SMART LOGISTIC BASED ON MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

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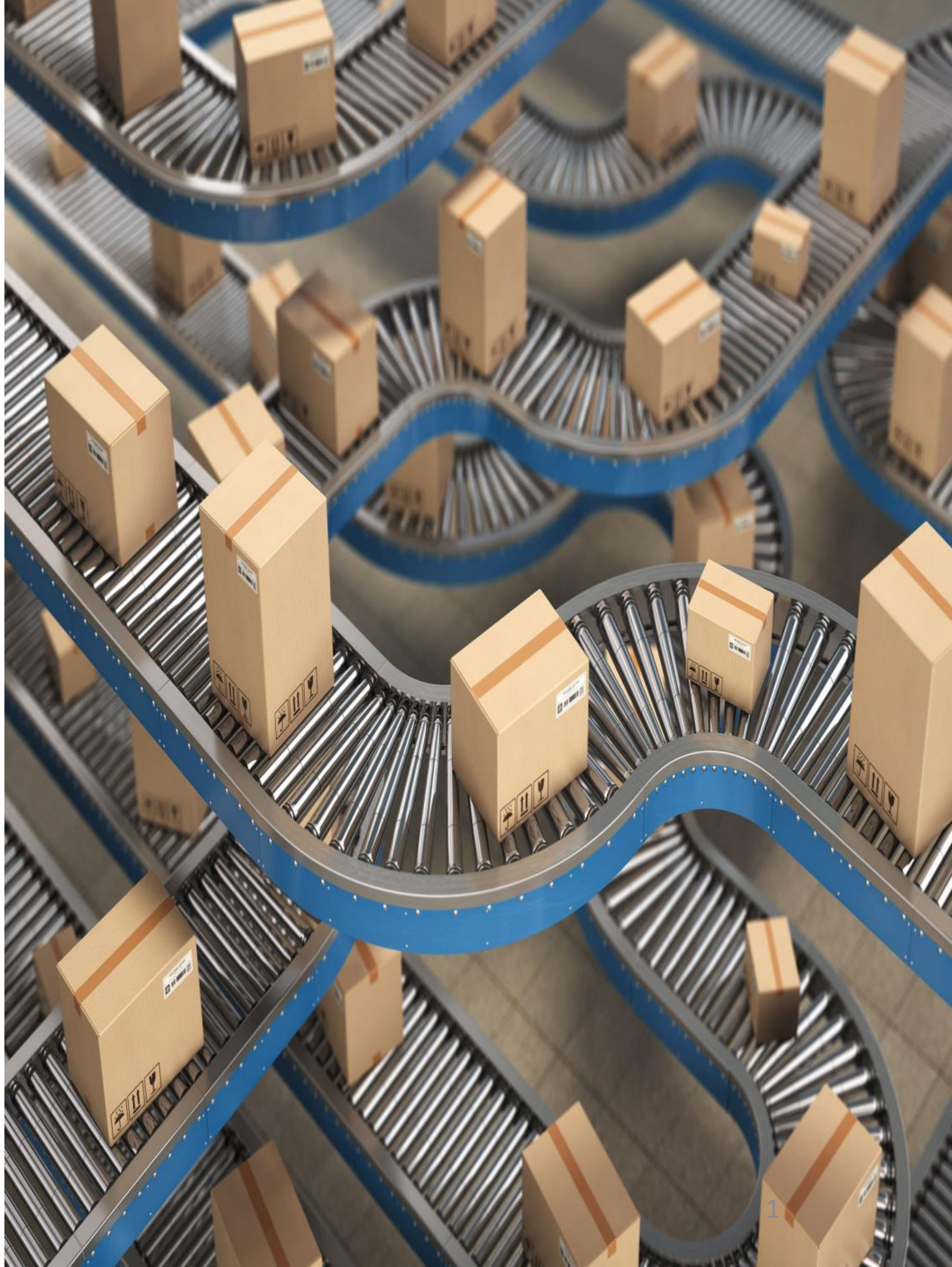
SUBJECT: Artificial Intelligence and Machine Learning



CONTENT

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INTRODUCTION

- What is Smart Maintenance?

Smart Maintenance means a move to a smaller, more centralized maintenance operation with end-to-end ownership. Data is easy to access and can be shared with technology partners and OEMs.

Maintenance is performed proactively as a result of the actual condition of each component and data-driven analyses that flag potential problems before they happen. Communication flows seamlessly across the organization, making it simple to weigh costs and benefits to optimize operational decisions (Çinar et al., 2020).

Smart Maintenance will substantially impact how companies in heavy-asset industries operate. Today, many companies run large maintenance operations with distributed ownership. Information such as equipment health history, sensor data, and documentation is locked away in different systems, meaning that alarms, calendars, and personal experience drive maintenance analyses and decisions (Calabrese et al., 2020).

