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IoT devices enabled for data analytics intelligent decision making using machine learning algortihms: A Brief Literature Review

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Abstract - *New advances in the realm of information technology have led to an exponential increase in the amount of IoT data. IoT data, which is produced at enormous volumes and from a range of devices and sensors, including those that measure temperature, motion, sound, and other variables, has substantial gaps, is loud, and is extremely unstructured. Therefore, it is challenging for general analytics and business intelligence tools that are accessible to handle large amounts of Internet of Things data. The only way to solve the aforementioned issue is using big IoT data analytics. This work analyzed open-sourced and proprietary big IoT data analytics platforms and presented a comparative analysis with the aim of assisting future big IoT data analytics research.*

In order to gain insightful knowledge and make wise decisions, businesses now depend on big data analytics. The well-known frameworks for big data processing and analytics mentioned in the paper. In terms of functionality, ease of use, scalability, and performance, this study compares and contrasts different data analytics tools. We seek to ascertain the advantages and disadvantages of each framework by examining a number of factors, including fault tolerance, programming paradigms, data processing models, and ecosystem tools. Businesses can choose the best framework for their unique Big Data analytics needs with the aid of the study's findings.

Key Words: IoT, Data analytics, Machine Learning, Decision making

1. INTRODUCTION

Data from the Internet of Things (IoT) has increased rapidly in volume and size, impacting many facets of business and technology by piquing people's and organizations' interests. According to the Statistical Report [5], the consumer community will employ 12.86 billion IoT sensors and devices by 2020, growing at a rate of 34.89% annually based on the CAGR of 2017. The Internet of Things is predicted to have a 7.1 trillion US dollar worldwide market value by 2020. [8] data indicates that by 2030, there will be one trillion more sensors. Big IoT data growth will be impacted by this expansion. The Internet of Things analytics market [6] is anticipated to increase in size from $7.19 billion. But one of the most demanding and developing markets in the world today is IoT analytics, therefore there's pressure to discover a trustworthy big data analytics solution to extract useful information from IoT data.

1. **Internet of Things (IoT):** The term "Internet of Things" (IoT) describes a network of objects or gadgets that are linked to the internet and have sensors, software, and other electronics built into them that allow them to gather and share data. Kevin Ashton is recognized as the father of the Internet of Things, having invented the term "The Internet of Things" in 1999. The Internet of Things is a new data source that was created with the intention of improving resource efficiency and helping to make decisions about how best to use resources.

2. **Big data from the Internet of Things:** The enormous amount of data generated by various types of sensors at high speed is called IoT big data. Sensors are in demand in almost every industry, and the Internet of Things will bring a huge influx of big data called IoT big data. The Internet of Things (IoT) and Big Data are two different fields that are closely intertwined, but talking about IoT without Big Data is not very relevant to end users and technocrats.

3. **Big IoT Data Analytics:** The rapid deployment of IoT devices will generate Big IoT Data, but without analytics, Big IoT Data will be like trying to hear a single voice in a crowd of millions. Also, organizations are under constant pressure to gain insight value from Big IoT Data in order to gain a competitive advantage and improve their lives. This is where big data analysis comes in. Big IoT data analytics can handle large amounts of data generated by IoT devices, resulting in a continuous stream of information. Big data analysis has been used in a variety of fields and domains, including medical research, transportation and logistics solutions, global security, and prediction and management of environmental issues.

3.1 What distinguishes IoT analytics from other analytics?: Analytics is a tool that extracts value from massive amounts of data generated by connected Internet of Things devices and converts it into actionable intelligence.

The domain of analytics is determined by the type of data and the type of knowledge extracted from it. IoT data analytics is not the same as mobile analytics, web analytics, or log analytics.

