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Intelligent Engines: Revolutionizing Manufacturing and Supply Chains with AI

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Abstract:- Artificial intelligence (AI) technologies are becoming a reality, with intelligent engines that can learn and simulate human thinking. These engines have three key features: micro-level intelligence with sensors, logic-based intelligence with software tools, and the ability to adapt and learn using algorithms. AI reduces the need for human intervention and cognitive thinking, finding more efficient solutions to complex problems in manufacturing and supply chain industries. AI simulates human cognition using software tools, allowing for the automation of tasks and analysis of complex systems. However, it raises questions about whether problems can be solved differently and the limitations of explicit algorithms.

Keywords:- *Intelligent Engines, Supply Chain, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM).*

I. INTRODUCTION

This book focuses on the design of 'intelligent' engines, using modern Information Technology (IT) to automate tasks currently done by humans. The goal is to have a cost or performance advantage over alternative automation methods. The field chosen for examination is optimization, which involves finding the best solution to a problem by minimizing a cost function. The book aims to develop general methods applicable to specific problems, with a single application example being manufacturing process automation. This choice allows for using proven methods that are familiar to most readers.

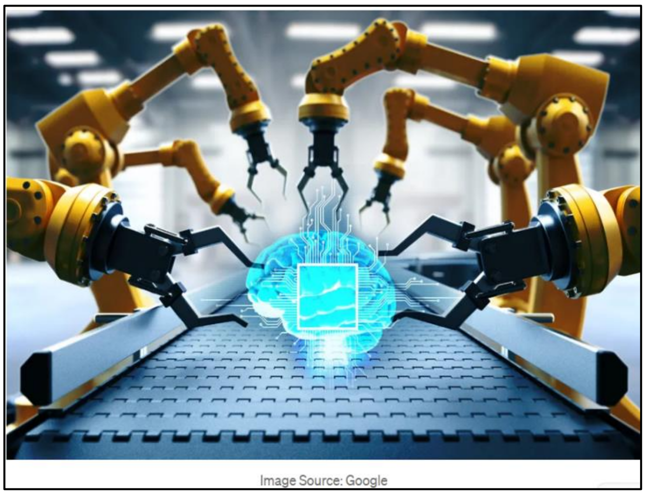

Fig 1: The Industrial Revolution – Scientific View

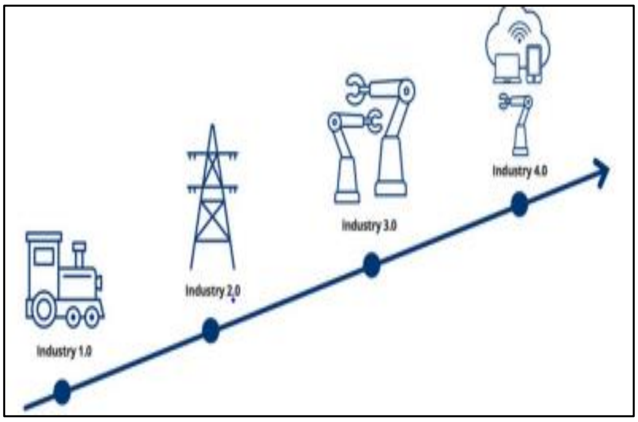

Fig 2: The Industrial Revolution

A. Background

AI is a technology that imitates intelligent behavior and has widespread applications in manufacturing. It enhances data analysis and reduces machinery upkeep costs. AI can be used for preventative maintenance and developing systems that maximize goal achievements. Like analyzing vehicle downtime statistics, intelligent engines can revolutionize manufacturing and supply chains. Caterpillar's research showed that AI can be used to configure machine systems for more reliable products. This is advantageous for reconfiguring production machinery and improving end-product quality and reliability.

Fig 3: Supply Chain Starts With Shop Floor

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B. Purpose of the Research

A theoretical module is proposed to facilitate more proactive and autonomous decision-making by individual factories and their network partners in supply network design and planning. This module leverages artificial intelligence planning methods to provide a detailed network configuration and the associated operational plan. Past work on supply network design and planning has laid the foundation for this research. However, a significant gap still needs to be found between the complexity of real-world supply networks and the decision-making capabilities of managers. This research takes a first step towards providing tools to automate the more routine aspects of supply network decision-making, freeing human managers to focus on more strategic and creative problem-solving. Said another way, the goal is not to replace human decision-makers but to make them more effective by automating routine decisions and providing intelligent decision support at all levels of the supply network. In pursuing this goal, specific scope and limitations must be set.

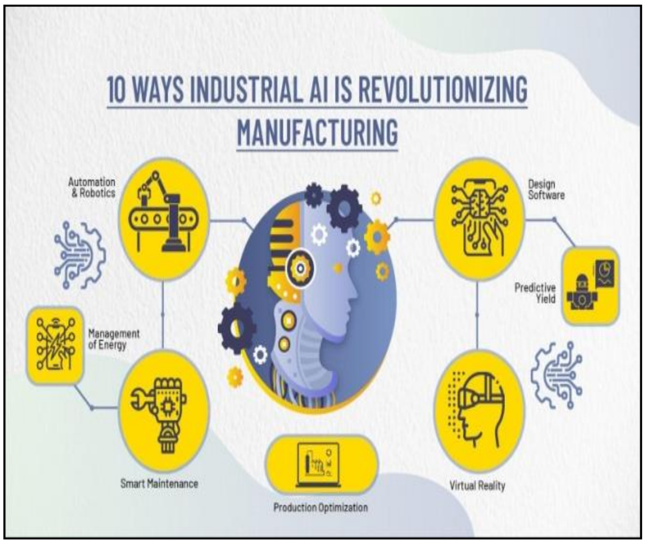

Fig 4: Industrial AI is Revolutionizing Manufacturing

C. Scope and Limitations

This paper will focus specifically on artificial narrow intelligence (ANI) to ensure an accurate understanding of AI's capabilities and potential impacts. ANI has already revolutionized the manufacturing industry, as seen in the robotic automation of assembly lines. The scope of this paper will be confined to AI's impacts on improving or restructuring the current processes of manufacturing consumer goods, utilizing the example of an intelligent engine developed by a fictional company.

Table 1: AI and Prior AI Trends/Key Improvement in Timelines

1900-1950	Electrification & Industrial Controllers
1970-1980	Hardware explosion key to point
1990-2000	Internet
2010-2020	Manufacturing Automation, AI, ML
2020-2024	Rapid Growth – LLM's

II. THE ROLE OF AI IN MANUFACTURING

The manufacturing environment is a perfect platform for understanding how AI can add learning and decision-making capabilities to complex tasks. There are many well-developed AI techniques that have the potential to be integrated into the manufacturing system. These techniques include:

- Case-based reasoning for new product design and recycling knowledge from past cases.
- Intelligent scheduling optimizes resource use and minimizes make pan under production environment constraints. Expert planning and rescheduling perform production activities in a more complex environment.
- Monitoring and diagnostics are used to detect the tolerance process, and facility monitoring is used to anticipate system failure.
- Autonomous design to self-develop software design tools that are designed to improve software weaknesses and many more.

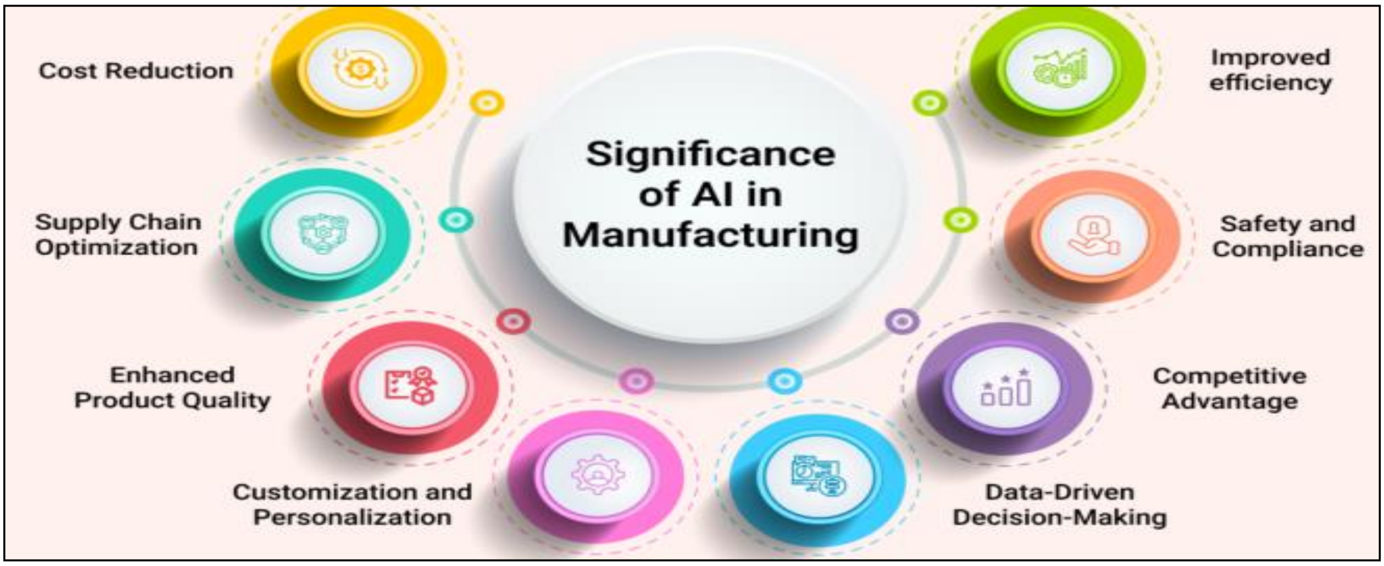

Fig 5: Significance of AI in Manufacturing

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Table 2: AI-Enhanced/Enabled Supply Chain Management Process