Fig:1 Smart Maintenance Management

PROBLEM STATEMENT

There is a logistic company that is experiencing delays in maintenance completion, difficulties in replacing spare parts and there’s an inability to measure the impact of the performance of fleet maintenance and delivery services, which is a problem for smart maintenance management, especially considering the ongoing rapid transition towards an industrial environment with pervasive digital technologies. This issue intriguing potential overspending on unnecessary replacement parts up to 20% from USD 24Mil of its operating cost .

Problems

- Delays in maintenance completion
- Difficulties in replacing spare parts
- Impact of fleet maintenance and Delivery services
- Lack of Smart maintenance management
- Increased downtime and Reduced equipment performance
- Increased cost and time consumption process.

Solutions

- Implement a smart maintenance management system
- IoT sensors and machine learning technologies
- Predictive maintenance to manage maintenance schedules, work orders, and inventory of spare parts
- K- means clustering
- Automating maintenance processes and procedures through digital tools and digital twin technology to optimize their performance
- Problems related spare part availability can be addressed using t Selective Inventory control for fast moving parts: This involves identify most critical equipment and their failure patterns using data analytics, Find

➢ Frequency of failure, type of failure

➢ Level of difficulty in detecting the failure

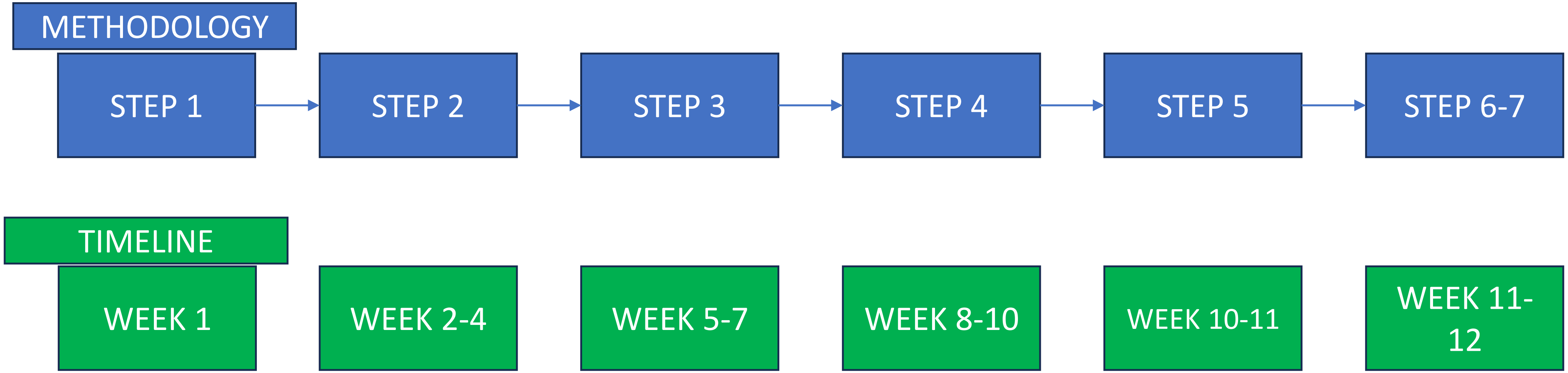
➢ The impact/time delay caused by the failure of overall operations

Methodology & Timeline

- STEP 1 - **Data Collection and Integration:** Collect relevant data from various sources, including maintenance records, historical spare parts usage, equipment sensor data, and operational data. Integrate the collected data into a centralized data management system, ensuring data quality and consistency.
- STEP 2 - **Data Preprocessing and Feature Engineering:** Clean and preprocess the data, handling missing values, outliers, and inconsistencies. Perform feature engineering to derive meaningful features from the data. This can include variables like equipment age, usage patterns, maintenance history, sensor readings, and any other relevant information.
- STEP 3 - **Predictive Maintenance Model Development:** Select an appropriate machine learning algorithm for predictive maintenance, such as regression, classification, or time-series analysis, depending on the nature of the problem and the available data. Split the data into training and testing sets, ensuring the model is trained on historical data and evaluated on unseen data. Train the model using historical data, considering features related to maintenance, spare parts, and equipment performance. Tune the model's hyperparameters to optimize its performance and generalization ability.
- STEP 4 - **Spare Parts Optimization:** Utilize the predictive maintenance model to forecast the likelihood of component failures or maintenance needs. Set a threshold or probability level to determine when replacement parts should be ordered or replaced. Implement an optimized spare parts management system that considers the predicted maintenance needs, lead times, costs, and criticality of parts. Ensure seamless integration with suppliers to streamline the procurement process and minimize inventory costs.