4. **Massive IoT Data Analytics Platforms:** There are numerous options available for big IoT data analytics. AWS IoT Analytics, Micorsoft Azure IoT Suit, IBM Watson IoT Analytics, and Splunk Big Data Analytics are a few examples of proprietary solutions. Open source solutions include FIWARE3, OpenMTC4, SmartThings5, Hadoop with Map Reduce, Hive, and Spark. In order to create an automated system to control the devices, we can connect various devices using the aforementioned solutions. However, because there is a lack of standardization for the Internet of Things, different IoT platforms and tools use different terminology and different technological concepts for implementation. The platform and the tools are not uniform as a result of the same. Consequently, it takes a lot of time to identify the best platform for implementing IoT-based solutions, especially when multiple platforms and technologies are used by each solution.

2. LITERATURE REVIEW

In this review, we examine the body of research on big data analytics for the Internet of Things and identify its obstacles, including technological ones.

1. **IBM Watson IoT Platform & Analytics:** The cloud-hosted, fully managed IBM Watson® IoT Platform service makes it easy to get value out of Internet of Things (IoT) devices. By connecting a wide range of devices and gateway devices, we can perform powerful device management operations, store and access device data, and leverage IBM Watson IoT Platform for IoT analytics. The Business Intelligence (BI) field is well-known for IBM Watson Analytics (WA). In the IBM cloud, IBM Watson Analytics (WA) is a sophisticated data analysis and visualization tool for identifying and evaluating hidden values.

With IBM Watson Analytics, you can create robust queries for a range of databases, such as Cloudera Impala, MySQL, Oracle, PostgreSQL, PostgreSQL on Compose, Sybase, Sybase IQ, and Teradata. Together with the IBM Watson IoT Platform, Data Science Experience (DSX) is a potent machine learning tool that helps users visualize and understand the data that is sent from connected devices. IBM Watson analytics's inability to perform streaming data analytics is one of its limitations.

2. **AWS IoT Platform & Analytics:** The processes necessary to analyze data from IoT devices are automated by AWS IoT Analytics. IoT data is filtered, transformed, and enhanced by AWS IoT Analytics before being saved in a time-series data store for further examination. The platform known as AWS IoT Core makes it possible to link Internet of Things (IoT)-enabled devices to AWS services. It also protects data and interactions between processes, devices, and data, and allows us to interact with devices even when they are not online. With the help of AWS IoT Analytics, a fully managed service, you can easily analyze vast amounts of IoT data without having to worry about the expense and complexity of developing your own IoT analytics platform. Fully managed AWS IoT Analytics automates the analysis and scaling to accommodate petabytes of IoT data.

3. **Microsoft's Azure IoT Platform & Analytics:** We can connect, monitor, and control your IoT assets at scale with the Azure Internet of Things (IoT) analytics suite, which is a collection of Microsoft-managed cloud services, edge components, and software development kits. Create Internet of Things (IoT) applications by securely connecting, managing, and tracking billions of devices with Azure IoT Hub. IoT Hub is a versatile cloud platform that works with several protocols and open source SDKs.

Azure Databricks, HDInsight, Data Factory, Machine Learning, Data Lake Analytics, Stream Analytics, Azure Analysis Services, and Azure Data Explorer are just a few of the analytics-specific tools that Microsoft Azure offers.

4. **Tableau Big Data Platform & Analytics:** With Tableau, we can prepare, analyze, collaborate, and share your big data insights using an end-to-end data analytics platform. Tableau is a master at self-service visual analysis, enabling users to explore governed big data and pose new questions and quickly share their findings with others in the company. One of the business intelligence (BI) and data visualization tools that is developing the fastest is Tableau. More data can be gathered, stored, and managed than ever before thanks to the Tableau Big Data platform.

Enterprise-grade security, governance, deployment flexibility, and management are all integrated into Tableau's analytics platform to empower IT. An organization can optimize the value of its people and data with the help of Tableau Analytics. Tableau eliminates the need to extract specific reports from various databases or applications. Tableau offers a variety of analytics solutions, such as Tableau Desktop, Tableau Prep, Tableau Server, and Tableau Online.

