Artificial Intelligence in Manufacturing Industry

Harun Pirim, IME Faculty
Connect Elicit Learn Lab
harun.pirim@ndsu.edu

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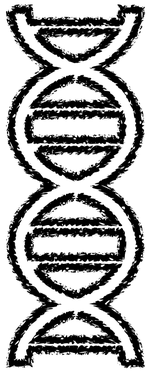
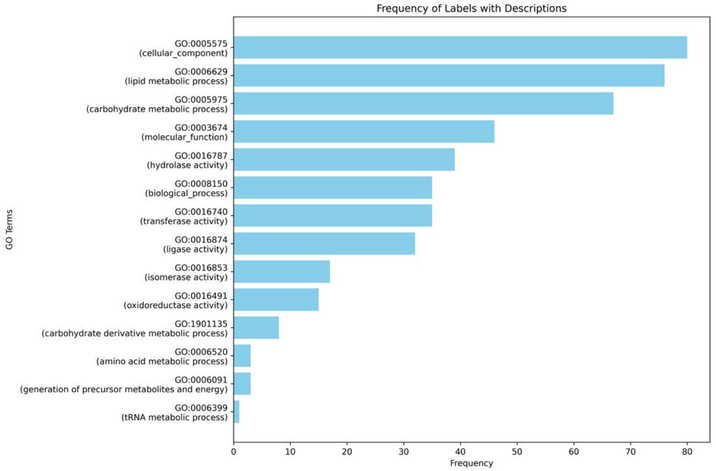
Bioinformatics

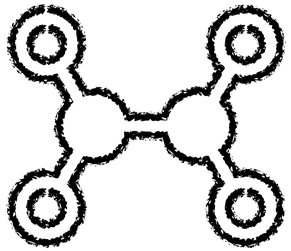


Supervised learning

Predict one or more functions of a hypothetical protein using ML

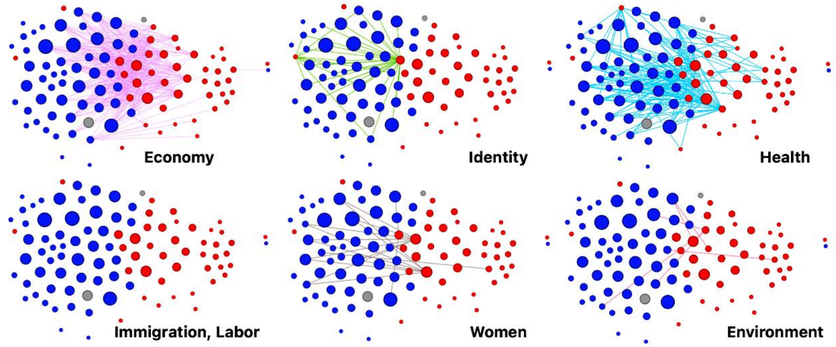


Computational Social Science



Unsupervised learning

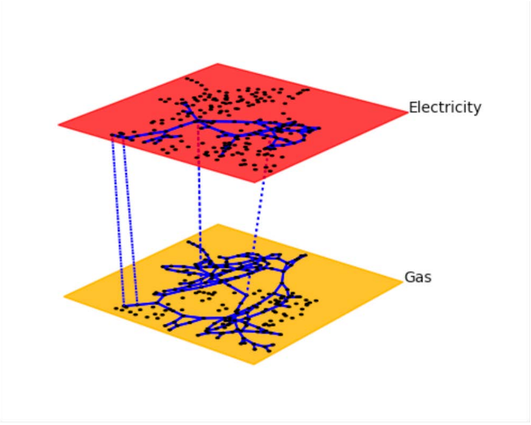
Which subjects cause the most polarization among political elites?