- STEP 5 – **Performance Monitoring and Evaluation:** Define key performance indicators (KPIs) to measure the effectiveness of the predictive maintenance model and spare parts optimization. Continuously monitor and evaluate the model's performance and the impact of spare parts optimization on operational efficiency, maintenance completion time, and costs.
- STEP 6 – **Building Dashboard and Indicating KPIs:** Provide a bird’s-eye view of all the maintenance activities and status whether not-started, in-process, or complete. View the maintenance queue in both a calendar and a detailed list view.
- STEP 7 – **Integrating triggers and notifications:** Build triggers based on the live dashboard when certain KPI’s reach a range of critical levels and then send a notification to all the members to take action and fix the problem.

- Agile project management is used for this project due to its adaptability and flexibility. The project is divided into iterative sprints, and regular feedback from stakeholders allows for adjustments during development. Implementing this project based on the above-mentioned methodology could take up to 15 weeks to execute each step.



Project Timeline		Month											
Sr.No/ Step Number	Task	1	2	3	4	5	6	7	8	9	10	11	12
1	Data Collection and Integration												
2	Data PreProcessing and Feature Selection												
3	Predictive Model Implementation / ANN Implementation												
4	Spare Parts Optimization												
5	Performance Monitoring and Evaluation												
6	Building Dashboard and Indication KPI												
7	Integrating Triggers and Notifications												
Milestones:		Data Collected from Sensors is to be processed and Integrated in the system. Also, Preprocessing of Data should be done		After Preprocessing of data ,appropriate Feature is to be selected .		In these timeline, Implementation of model along with Dashboard creation, KPI creation and Notification setting is to be done.							

IOT sensors in logistic supply chain

- Sensors are used to collect data on various aspects of the logistics process, such as the location of goods, temperature, humidity, and shock and vibration levels, wear and tear condition of the part. This data is then transmitted to IoT devices, which process and analyze the data, providing actionable insights to logistics companies

Data Collection and Integration

What is Data Collection?

- Data is various kinds of information formatted in a particular way. Therefore, data collection is the process of gathering, measuring, and analyzing accurate data from a variety of relevant sources to find answers to research problems, answer questions, evaluate outcomes, and forecast trends and probabilities.
- Collect relevant data from various sources, including maintenance records, historical spare parts usage, equipment sensor data, and operational data.
- Integrate the collected data into a centralized data management system, ensuring data quality and consistency.

Data Preprocessing and Feature Engineering:

❑Data Preprocessing:

- Data is processed for getting detailed summary of the KPI’s and this is done using exploratory data analytics
- It involves Vectorization, Normalization, Handling Missing Values, Imputing missing data, Feature engineering

❑Feature Engineering:

- Feature engineering is the process of using your own knowledge about the data and about the machine-learning algorithms at hand to make the algorithm work better by applying hardcoded transformations to the data before it goes to the machine learning model.

Key Performance Indicators

- **Maintenance cost**:

  Total Maintenance Cost = (Labor Costs + Material Costs + Equipment Costs) x (Number of Maintenance Events)

- **Equipment downtime:**

  Downtime (hours) = Total Time (hours) - Operating Time (hours)

- **Mean time between failures (MTBF):**

  MTBF = Total Operating Time (hours) / Number of Failures

- **Mean time to repair (MTTR):**

  MTTR = Total Repair Time (hours) / Number of Repairs

- **Predictive accuracy:**

  Accuracy = (Number of Correct Predictions) / (Total Number of Predictions)

- **False Alarm rate:**

  False Alarm Rate = (Number of False Alarms) / (Number of Alarms)

- Cost incurred in IOT sensor system in place
  - Sensors cost
  - Implementation on the system

Predictive Maintenance Modeling

Data capturing, digitalization, and transmission

Data storage and evaluation

Calculation of probabilities of the occurrence of specific events

- We are using IoT based Predictive Maintenance Modeling.
- Data will be collected from sensors. Like corrosion, carbon emission, vibrations, temperature, pressure, thermal images, etc.
- Unsupervised Learning method
- Unlabeled data.

