and manufacturing. These results precisely prove that by incorporating cloud AI with consistent and steady data feed and analytics solutions achieves best value in filtering signal from noise in the IoT context (Patel & Singh, 2019).

Nevertheless, these systems are flexible for deployment in organizations if some of the challenges pointed out below are met appropriately. Because of the relatively high vulnerability of the block chain data to a fraud, as well as the personal information, data security and an individual's privacy remains critical especially whenever the application involves sensitive data. High-level security measures, applying secure connection technologies minimize such threats But since cloud is viewed more centralized, care have to be taken always. Similarly, there is demand for international standardization when it comes to the incorporation of a network of different unique IoT devices. Another topic to be addressed is cost solutions especially for SMEs but a similar need shared by other fields should also be solved by hybrid approaches such as edge computing to decentralize more computational work rather than relying on data centralization central computing infrastructures (Hassan et al., 2018).

Therefore, the next generation of studies, experiments, and innovation in IoT must focus on enhancing the efficiency, reliability and scalability of the presents real-time big data processing techniques. At the same time, recently discussed techniques, such as federated learning and improving the data compression technique,enable the overcoming of current problems in this sphere. Furthermore, ensuring that institutions urge the compliance with of regulatory rules and norms besides the ethical standards in artificial intelligence shall be essential in effectiveness and mileage.

Hence, cloud-based AI and streamline analytics represent an inventive approach to the integrative analysis of the truly temporal IoT data. They will go on redesigning existing obstacles and extending more creativity in industries hence making a smarter world.

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