Operations Research

Unsupervised learning

Analyze dependability between electricity and gas networks



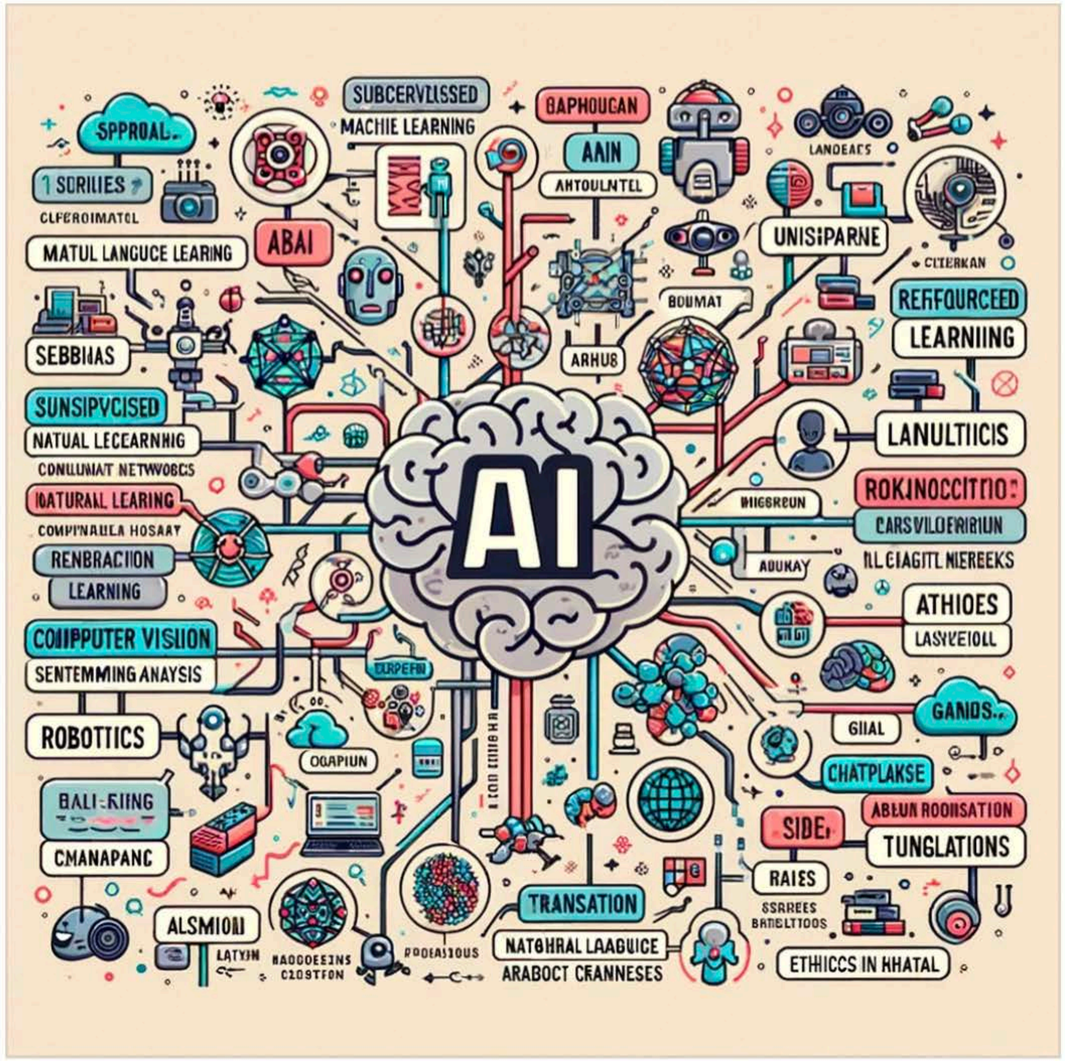
Flow of the presentation

- Introduction to AI
- Motivating quotes from experts
- Use cases in manufacturing
- What we can do further...

You

make a nice visual to categorize AI topics

ChatGPT



You

make this a table

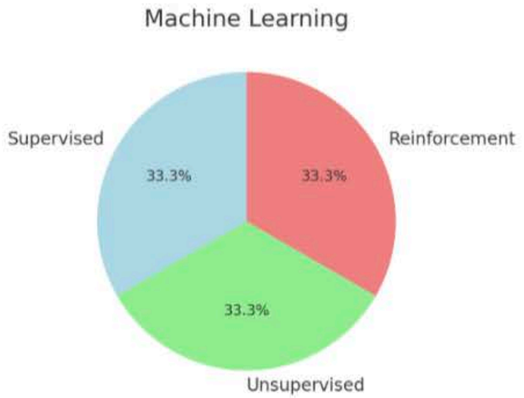
Main Category	Sub-Category
Machine Learning	Supervised Learning
Machine Learning	Unsupervised Learning
Machine Learning	Reinforcement Learning
Neural Networks	Convolutional Neural Networks
Neural Networks	Recurrent Neural Networks
Neural Networks	Generative Adversarial Networks (GANs)
Natural Language Processing	Sentiment Analysis
Natural Language Processing	Translation
Natural Language Processing	Chatbots
Robotics	Path Planning
Robotics	Manipulation
Robotics	Human-Robot Interaction
Computer Vision	Image Recognition
Computer Vision	Object Detection
Computer Vision	3D Modeling
Ethics in AI	Bias
Ethics in AI	Privacy
Ethics in AI	Transparency

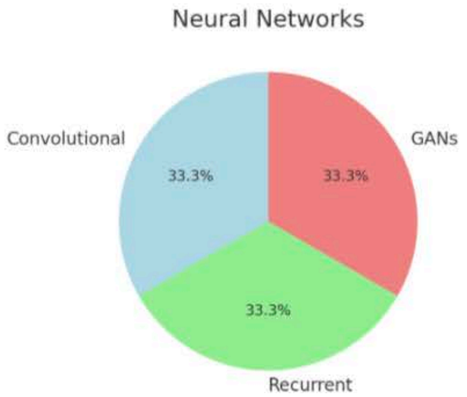
You

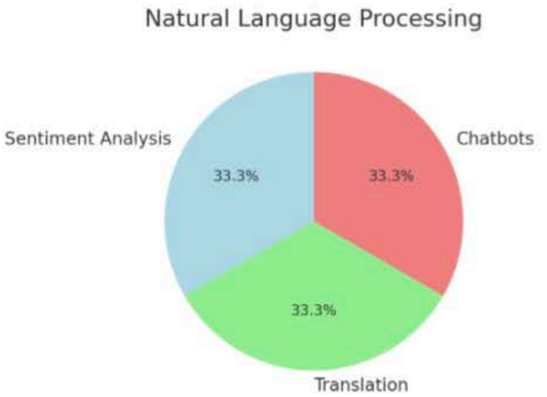
You

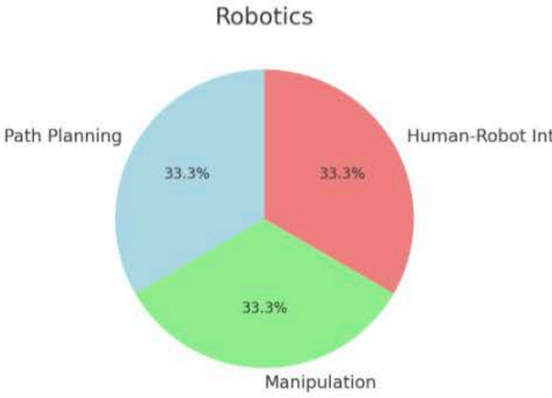
each pie chart has sub-categories, show the subcategories inside each pie chart