IoT based Predictive Maintenance Architecture

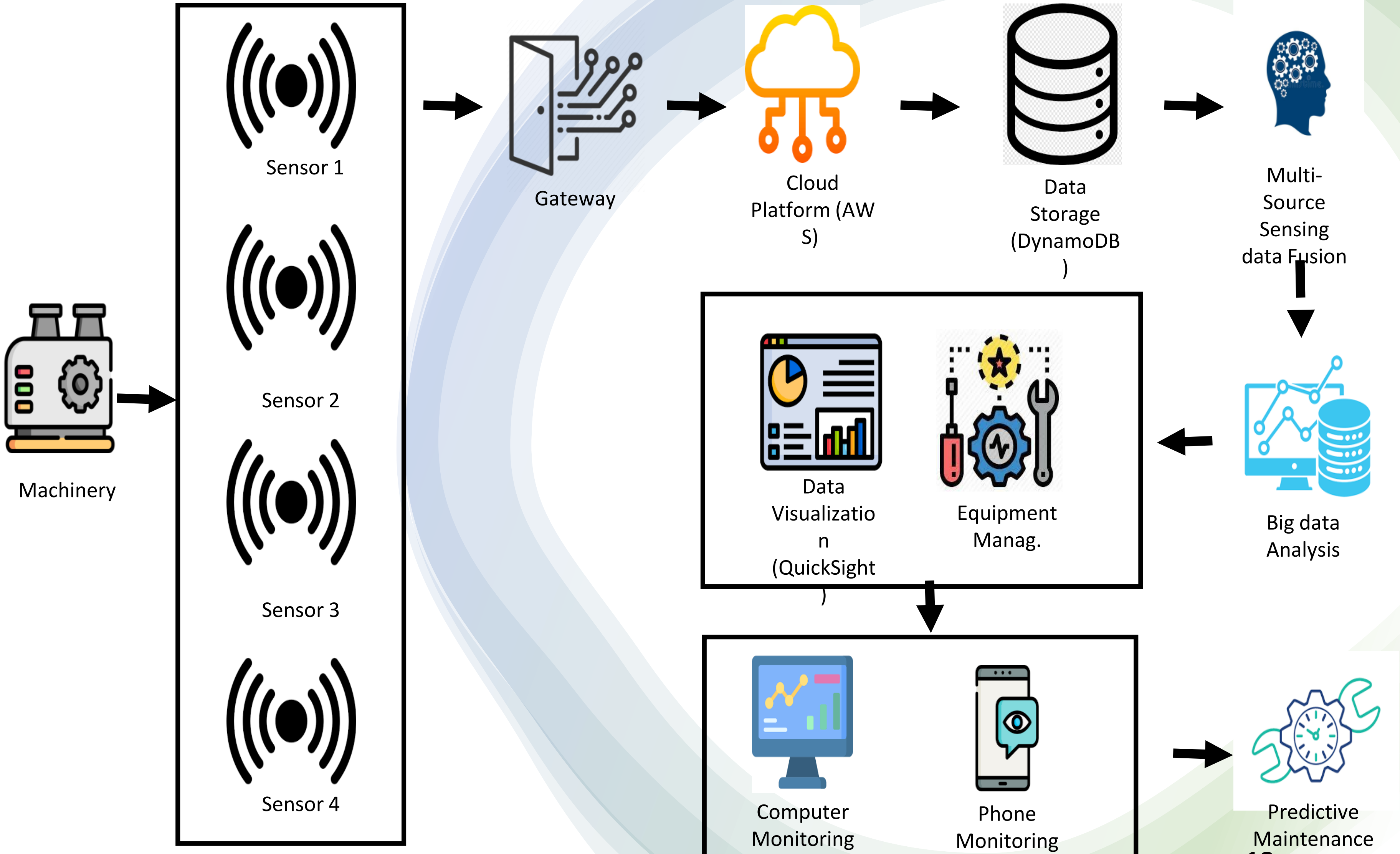
Sensor

Data Communication

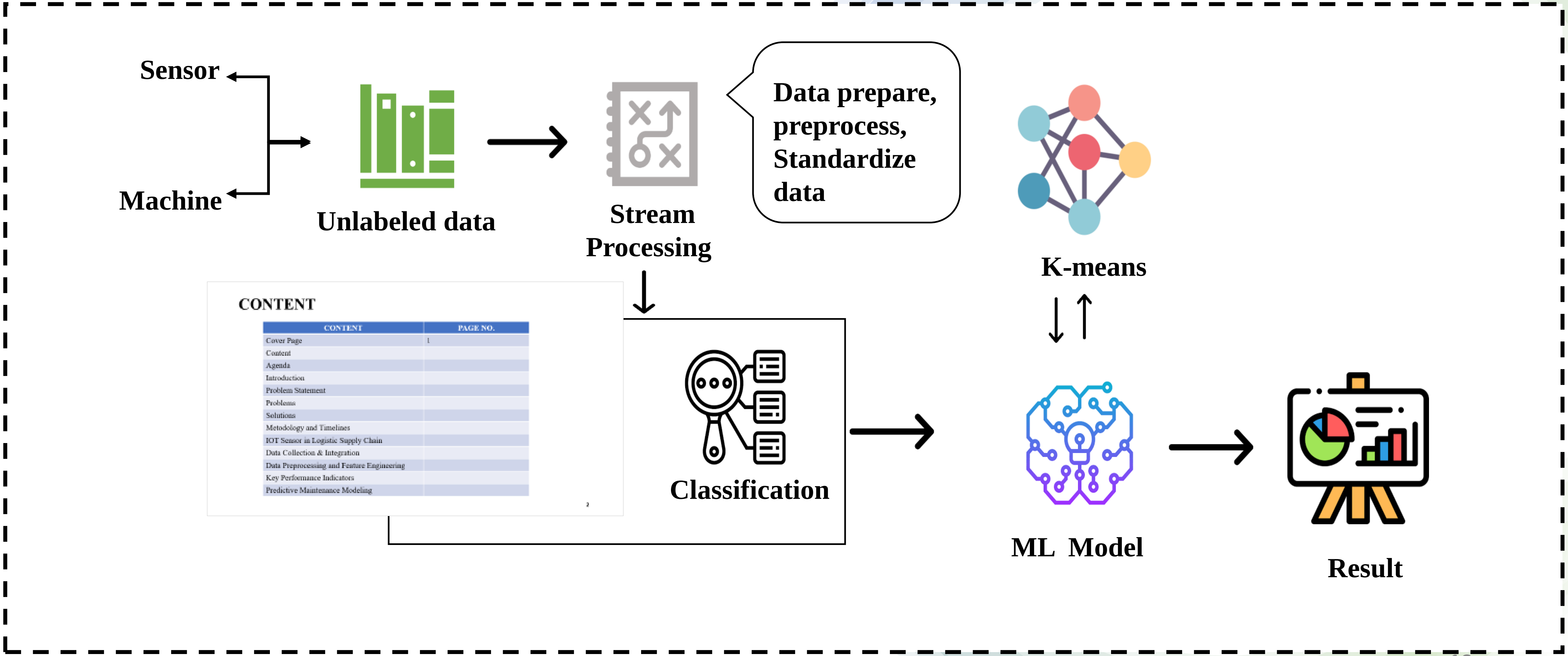
Central data storage system

Predictive maintenance platform

Predictive analytics tool