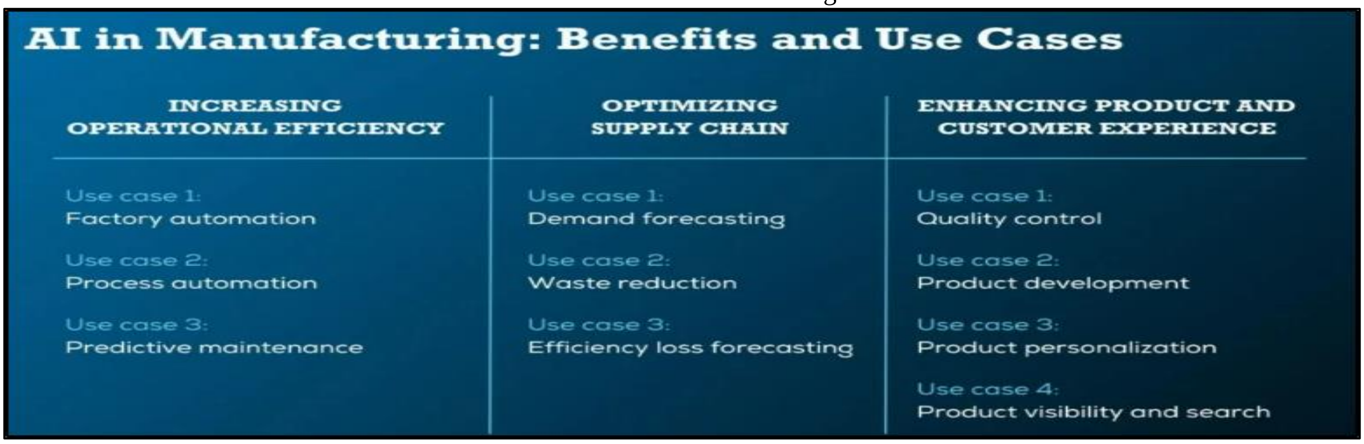
Technology	Role in SCM	Benefits in SCM
Cloud Computing and Storage	Enables integrated and seamless data storage and access	Improves operational efficiency and speed of data access and analysis
Inventory and Network Optimization Tools	Facilitates efficient management and distribution of inventory. Used for tracking and identification of goods within the supply chain	Reduces inventory costs, improves customer service
Sensors and Automatic Identification	Automates tasks such as demand planning, inventory management, and product development. Used in warehousing operations, production lines, and transport. Enables real-time visibility across the supply chain	Improves tracking accuracy and security in the supply chain
Artificial Intelligence Robotics and Automation	Allows for anticipation of demand fluctuations and optimization of resources. Provides opportunities for onsite production, reducing the need for transportation and storage	Improves efficiency, accuracy, and cost savings. Increases productivity, reduces labor costs,improves decision-making, increases the speed of delivery
Industrial Internet-of-Things (IoT) Predictive and Prescriptive Analytics, Autonomous Vehicles and Drones	Used for transportation of goods within and between facilities. Enhances real-time communication and information access in the supply chain	Reduces transportation and storage costs andallows for customization of products. Improves delivery speed andreduces transportation costs and human errors.

A. *Automation and Efficiency*

Once a business decides to manufacture, its primary goal is to stay competitive. Growth and profit drive the business, leading to increased pressure for better and cheaper products. Small and medium-sized businesses need help investing in large-scale production lines to meet production demands. However, computer-aided manufacturing and intelligent software have overcome this issue and provide efficient solutions. These tools are crucial for thriving businesses and avoiding closure due to market decline.

Machine shops and manufacturing businesses may still need to start using outdated processes and methods. However, this may not continue due to the retiring skilled workers and the fewer younger workers interested in the field. Increased competition and material costs also make current processes less effective. Intelligent software and AI can offer a solution by optimizing processes like high-speed machine-making, reducing cycle time without requiring costly changes in the entire process. Due to limited time and resources, this ability to improve existing processes is highly sought after.

Table 3: Automation Advantages



B. *Predictive Maintenance*

Intelligent AI engines increase downtime intervals by implementing predictive maintenance strategies. AI uses statistical analysis, supervised learning, and unsupervised learning methods to forecast system failures. This approach differs from preventive maintenance and saves on costs. Implementing predictive maintenance has been prevalent in the aerospace and defense industries, resulting in significant savings and prevention of engine removals. Companies like Delta Airlines and American Airlines use predictive maintenance systems to improve operational efficiencies. Predictive maintenance's success and cost efficiency will make current manufacturing methods appear outdated.

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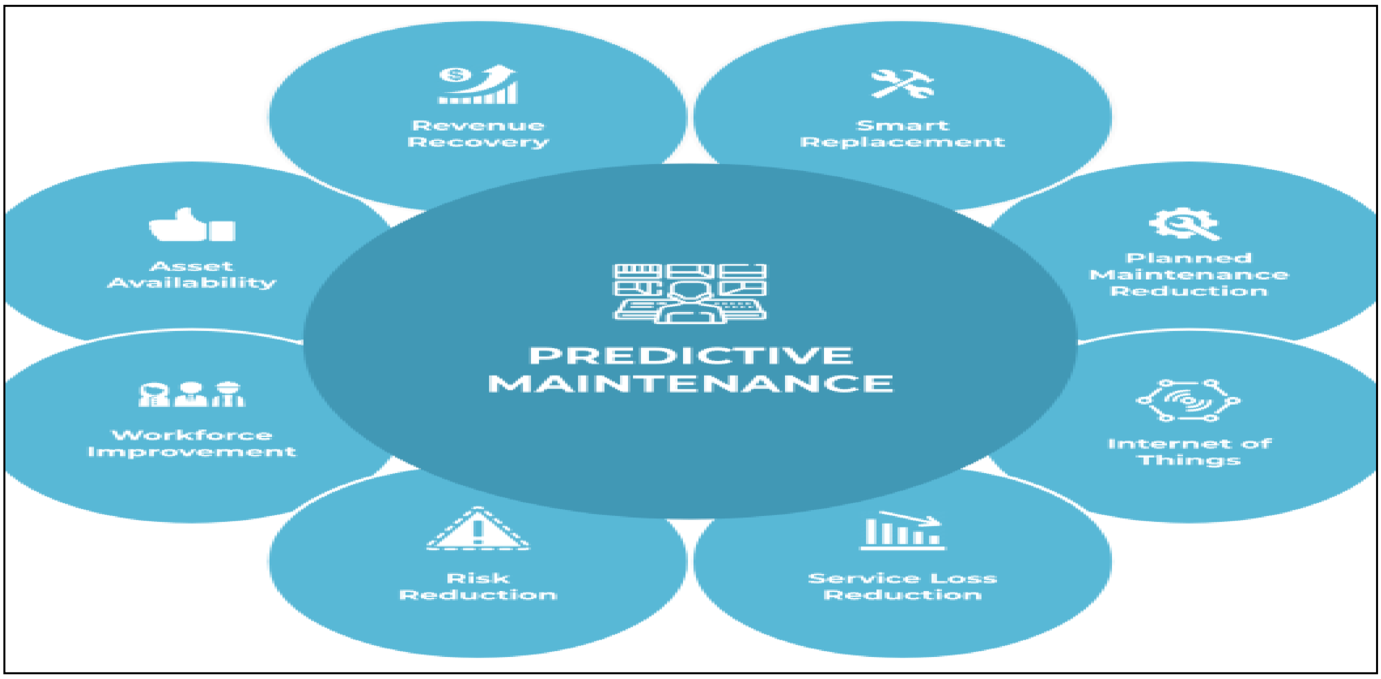

Fig 6: Predictive Maintenance

C. *Quality Control*

The second most significant cited problem was manufacturers' inability to utilize the information available to them to make informative decisions, with a third of manufacturers saying data needed to be more bulky and complex to manage. AI can help manufacturers sift through this data to detect patterns, diagnose issues, and recommend action.