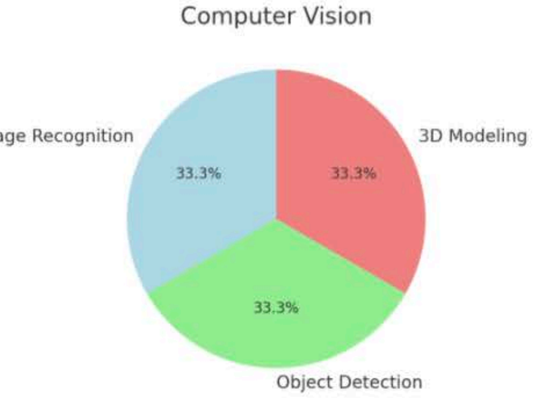
ChatGPT

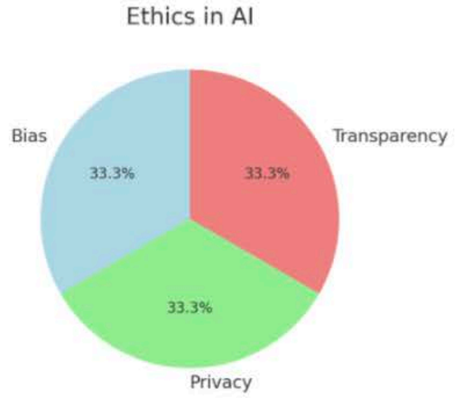


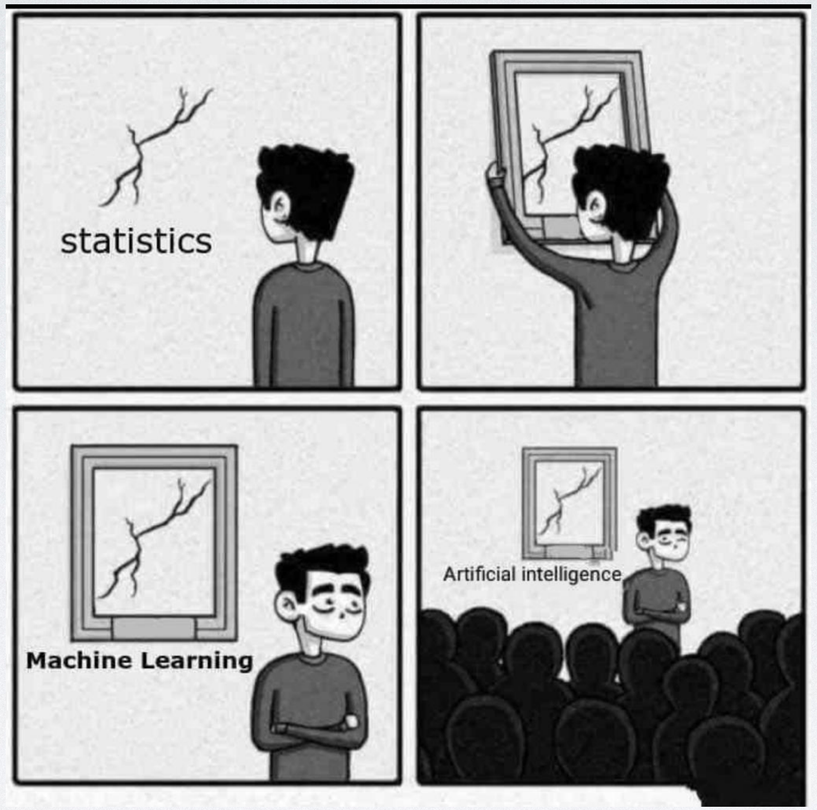












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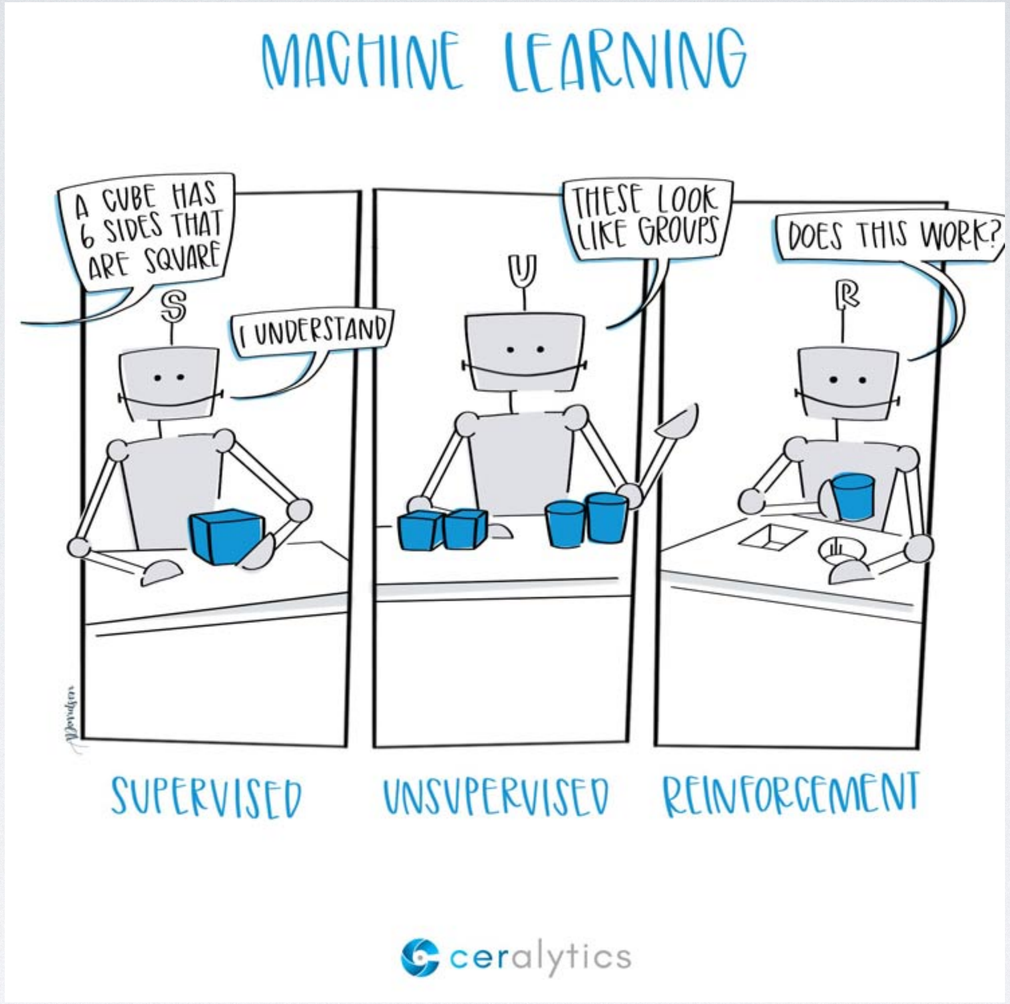