Design ML Architecture for Smart Logistic



Spare part optimization

- Utilize the predictive maintenance model to forecast the likelihood of component failures or maintenance needs.
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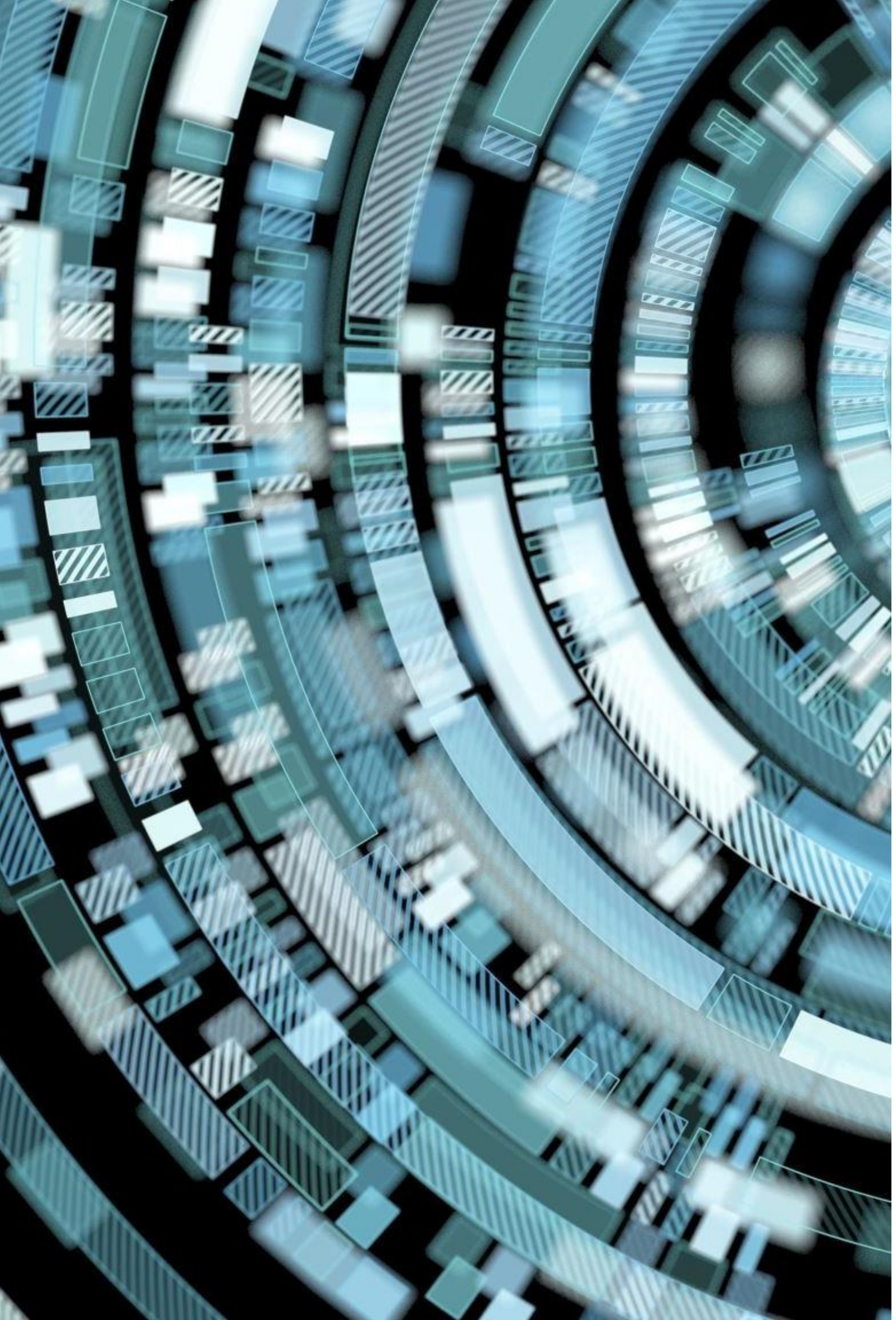