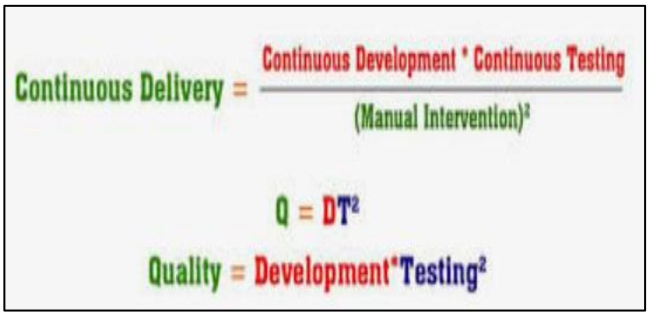

Fig 7: Quality Control Equation

This has the potential to improve quality, prevent costly defects, and reduce rework, an area where manufacturers currently need help to make informed decisions using inductive problem-solving. 30% of AI early adopters in manufacturing are using or planning to use AI for predictive maintenance, compared to only 6% of manufacturers overall, which tells of AI's potential to improve maintenance activities and shift away from the current cost-intensive run-to-fail maintenance strategy.

Fig 8: Quality Control

D. *Supply Chain Optimization*

Supply chains are vital but complex and fragile. AI can predict and solve problems, like disruptions and risks. IBM's Watson Supply Chain and UPS's ORION platform are examples. They optimize routes and offer responsive systems. AI can also simulate and predict cash flow impacts. AmBev and AB InBev's case showed the risks of extending payment terms. AI estimated a cost of US$200 million for AB InBev and risk to relationships with small suppliers and farmers.

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Fig 9: Supply Chain Optimization

III. INTELLIGENT ENGINES: TRANSFORMING MANUFACTURING PROCESSES

ML techniques are used in manufacturing. IBM's Watson, a well-known ML application, optimizes its function as a Quality Engineer. ML algorithms predict machinery failure and reduce costs. Ecolab used ML to analyze soil loading, resulting in reduced costs. Manufacturers are increasingly using analytics and AI. CEOs plan to integrate cognitive computing/AI for various purposes in the next 3-5 years.

Machine learning is AI that improves prediction accuracy without explicit programming. Algorithms use input data and statistical analysis to predict outcomes. There are three types of learning: supervised, unsupervised, and reinforcement.

Machine learning technologies are already being used effectively in manufacturing and can only become more prevalent in the future. The study "The Learning Enterprise" sponsored by Accenture, and authored by Sam Khan, states that top executives believe machine learning can generate substantial value in terms of increased productivity, higher efficiency, and lower operational costs.

A. Machine Learning Algorithms -Data Collection

Data Collection Code sudo code snippets are provided below.

```
import requests
import os
from kaggle.api.kaggle_api_extended import KaggleApi
def download_dataset(dataset_name, path_to_save):
    """
    Function to download dataset using Kaggle API.
    Args:
    dataset_name (str): Full path of the dataset on Kaggle.
    path_to_save (str): Local path where the dataset should be saved.
    """
    api = KaggleApi()
    api.authenticate()
    api.dataset_download_files(dataset_name, path=path_to_save, unzip=True)

def load_data(file_path):
    """
    Function to load the data from a CSV file.
    Args:
    file_path (str): Path to the CSV file.
    """
    import pandas as pd
    return pd.read_csv(file_path)

if __name__ == '__main__':
    # Define the dataset and path
    dataset = 'username/dataset-name'  # Example: 'username/manufacturing-engine-data'
    save_path = './dataset'
    file_name = 'data.csv'  # Adjust based on actual file name in the dataset

    # Download the dataset
    download_dataset(dataset, save_path)

    # Load the data
    data = load_data(os.path.join(save_path, file_name))
    print(data.head())

# Author: Vishwanadham Mandala
# Date: 2024-04-14
```

Code 1.Python data collection program

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B. Machine Learning Algorithms – Train the model

Sudo Code for AI Algorithm.

```
# Author: Vishwanadham Mandala
# Date: 2024-04-14

import requests
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier
from sklearn.metrics import accuracy_score,
classification_report

def fetch_data(api_url):
    """Fetch data from API."""
    response = requests.get(api_url)
    data = response.json()
    return pd.DataFrame(data)

def prepare_data(df):
    """Preprocess and split the data."""
    X = df.drop('target', axis=1)  # Assuming 'target' is the
column to predict
    y = df['target']
    X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
    return X_train, X_test, y_train, y_test

def train_model(X_train, y_train, model):
    """Train the model."""
model.fit(X_train, y_train)
return model

def evaluate_model(model, X_test, y_test):
    """Evaluate the model."""
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    report = classification_report(y_test, y_pred)
    return accuracy, report

def main():
    api_url = 'http://example.com/api/engine_heartbeat'
    data = fetch_data(api_url)
    X_train, X_test, y_train, y_test = prepare_data(data)

    # Initialize models
    rf_model = RandomForestClassifier(n_estimators=100,
random_state=42)
    gb_model =
GradientBoostingClassifier(n_estimators=100,
random_state=42)

    # Train models
    rf_model = train_model(X_train, y_train, rf_model)
    gb_model = train_model(X_train, y_train, gb_model)

    # Evaluate models
    rf_accuracy, rf_report = evaluate_model(rf_model,
X_test, y_test)
    gb_accuracy, gb_report = evaluate_model(gb_model,
X_test, y_test)

    print("Random Forest Model Accuracy:", rf_accuracy)
    print("Gradient Boosting Model Accuracy:",
gb_accuracy)
    print("\nRandom Forest Classification Report:\n",
rf_report)
    print("\nGradient Boosting Classification Report:\n",
gb_report)

    # Select the best model based on accuracy
    best_model = rf_model if rf_accuracy > gb_accuracy
else gb_model
    print("Best model selected:", "Random Forest" if
best_model == rf_model else "Gradient Boosting")

if __name__ == '__main__':
    main()
```