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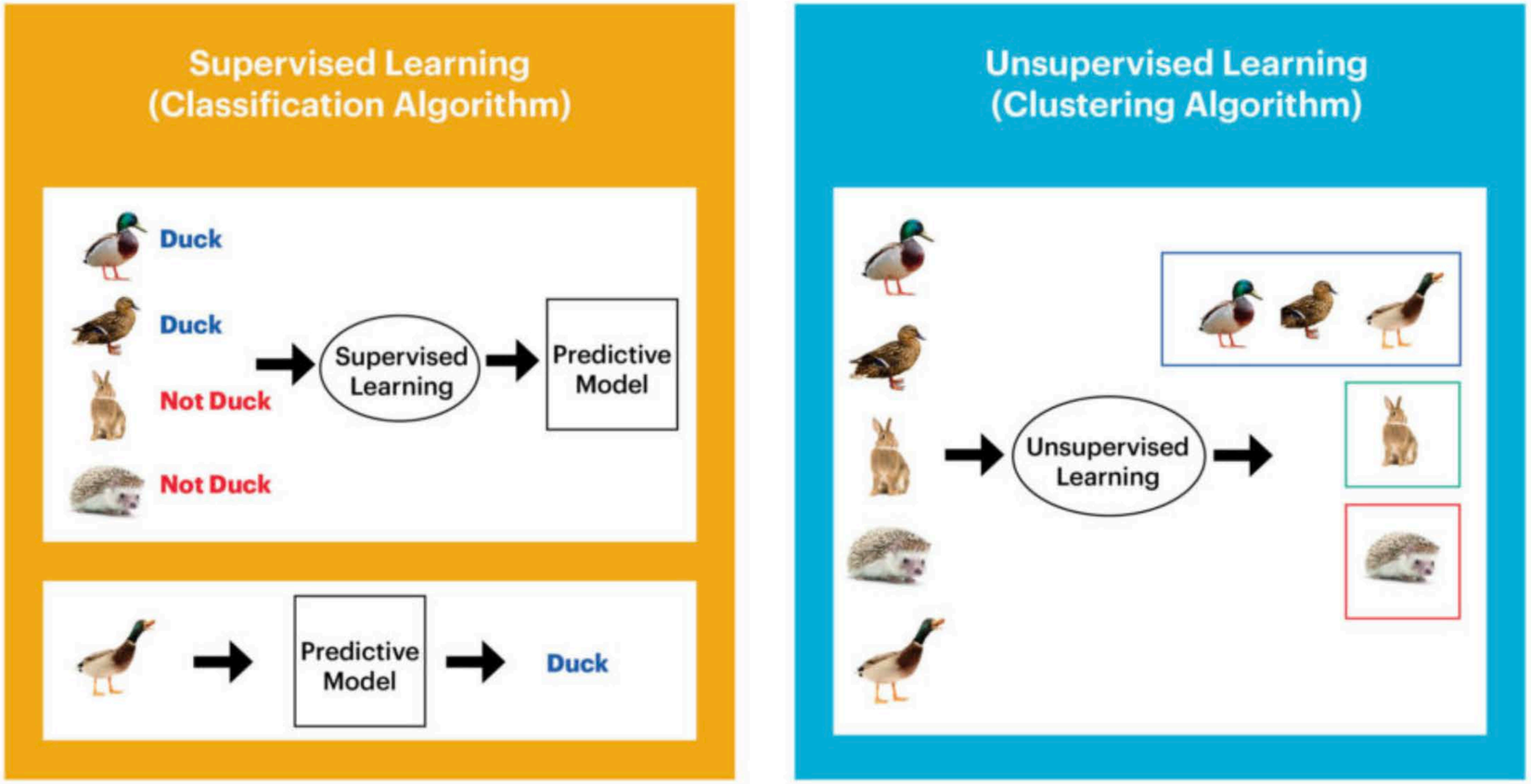
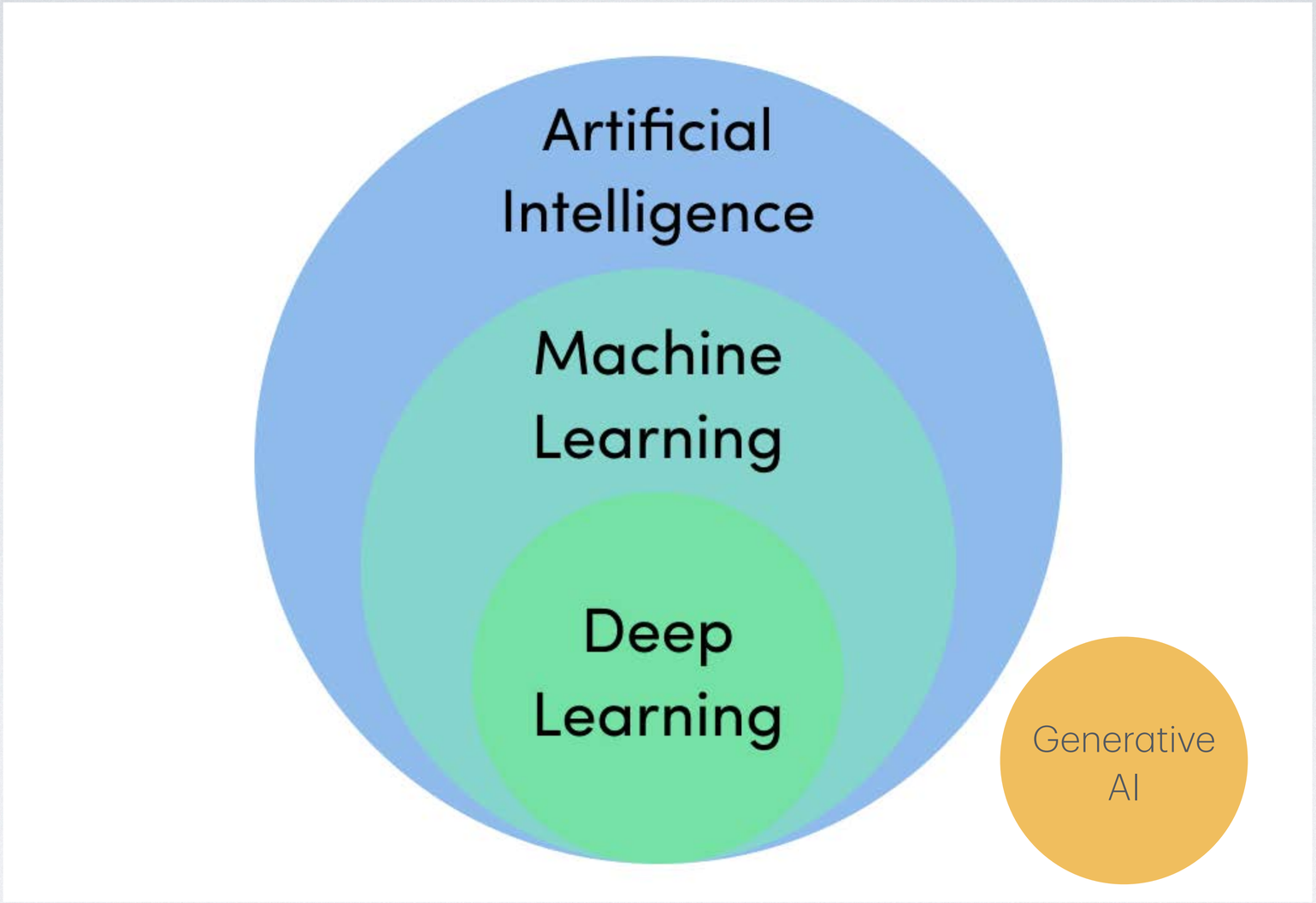