Why we are using ML approach?

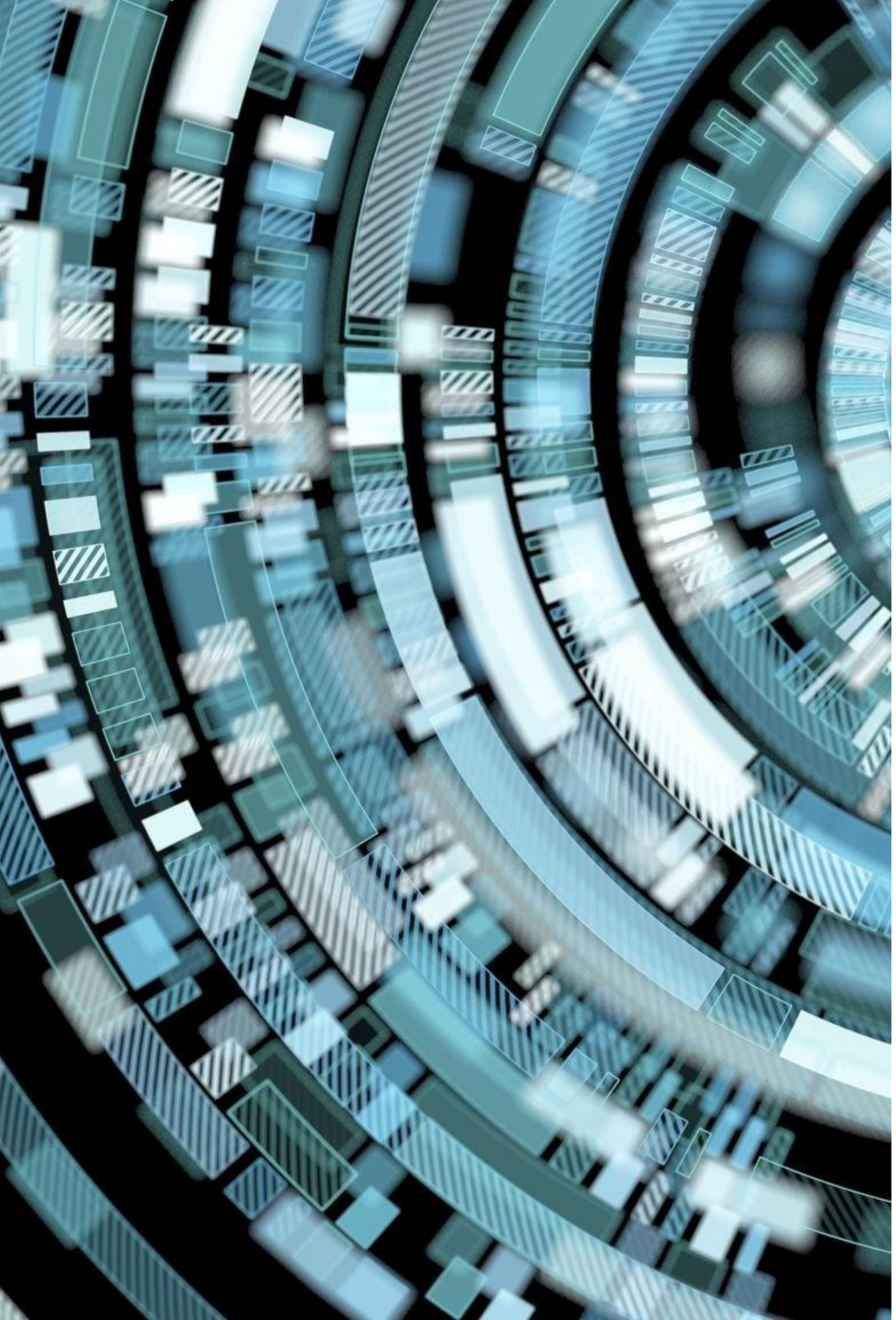
Unstructured Data (sensor/machine data), Image data of the spare parts, Video signals , Tabular data of the part condition