Code 2.Python code for AI Algorithms

➢ *Output Snippets.*

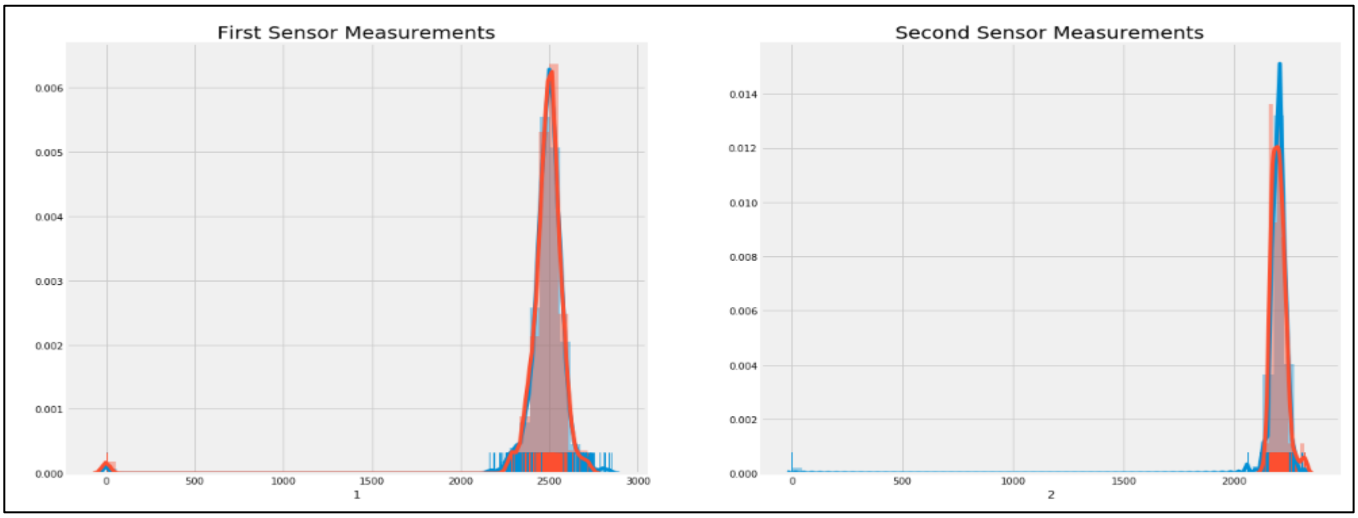

Fig 10: Output Snippets

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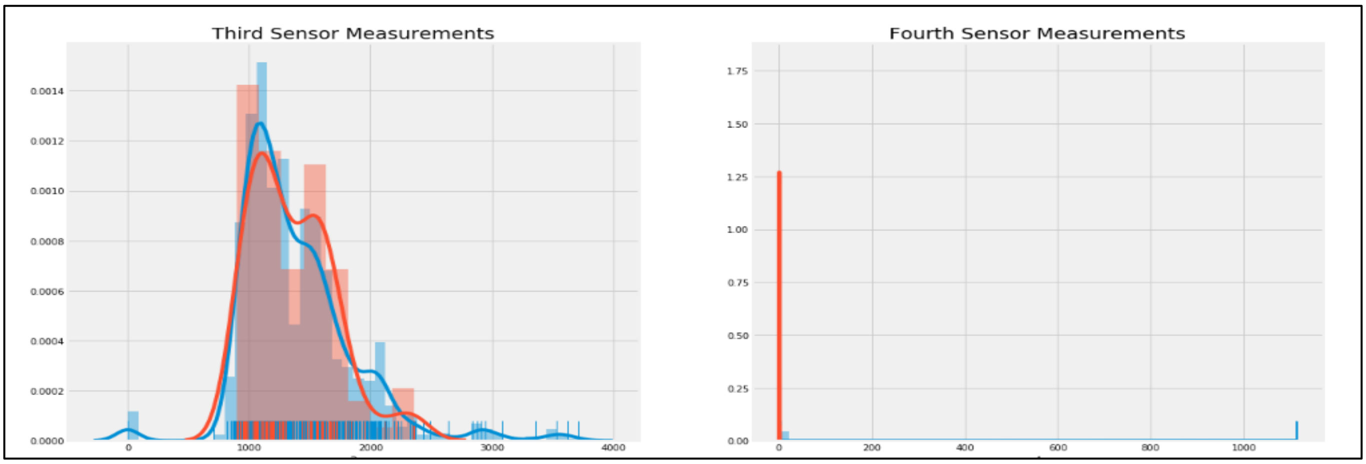

Fig 11: Output Snippets

C. *Machine Learning Algorithms – Explanation*

Machine learning is a process that uses models to improve systems and support decision-making. There are two types of learning: supervised and unsupervised. In supervised learning, a model is trained using input-output pairs, and predictions are corrected by the user until an acceptable level of performance is achieved. Unsupervised learning trains the model to recognize patterns and make decisions without prior information.

Machine learning can benefit manufacturing because it adapts and learns from real-time data. With modern manufacturing processes constantly changing, machine learning models can maintain the most relevant information and provide the most accurate decisions. This process can help prevent faulty machinery, increase product quality, and prevent costly downtime by providing useful predictive analytics to influence decision-making.

Machine learning (ML) uses statistical models to improve systems and decision-making. It has two types: supervised learning, where a model is trained using input-output pairs, and unsupervised learning, where the model recognizes patterns and makes decisions based on data.