Supervised Learning
(Classification Algorithm)
Duck
Duck
Not Duck
Not Duck
Supervised Learning
Predictive Model
Predictive Model
Duck
Unsupervised Learning
(Clustering Algorithm)
Unsupervised Learning
Western Digital.



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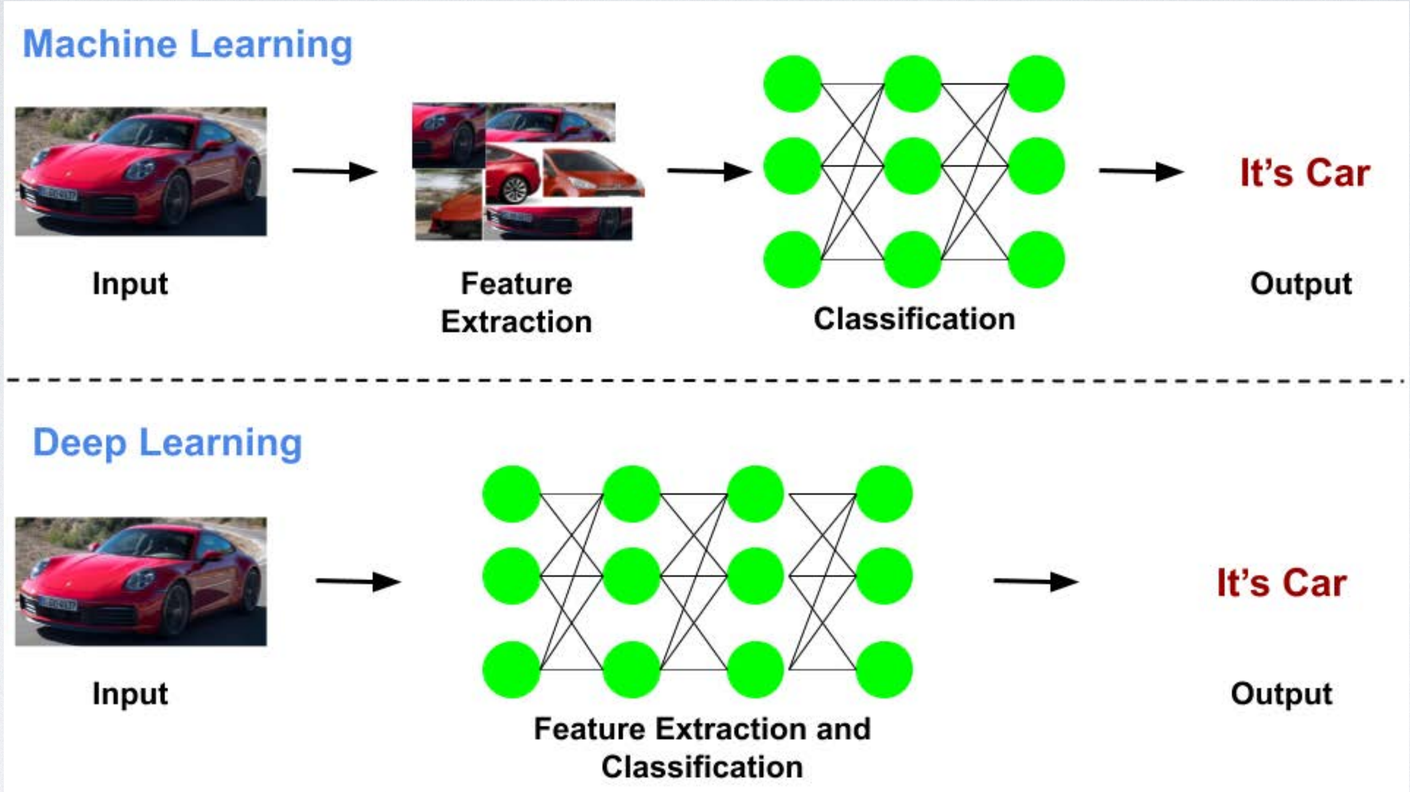