5. Splunk Big Data Platform & Analytics: Using a big data tool like Splunk, we can transform unstructured data into meaningful insights. A suite of tools is included with the Splunk architecture to facilitate integration with data sources and enable data collection, queries, indexing, analysis, and visualization. Splunk is an effective platform for machine learning. However, its significance is currently growing in both the technical and commercial domains [5]. With the exception of creating an index for the data, whichis akin to creating an index for text, Splunk is unique from the others. It does most of the work in this process, but it is not precisely an AI routine collection or report generation tool. Because of the great flexibility of this type of indexing, Splunk is an application-tunable platform that enables applications to be comprehended and learned from the log files. Several solution packages, including Microsoft Exchange Server Monitoring and Web Attack Detection, are used to market Splunk.

For correlating data in numerous common server-side scenarios, this index is highly helpful. Getting a text string and performing a broad search in the indicator is Splunk's goal. For instance, Splunk gathers the document's URLs or IP addresses and packages them into a timeline based on the detection of data. Drilling down into the data set is done using all other relevant fields. Even though this is a straightforward procedure, it works very well if the user looks up the right kind of needle in the data source. Splunk is a great tool for tracking text strings if the user can locate the right one.

The log file is a very large program. Currently, users can exchange data between systems and solidify Splunk data from Hadoop through the use of a new Splunk tool called Shep, which is being used for private beta [2].

6. Apache Hadoop: Using straightforward programming models, Apache Hadoop software is an open-source framework that enables the distributed processing and storing of massive datasets across computer clusters. For distributed processing and storage of massive data sets on commercial hardware clusters constructed in a dependable, fault-tolerant manner, Apache Hadoop is an open-source Java software framework.

The Hadoop Distributed File System (HDFS) for storage and MapReduce for processing comprise the core of Apache Hadoop. In the Hadoop stack, HDFS is at the bottom. The file system is distributed. Programming can be done using the MapReduce paradigm. Large datasets are managed by the distribution mode.Using mapping operations, the model's map() and reduce() functions apply data partitioning to the HDFS file's data, sorting and redistributing the results according to the output's key values. Using the matching key from the mapping stage of the job, the data then reduces the output data item group.

7. Apache Hive: Large-scale analytics are made possible by the fault-tolerant, distributed Apache Hive data warehouse system, which also makes it easier to read, write, and manage petabytes of data stored in distributed storage using SQL. For processing structured data in Hadoop, Hive is a data warehouse infrastructure. In order to compile large data and simplify querying and analysis, it is constructed on top of Hadoop. Hive offers a querying interface akin to SQL for data stored in multiple databases and file systems that are integrated with Hadoop. In the conventional RDBMS format, the data is kept.

Hive employs HiveQL, a query language that works similarly to SQL and gives users a way to query data. Because custom mappers and reducers are inefficient or inconvenient to express in Apache HiveQL, traditional MapReduce programmers are also permitted in Apache Hive. While the Hive framework offers optimization and usability features that UDF does not, Map Reduce does. The Metastore, which is used to store schema data, is a crucial part of Hive. Generally speaking, a relational database houses this metastore. Java Database Connectivity (JDBC) interfaces, Web GUIs, and other methods can be used to communicate with Hive.

8. Apache Spark: On single-node computers or clusters, Apache Spark is a multi-language engine that can be used to perform data science, machine learning, and data engineering. An open source framework for distributed cluster computing is called Apache Spark. After being created at the University of California, Berkeley's AMPLab, it was subsequently given to the Apache Software Foundation. Real-time streaming data is processed by the open-source, in-memory data processing engine Apache Spark.

To achieve high performance for batch and streaming data, Apache Spark makes use of the most sophisticated DAG scheduler, query optimizer, and physical execution engine available. In the global market, the share of Spark use cases in computer software and information technology and services is roughly 32% and 14%, respectively. The primary application of Apache Spark is streaming data, which can be read from sources such as disc files, Hadoop output, Kafka, and other sources for interactive queries on massive datasets.

3. COMPARATIVE REVIEW

The thorough evaluation of proprietary data analytics platforms is covered in detail in this section.