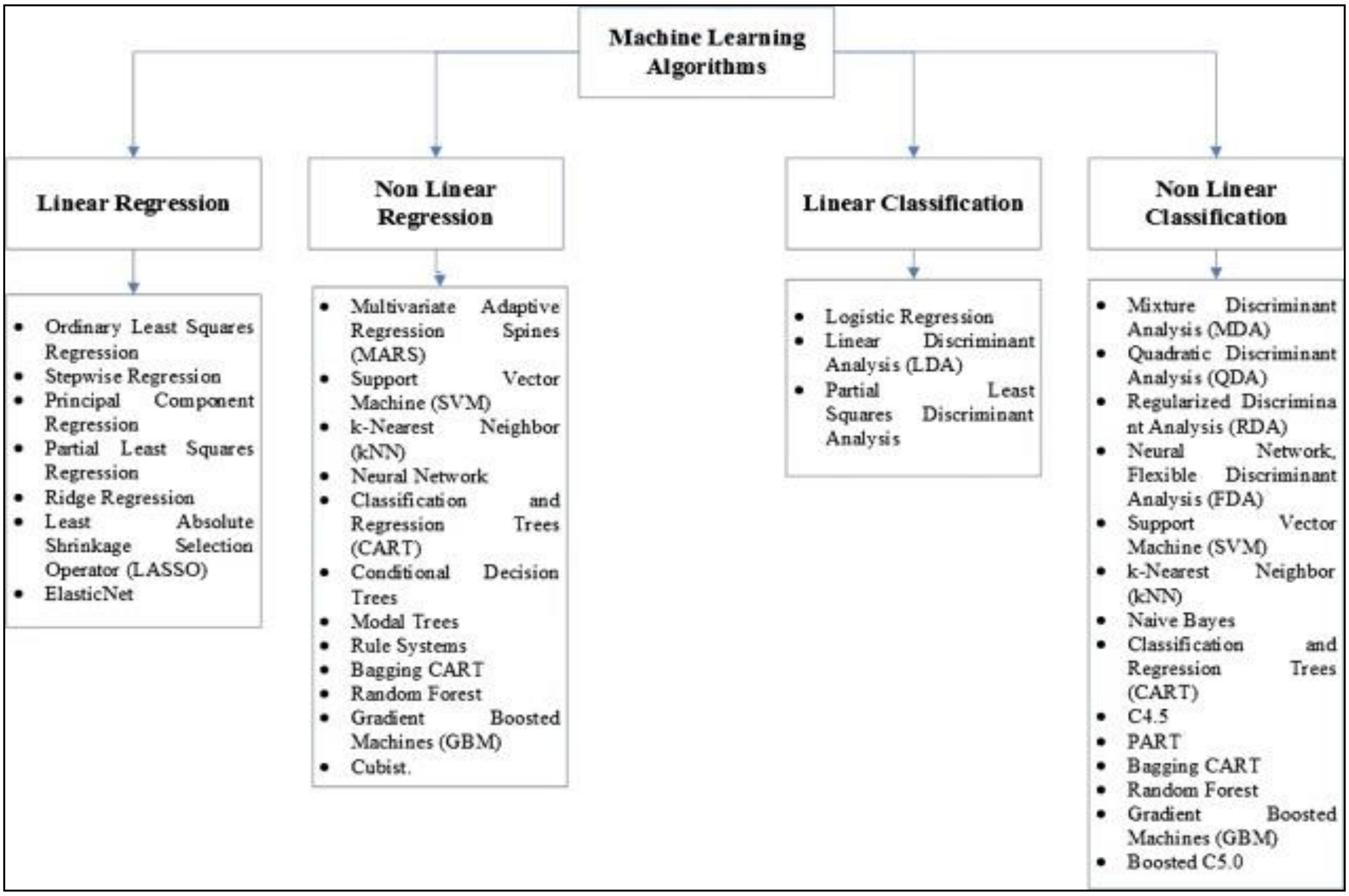

Fig 12: Machine Learning Algorithms

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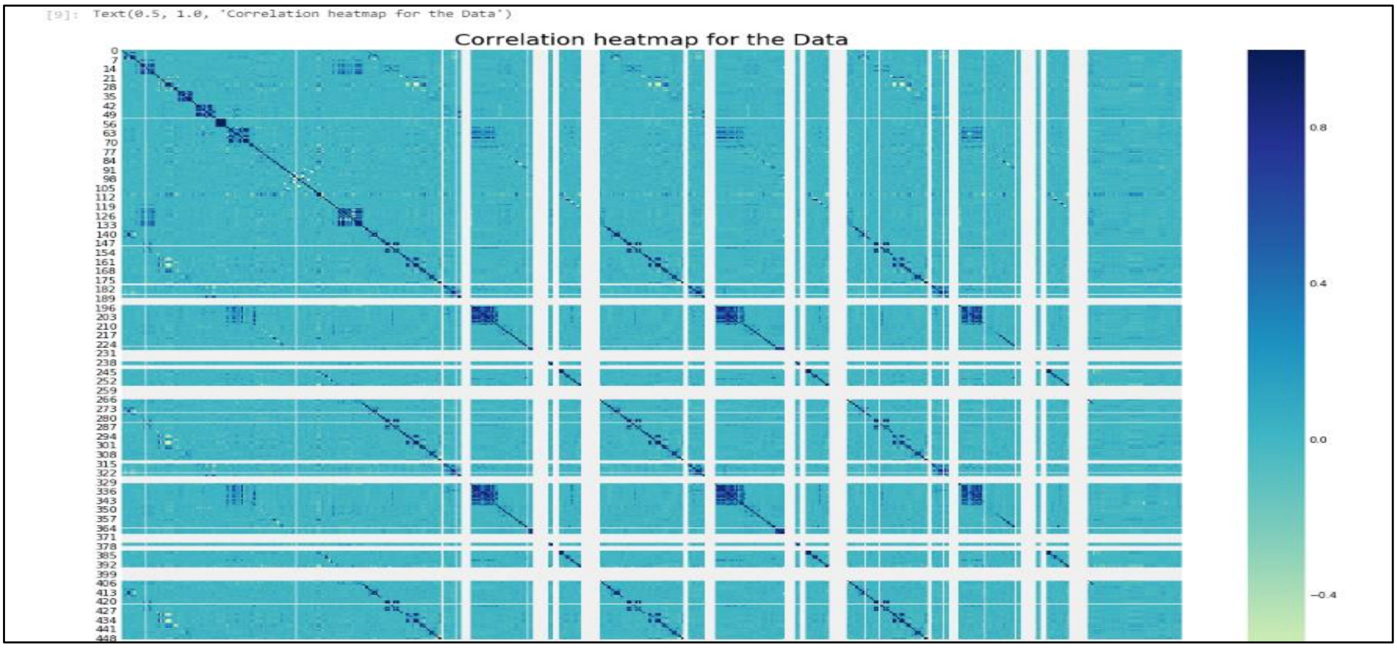

Fig 13: Heatmap. Output Snippets

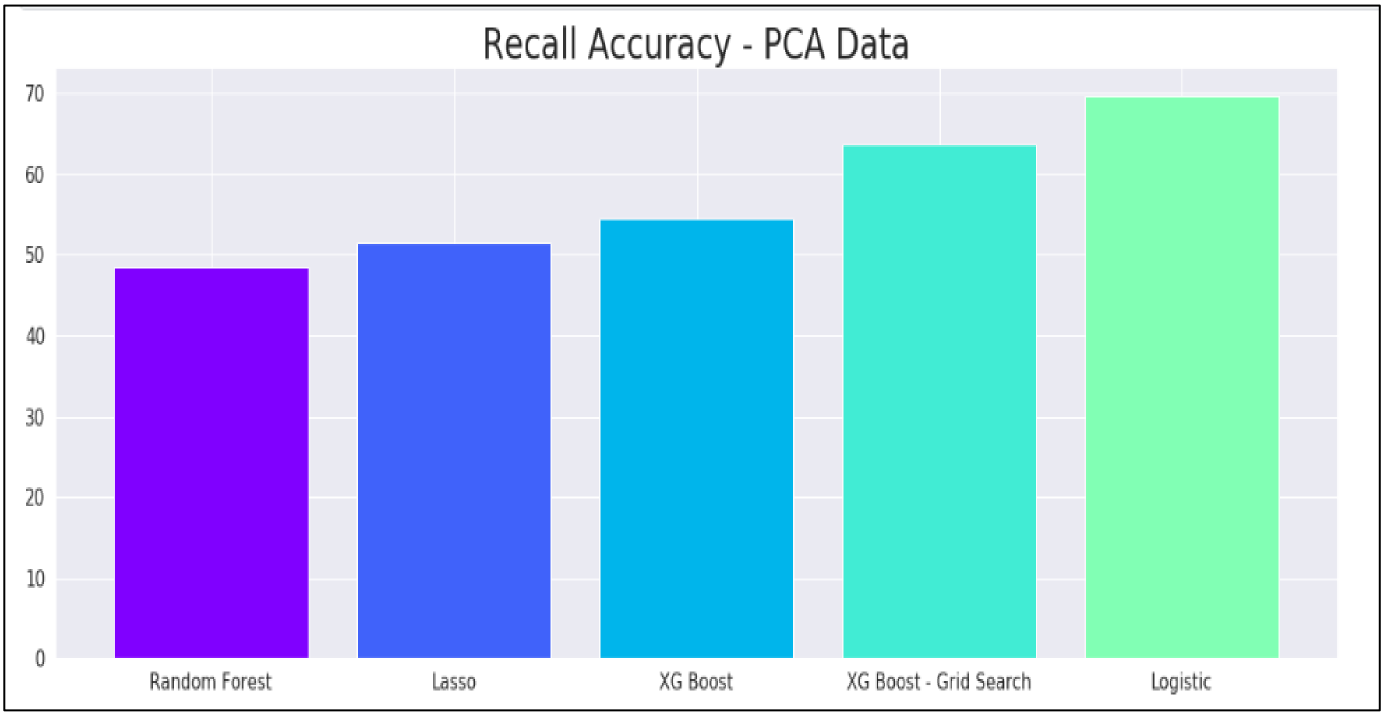

Fig 14: Algorithm Differences -Output Snippets

D. Robotics and Autonomous Systems

The popularity of robotics in manufacturing is increasing due to lower costs and more accessible programming. AI systems are being used to coordinate large numbers of robots, including CNC machines, for complex tasks like aircraft manufacturing. Inflexibility in programmed paths has been a barrier, but flexible robotics, where robots learn from experts or their own mistakes, is being researched. Error recovery is crucial for tasks like assembly. Modular robots that can reconfigure themselves are another option. AI techniques are used for coordination and planning. Robotics is expected to be a significant area for AI in manufacturing.

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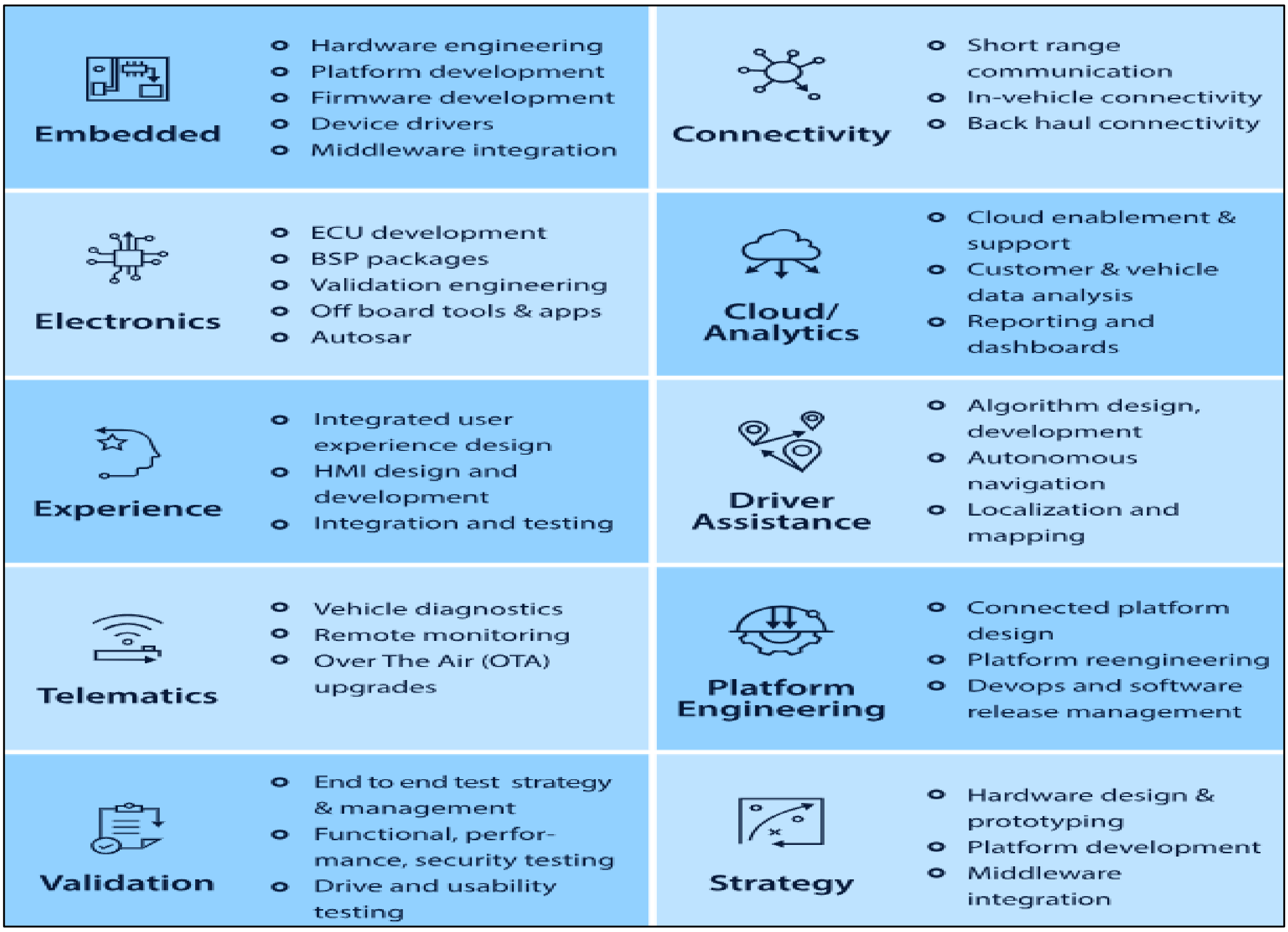