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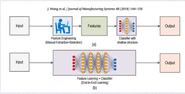
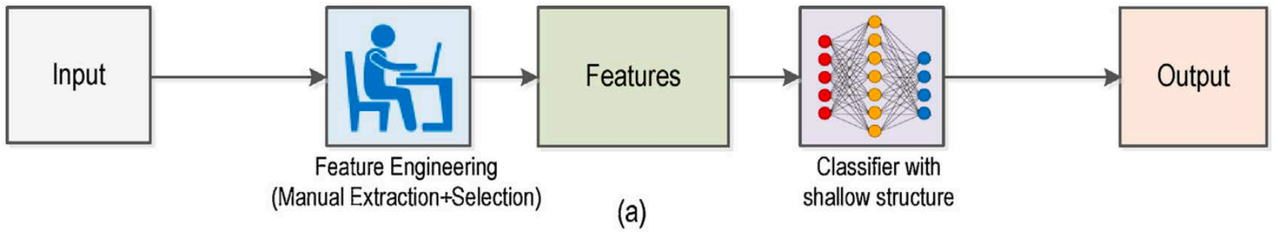
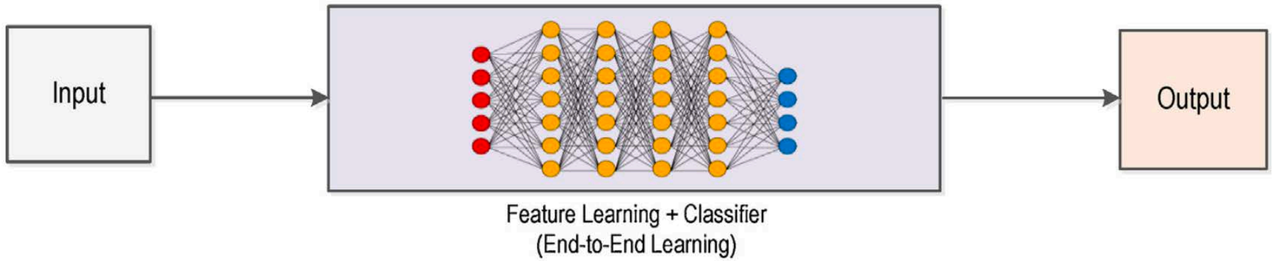
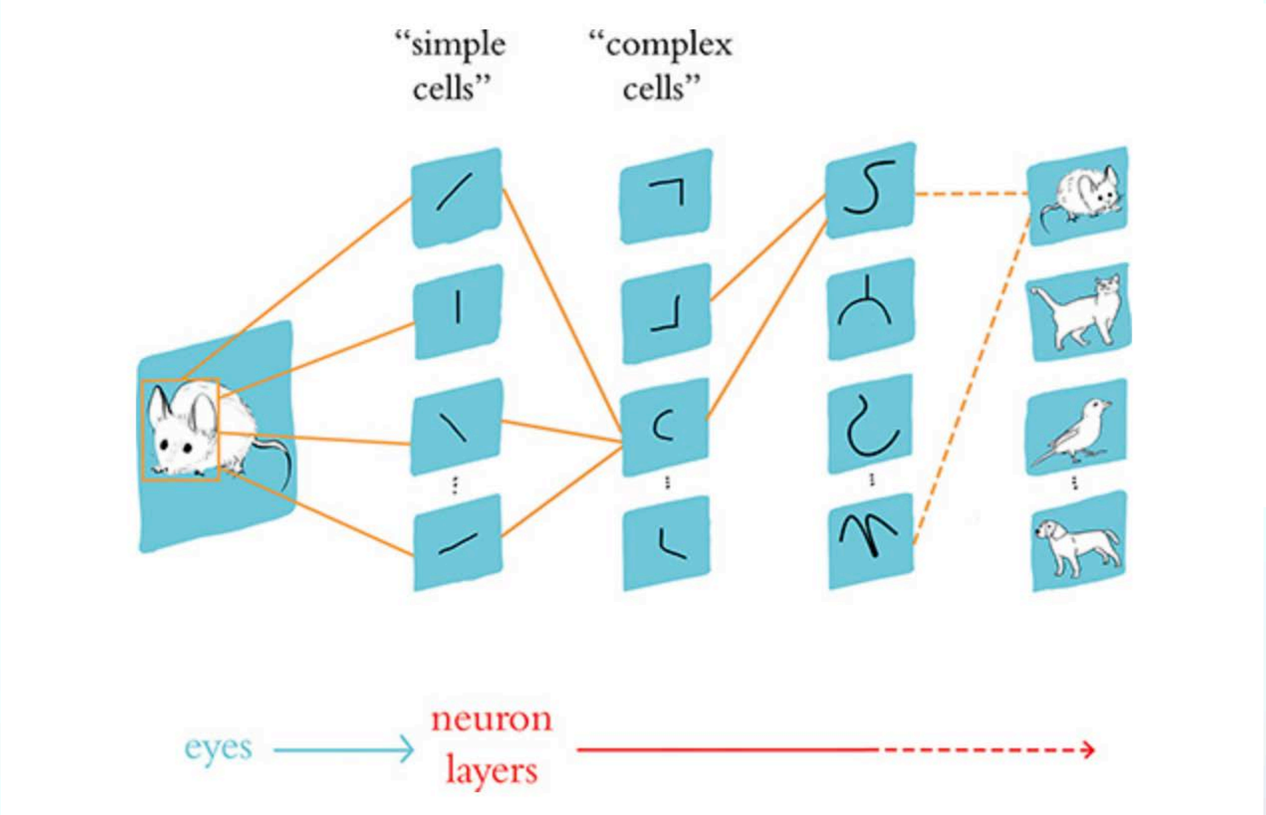


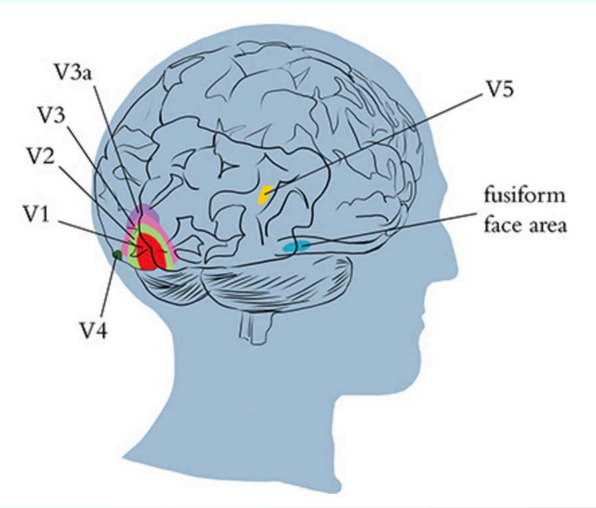

Input
Feature Engineering
(Manual Extraction+Selection)
Features
Classifier with
shallow structure
Output

(a)