3.1 IoT Data Big Data Analytics Platforms that are proprietary

Analytics for Big Data	Private/ Public Domains	Categories of Information	Analytics Category Assistance	Is cloud support available?	Assistance with Visualization	Storage	Assistance with machine learning algorithms	Interpretation Assistance	Protocol for Collecting Data	Security
IBM Watson IoT Analytics	Private	Both organized and unorganized	Offline Analytics, Edge Analytics	Yes	Yes	No SQL database, cloud-based	▪ Only Spark ML Classification and Regression are supported. ▪ scikit-learn ▪ TensorFlow TensorBoost	SQL, R, Python	Protocols like WebSockets HTTP	HTTPS, TLS
AWS IoT Big Data Analytics	Private	Both organized and unorganized	Yes	Yes	Yes (Amazon IoT Panel)	S3 and Dynamo Db	▪ Regression, ▪ Both binary and multi-class classification	No*(Uses In-Built Tools)	Protocols like WebSockets, HTTP 1.1, and MQTT	Transport Layer Security (TLS), Signed Verification (Sig V4, X.509)
Microsoft Azure IoT Suite	Private	Both organized and unorganized	Offline Analytics with Machine Learning Real Time Analytics In Memory Analytics	Yes	Yes(Using PowerBI for Visualization)	Document Database For storage, SQL Db, and SQLData Warehouse	▪ Regression, Decision Tree, Forest, Boosted, Bayes, SVM, Neural Network, Supervised Binary and Multiclass Classification ▪ Self-supervised: K-Means Identification of anomalies ▪ Text analytics	SQL, R, Python	Yes	Yes

Tableau Big Data Platform Analytics	Private	Both organized and unorganized	In-Memory and Disk Analytics	Yes	Yes	Exasol and MemSQL	Machine algorithms of all kinds	R	Yes	Yes
Splunk Big Data Analytics	Private	Both organized and unorganized	Real Time Analytics	Yes	Yes	Apache Cassandra, Couchbase, and MongoDB	Machine algorithms of all kinds	SQL, R, Python	Yes	Yes

3.2 IoT Big Data Analytics Tools Available in Open Source

Specification\Analytics for Big Data		**Hadoop**	**Hive**	**Apache Spark**
Categories of Information		Unorganized	Both organized and unorganized	Unorganized
Storage		Hadoop Distributed File System	Used Rational Data Base Management Model	Non-SQL database management system was used
Mechanism	**Operational Mechanism**	Map Reduce	Hive	Spark
	Types of Mechanism	batch mechanism	batch mechanism	Both Real Time & Batch mechanism
Analytics	**Method of Analytics**	Java based embedded quey	Hive-SQL	1. Spark-SQL 2. Graph Analysis 3. Machine Leaning Algorithms.
	Analytics types	Batch Analysis	Batch Analysis	In Memory Analysis & Batch Analysis
Assistance with Visualization		It is not necessary to use third-party software.	It is not necessary to use third-party software.	Yes
Is cloud support available?		both locally and on cloud servers	both in Th cloud and on-premise e s	both locally and on cloud servers
Reliability in scale		Manual	Manual	Manual
Interpretation Assistance		Java	Python,C++, PHP, Java, etc.	Scala, R, Python & Java
Technique of Access		JDBC	ODBC, JDBA & Thrift	ODBC, JDBA
Able to perform IoT Analytics and establish connections with IoT devices?		Yes	Yes	Yes

4. TECHNOLOGY-RELATED OBSTACLES AND DIFFICULTIES FOR IoT ANALYTICS

1. One of the main causes of the high failure rate of IoT projects is technology that was never intended for IoT analytics and is attempting to fit with the available IoT analytics.

2. The volume and velocity of Internet of Things data generated by sensors and devices, which must be processed and analysed instantly, are too much for traditional approaches to data integration to handle.

3. Regardless of the number of endpoints involved, the characteristics of IoT data present a unique set of challenges that call for data storage management solutions to enable quick decisions.

4. It is not possible to analyse complex IoT data and make accurate decisions with time lag as a performance parameter using the current IoT data analytics capabilities.

5. CONCLUSION

A review of the literature was done on various studies on underwater sensor routing protocols that were finished between 2018 and 2023. Different approaches were used to conduct the survey, and their benefits and drawbacks were examined and discussed in order to aid future researchers.

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