Fig 15: Robotics Automation

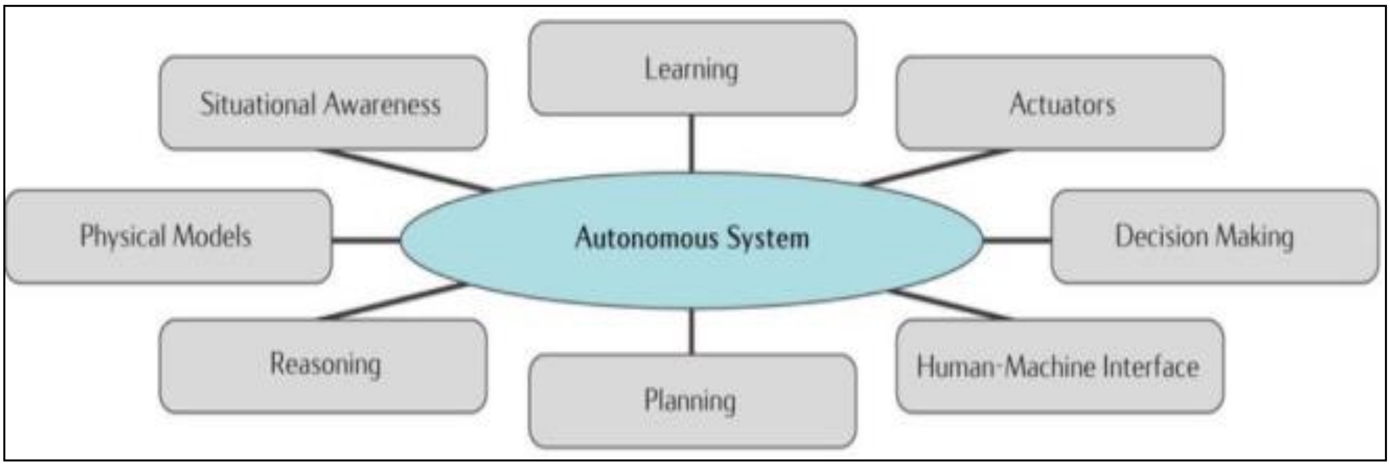

Fig 16: Autonomous System

E. Sensor Integration

Manufacturers using AI and sensors can improve machine understanding and response to system status. This saves money by identifying and diagnosing problems and avoiding unscheduled downtime. Traditional scheduled maintenance is costly and inefficient, as potential failures are not considered. AI and sensor integration predicts component failure, reducing downtime. Intelligent engine monitoring and diagnosis can be seen with mobile robots using sensors to compare map states. Diagnosis maneuvers are ranked, and decision-making tools aid in cost-effective repair. AI and sensors prevent costly failures and maintenance actions.

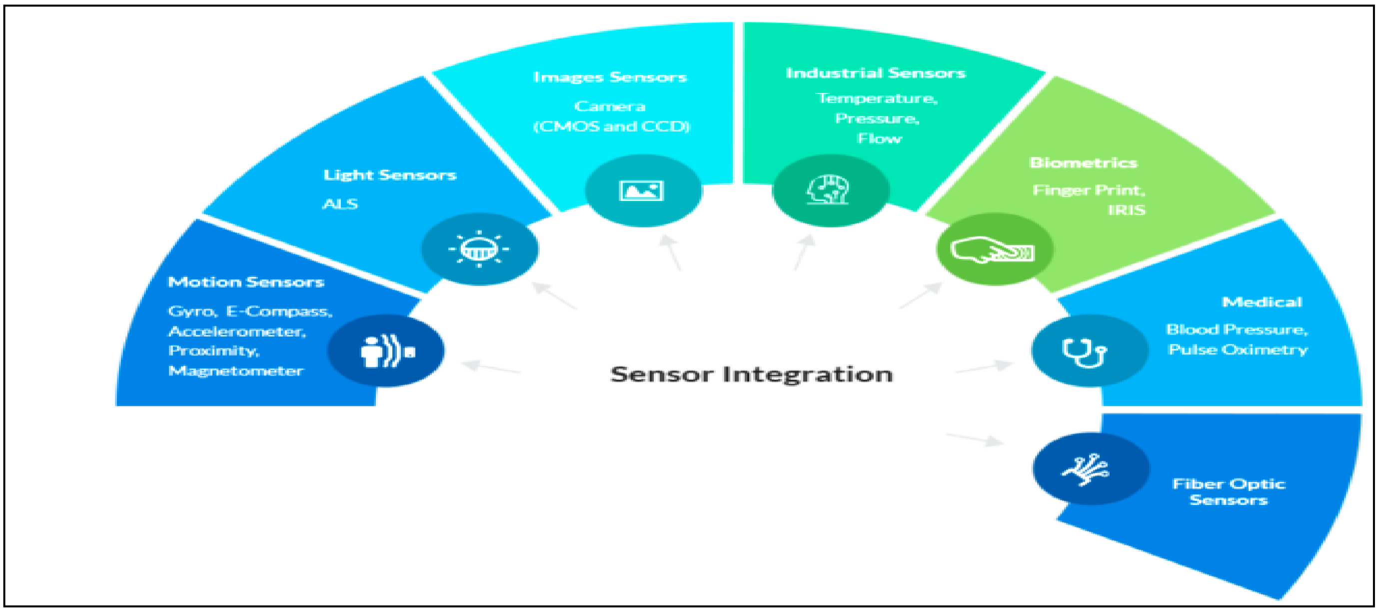

Fig 17: Sensor Integration

F. Data Analytics and Decision-Making

AI can enhance data analysis and decision-making by providing superior predictive analysis tools and algorithms. These tools simplify complex analytical procedures and allow all personnel to run complex analyses. AI also helps manufacturing sectors use existing data more effectively to plan inventory and meet customer demand. Additionally, AI-based tools can provide intelligence for ad-hoc analysis and simulation, enabling specific hypotheses testing and evaluating the effects of decisions.

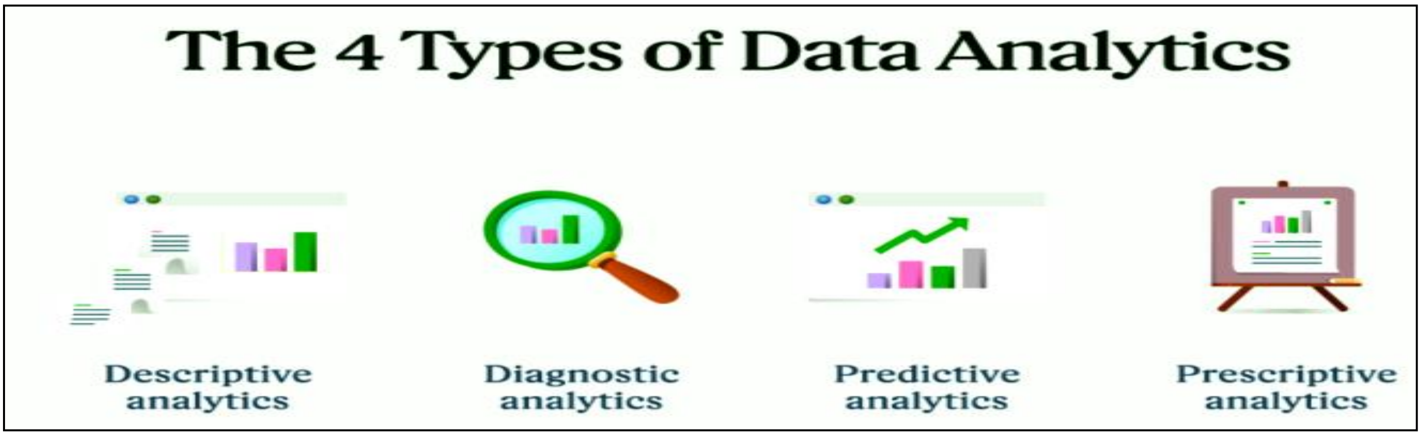

Fig 18: Types of Data Analytics

AI allows complex decision-making in data analysis and simulation. It can codify human expertise into a decision support system, offering specific recommendations and guiding users with no experience. AI tools store and reuse knowledge, combining specific intelligence about analysis techniques with subject knowledge. For instance, scheduling algorithms optimize task scheduling while leveraging knowledge of the task or machine.