Unlabeled Data

No human intervention need (automation), Unsupervised classification of quality of the equipment or the part. (Clustering, Manifold learning algorithms)

It can handel multi-dimension and multi-variety data

It has Wide range of application



Why we are using ML approach?

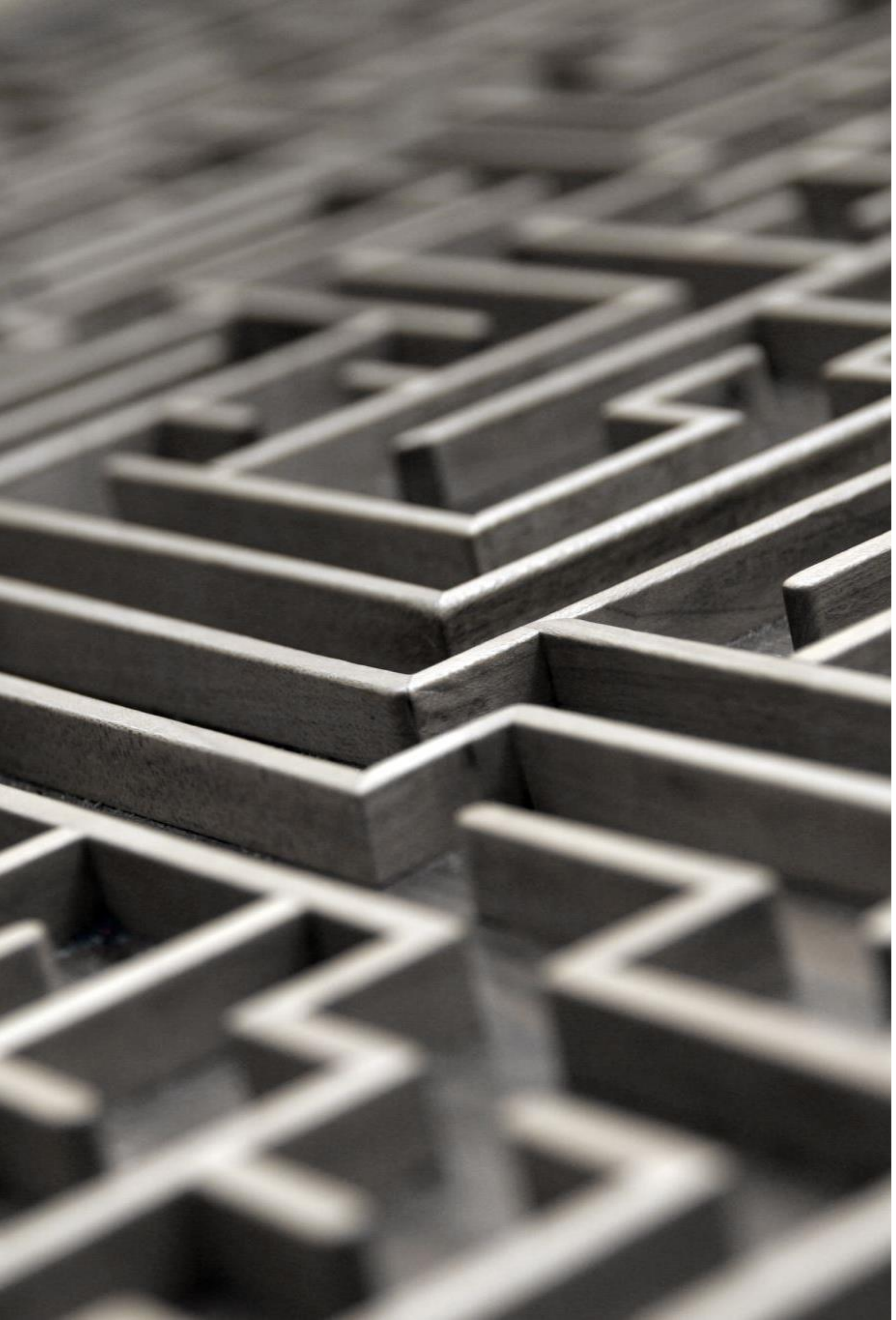
Unstructured Data (sensor/machine data), Image data of the spare parts, Video signals , Tabular data of the part condition