Input
Feature Learning + Classifier
(End-to-End Learning)
Output

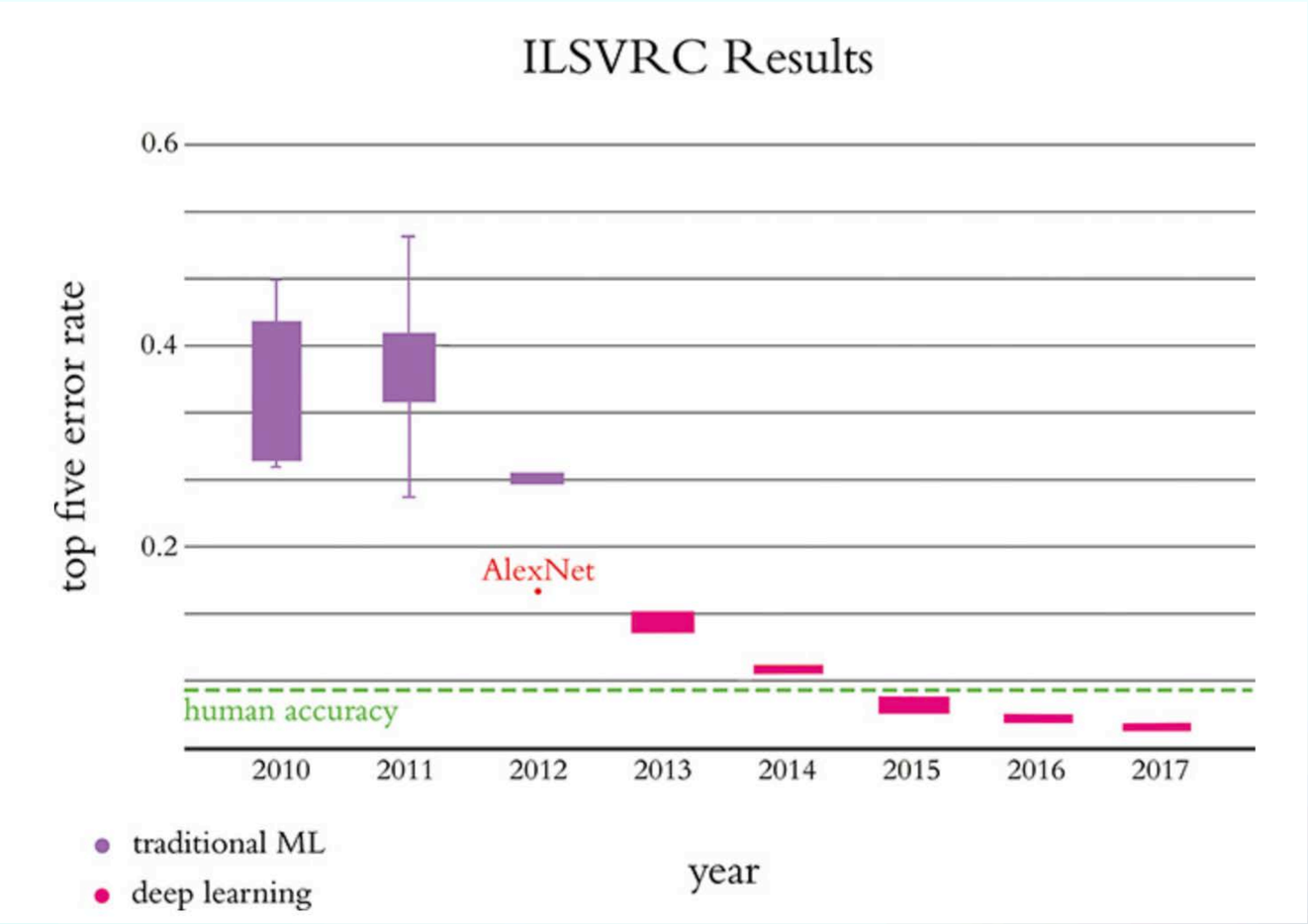
(b)





A caricature of how consecutive layers of biological neurons represent visual information in the brain of, for example, a cat or a human

Source: Krohn, Jon, et al. Deep Learning Illustrated. Available from: VitalSource Bookshelf, Pearson Technology Group, 2019.



Performance of the top entrants to the ILSVRC by year. AlexNet was the victor by a head-and-shoulders (40 percent!) margin in the 2012 iteration. All of the best algorithms since then have been deep learning models. In 2015, machines surpassed human accuracy.

Source: Krohn, Jon, et al. Deep Learning Illustrated. Available from: VitalSource Bookshelf, Pearson Technology Group, 2019.

Deep Learning Playground

“Electricity transformed industry
AI brings equally big transformation”

Andrew Ng, DeepLearning.AI

Hope to find a lingua franca!

What is AI

```python
def is_even(number):
    if number % 2 == 0:
        return "Even"
    else:
        return "Odd"

# Example usage
print(is_even(4))  # Output: Even
print(is_even(5))  # Output: Odd
```

Data

Rule

Classical programming

Data + Rule —> Output (even or odd)

Data + Output —> Rule

Machine learning

```python
from sklearn.tree import DecisionTreeClassifier

# Training data
X = [[0], [1], [2], [3], [4], [5], [6], [7], [8], [9]] # Features (numbers)
y = [0, 1, 0, 1, 0, 1, 0, 1, 0, 1] # Labels (0 for even, 1 for odd)

# Train the model
model = DecisionTreeClassifier()
model.fit(X, y)

# Make predictions
print(model.predict([[6]])[0])  # Output: 0 (Even)
print(model.predict([[9]])[0])  # Output: 1 (Odd)
```