IV. CHALLENGES AND FUTURE DIRECTIONS

A. Ethical Considerations

The concept of addressing the ethical aspects of AI and robotics with robust policy responses and international frameworks is recommended by various organizations. The focus should shift towards the potential benefits of these technologies rather than the perceived "evils." To ensure a positive impact, high-level discussions should lead to new laws, company codes, and customs. As intelligent engines develop rapidly, regulations specific to their use are essential. Flexibility and performance-based regulations are important to accommodate the challenges and changes brought by intelligent engines. Preemptive health and safety risk assessments will ensure their beneficial introduction in the workplace.

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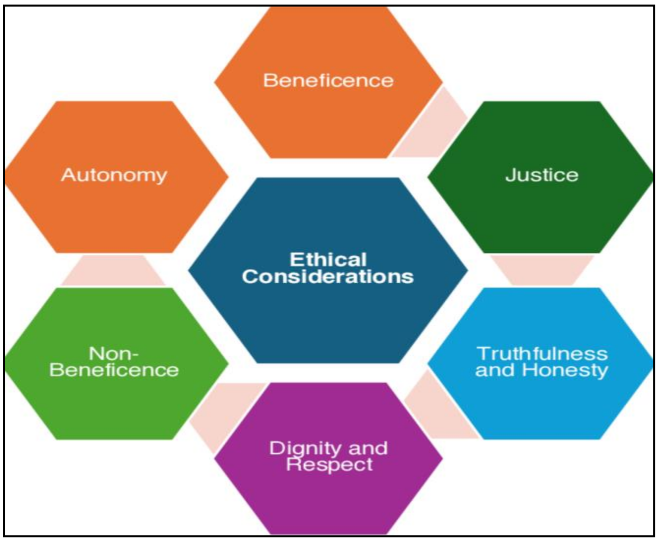

Fig 19: Ethical Considerations

B. *Workforce Adaptation and Training*

Intelligent engines disrupt industries globally, changing work nature and workforce. Machine learning focuses on replacing human workers with robots, bringing economic growth but harming the current workforce. Intelligent engines, however, augment human intelligence and enhance worker effectiveness.

Our project uses case-based systems to capture and reuse process knowledge in aerospace, explicitly targeting the design and planning phases. By preserving the knowledge base and involving human designers, our technology differs from typical automation approaches and ensures job security for designers.

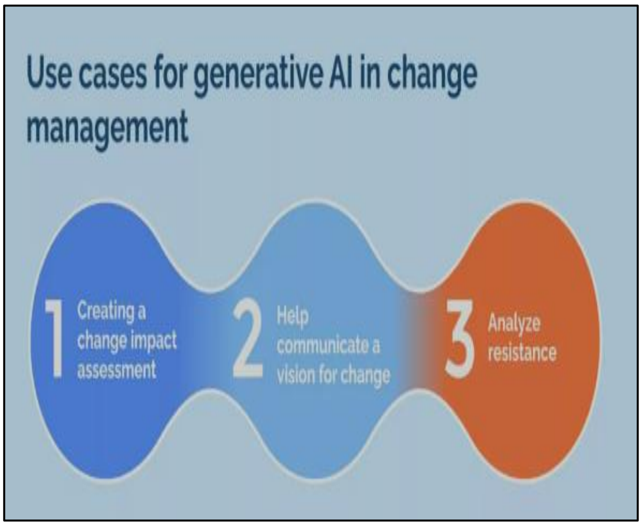

Fig 20: Change Management

C. *Cybersecurity Risks*

The latest digital and AI techniques and tactics challenge cybersecurity system developers. Cybersecurity is a critical issue for all as the threats can be severe economic threats to national security, let alone the effect on individual organizations that are hit by security breaches. The security vulnerabilities of intelligent systems are a significant issue, and further work is required to ensure that AI and intelligent system applications are secure and do not become a new attack on organizations or society. As intelligent systems begin controlling and optimizing more complex physical, biological, and societal systems, their positive or negative impact will increase. AI technologies have the potential to automate a range of tasks, for instance, from everyday daily life to mission-critical endeavors on the road and in the workplace.

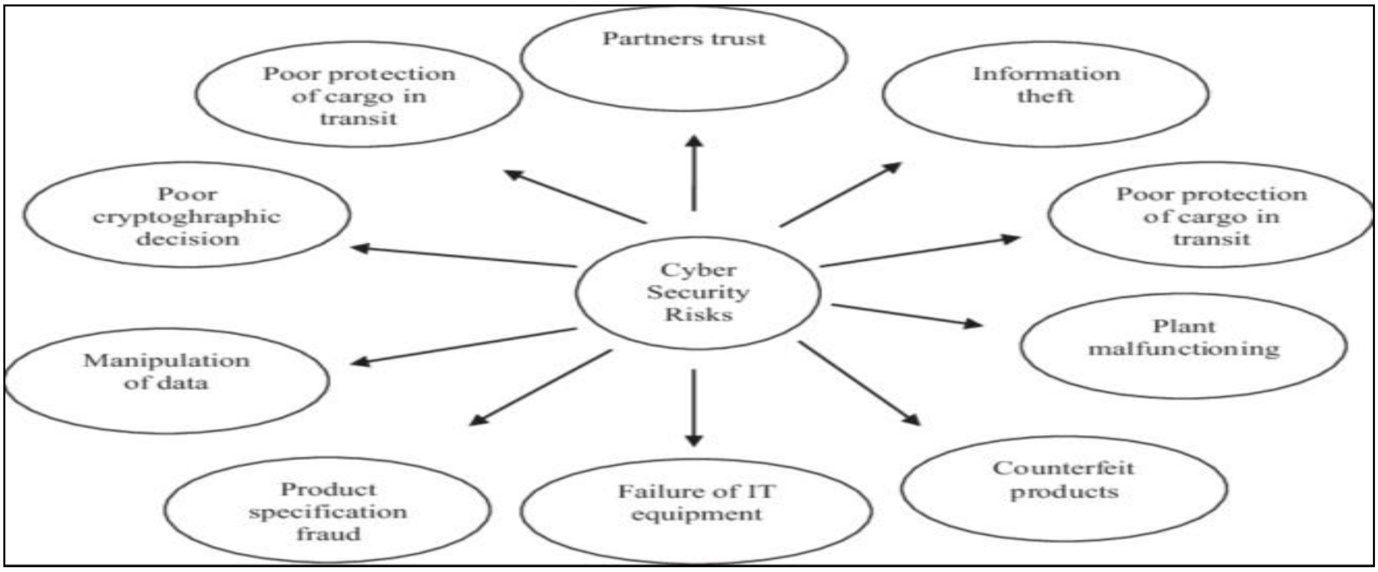

Fig 21: Cybersecurity Risks

A security breach in an AI system has the potential to have a severe impact on society's quality of life. Measures to ensure the security and safety of AI systems present a significant challenge. They will require more research into providing end-to-end security and safety assurance for AI technologies. Additionally, it will require a shift in how society approaches security and safety as it becomes reliant on intelligent systems.