History or previous records (labels)

No human intervention need (automation), Supervised classification regression to predict the maintenance delay or cost. (Regression, KNN, SVM< Random Forest models)

It can handel multi-dimension and multi-variety data

It has wide range of application



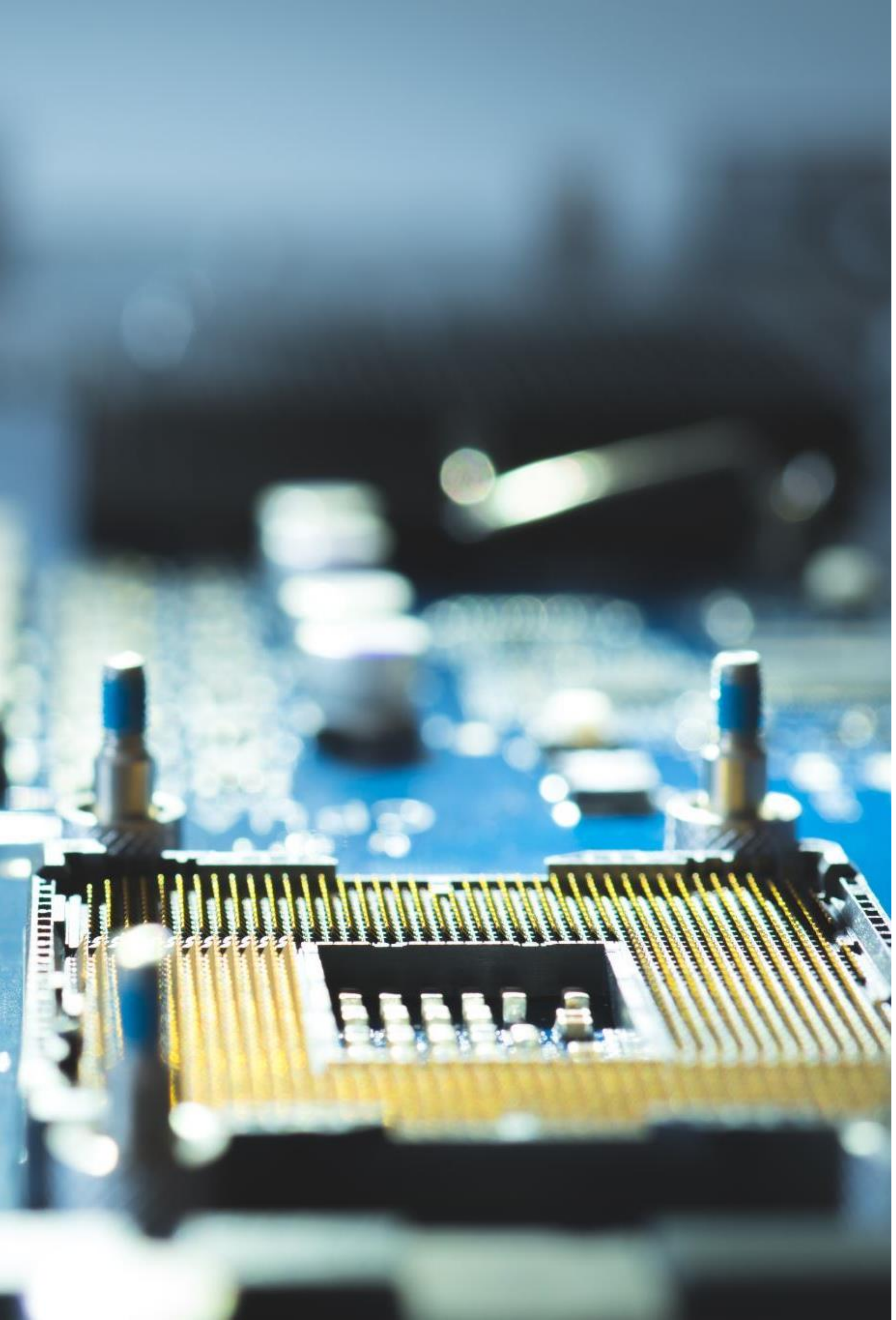
Why we are using K-means algorithm?

Easy to Implement

High performance

It is simple, highly flexible, and efficient. The simplicity of k-means makes it easy to explain the results in contrast to Neural Networks

It generalizes to clusters of different shapes and sizes, like elliptical clusters.



Tools

- QuickSight
- AWS
- DynamoDB
- IoT

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Thank You