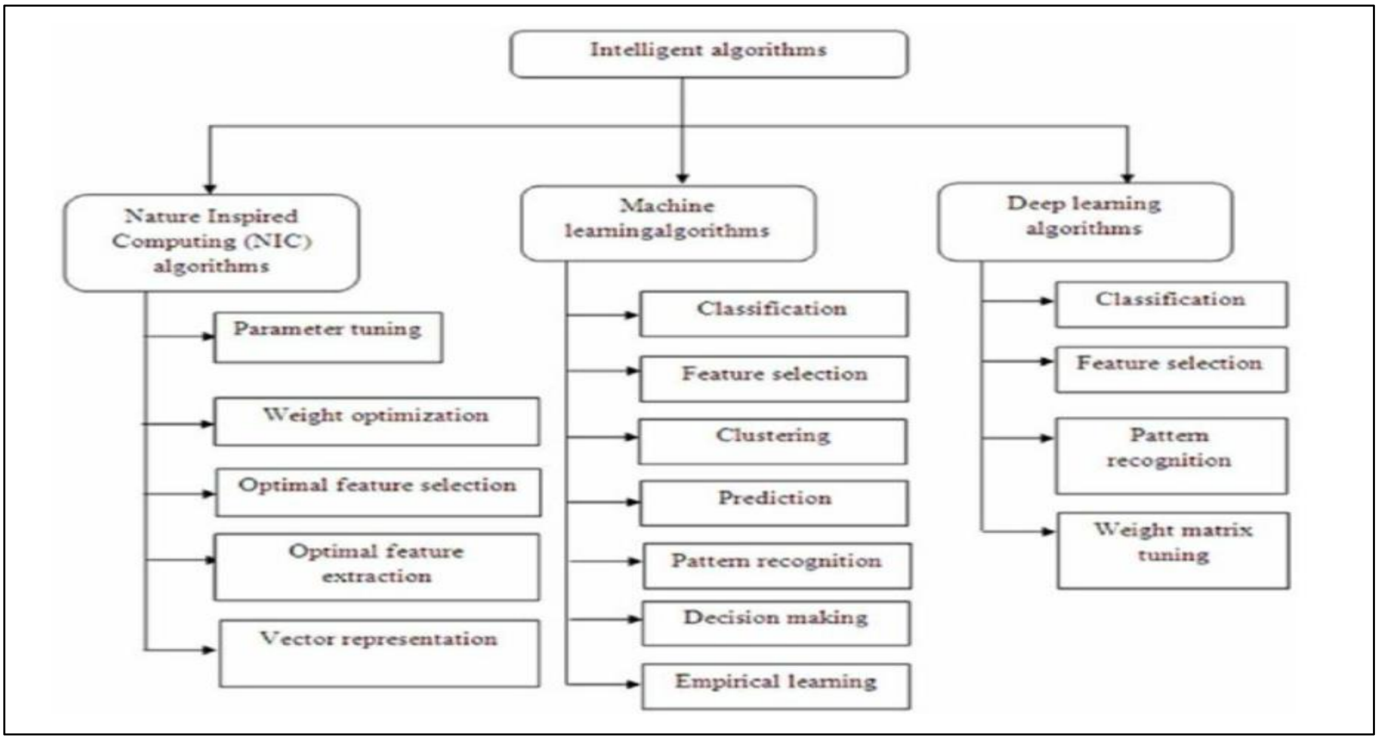

Fig 22: Cybersecurity Algorithm

D. Potential Applications in Other Industries

In the case study, we found the successful implementation of the Intelligent Engine within one company. The system was demonstrated in a single facility in the manufacturing sector, specifically the supply chain for an automotive parts warehouse.

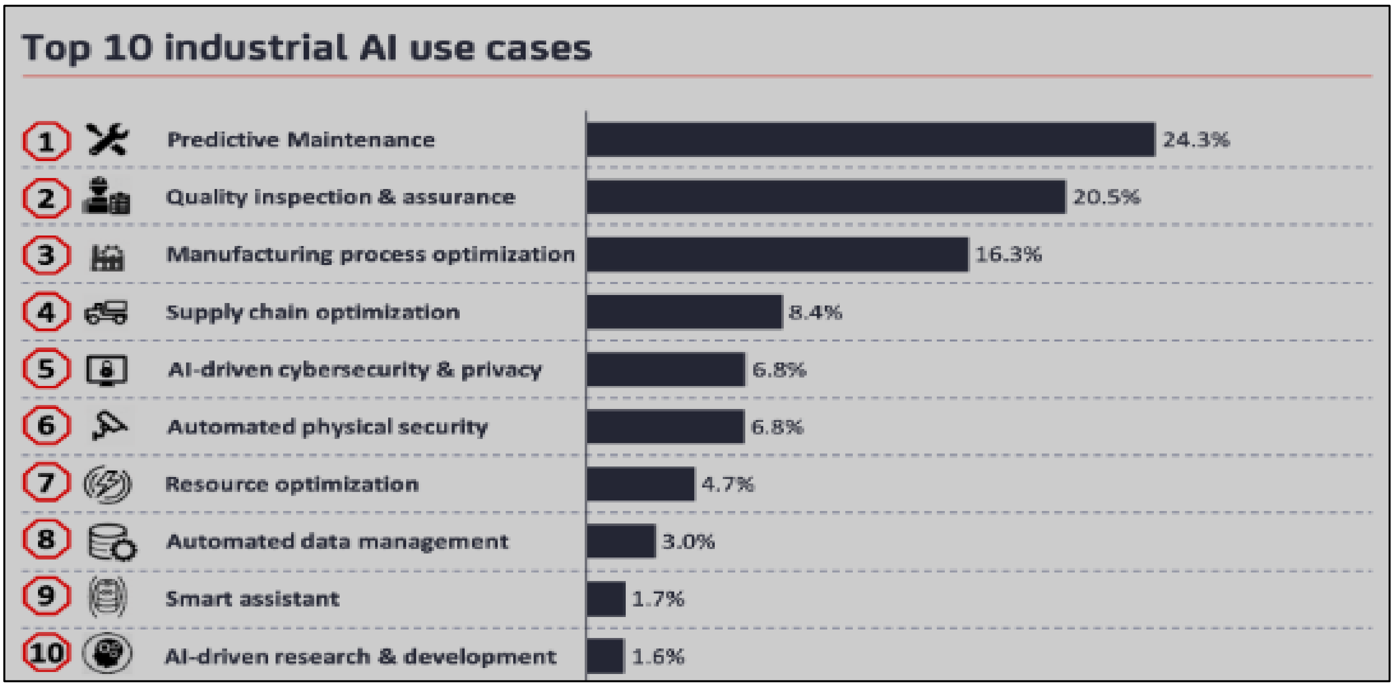

Fig 23: AI Application

It was found that the intelligent engine improved the quality of scheduling. A team of six engineers did the original scheduling within the plant. Their schedules were often found to be of poor quality, and the only feasible way to get good results was through extensive debugging within the simulation environment.

The intelligent engine improved the human engineers' schedules in only a fraction of the computational time. It is important to note that the operation research team at the warehouse could have been more enthusiastic about the simulation result on the first day.

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Table 4: AI Application Types

Narrow AI	General AI
Application specific/ task limited	Perform general (human) intelligent action
Fixed domain models provided by programmers	Self-learns and reasons with its operating environment
Learns from thousands of labeled examples	Learns from few examples and/or from unstructured data
Reflexive tasks with no understanding	Full range of human cognitive abilities
Knowledge does not transfer to other domains or tasks	Leverages knowledge transfer to new domains and tasks
Today's AI	Future AI?

This was because the quality of engine schedules was very high, and the research team did not believe it was feasible to get such good results. However, once the engine schedules were implemented, the research team found the quality of work to be much improved, and they were able to use the schedules to direct the factory in a way consistent with the global optimality of the engine schedules. The research team relinquished their scheduling control to the engine, which was deemed automatic within two weeks.

Table 5: Industrial Field of Application

Industrial fields of application	Phases of the product life cycle	Value-adding potential
Co-creation	Product idea, product planning	Customer value, individualization
Rapid prototyping	Product planning, product development	Shorter product development time, reduction of time-to market
Rapid tooling	Product development, production	Supplier independence, interim solution
Efficient product	Product planning, product development,	Ligthweight design, freedom of design
Co-production	Product planning, product development, production	Local production, Know-how growth
Rapid manufacturing	Production	Complementary manufacturing technology
Spare parts on demand	Product application and service	Reduction of warehouse and transportation costs
Repair of wear parts	Product application and service, reprocessing	Product preservation

V. CONCLUSIONS

Looking beyond control, AI methods are starting to be applied to system understanding and failure mitigation. Machine learning techniques are used to learn complex equipment and systems models from sensor data and for decision support in maintenance and other operations. This development is strongly aligned with the evolution of intelligent engines. Model-based learning and reasoning for diagnosis and reconfiguration will provide a unifying framework for system understanding and control. They will significantly impact the safety of intelligent engines, ensure that they are robust and reliable, and minimize the life cycle costs for complex systems. The effective deployment of AI technologies represents a major opportunity to improve manufacturing and supply chains in the global economy. The UK industry needs to stay competitive in the future.

IIoT improves manufacturing and supply chains, including resource utilization, waste reduction, and higher-quality products. Intelligent engines and AI are leading this transformation by optimizing system performance, minimizing downtime, and automating control system design and maintenance. AI methods support the computerization of control and automate the automation process. This solves the problem of knowledge acquisition for control and enables advanced control technology to solve complex problems.

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