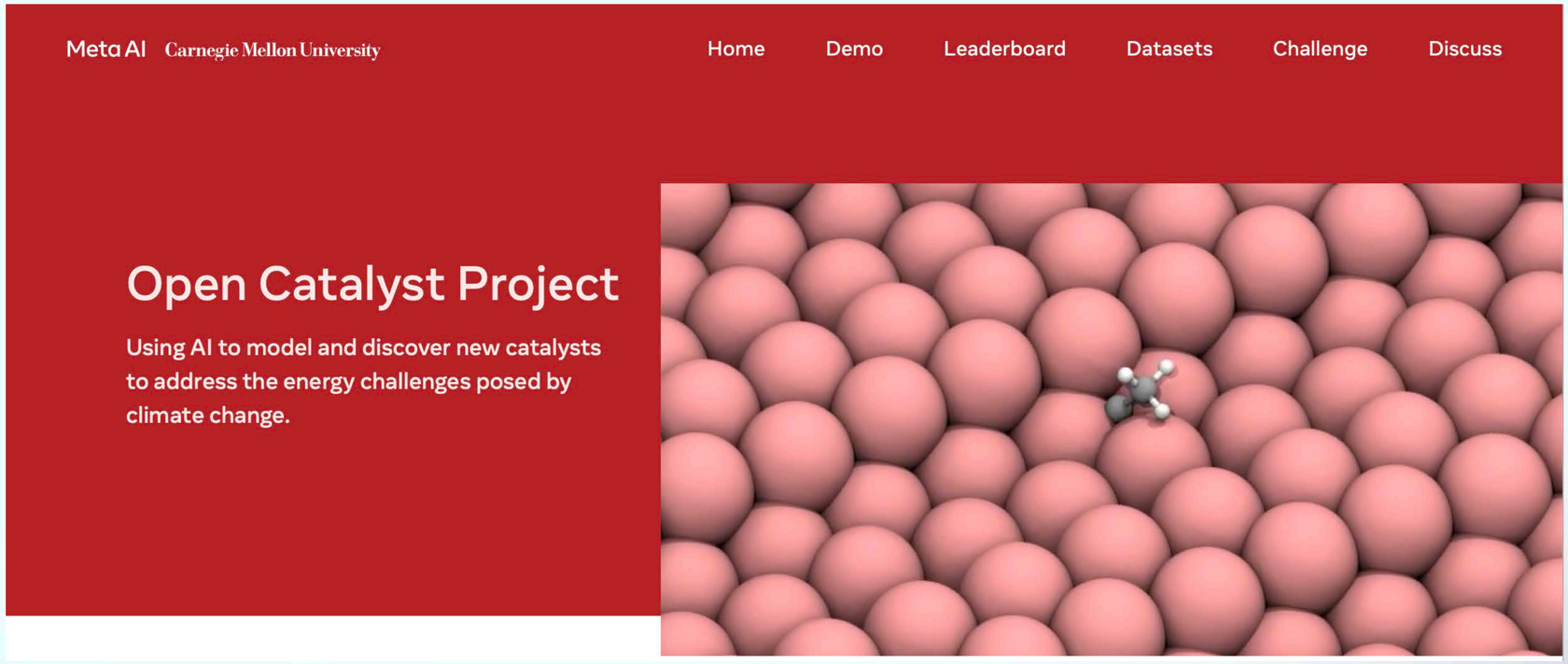
Data

Output

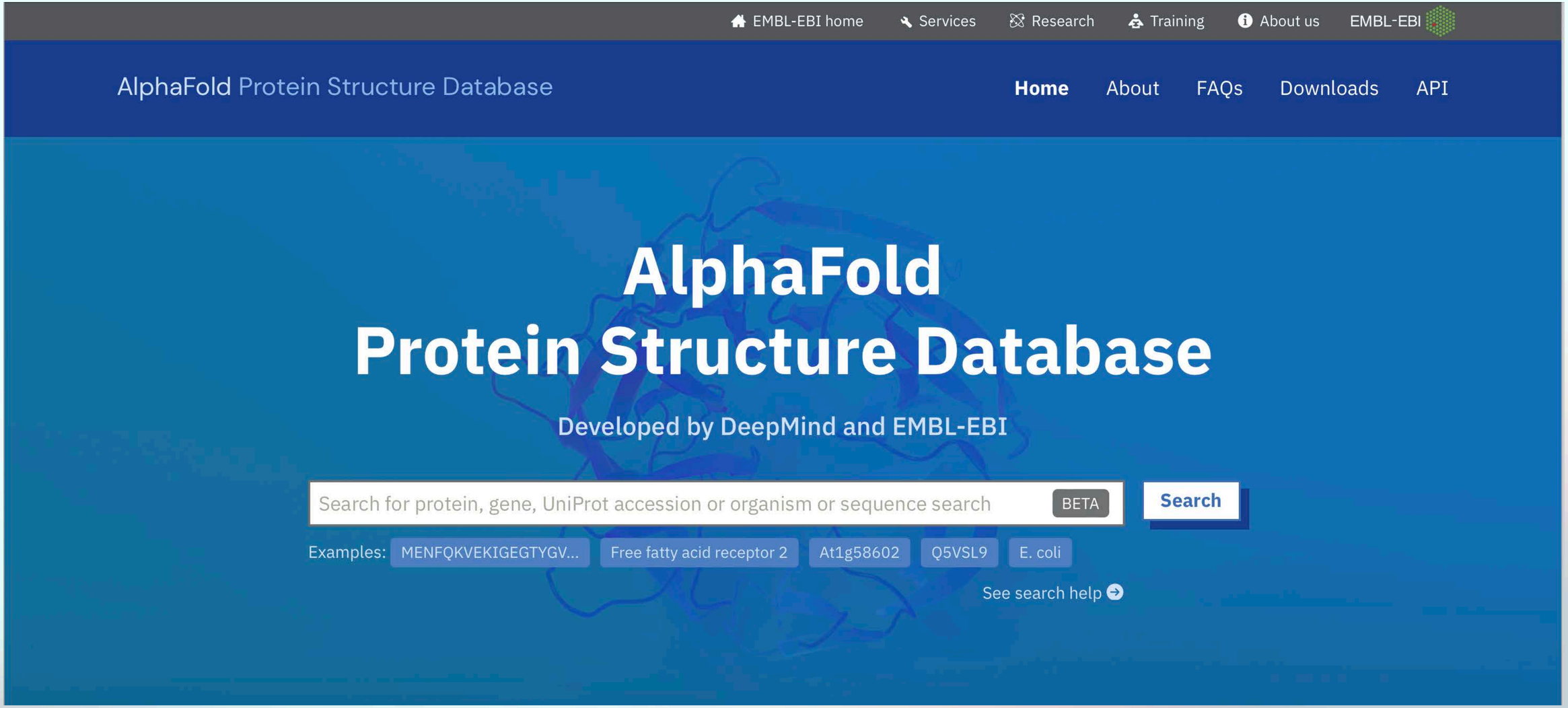
Rule

Collection of Software and Hardware

AI Application	Product Use Case	Core AI Technology
Face Recognition	Smartphones (e.g., iPhone)	Convolutional Neural Networks
Voice Assistants	Smart Speakers (e.g., Alexa)	Natural Language Processing
Recommendation Systems	Online Platforms (e.g., Netflix)	Machine Learning Algorithms
Autonomous Vehicles	Self-driving Cars (e.g., Tesla)	Computer Vision, Sensor Fusion
Fraud Detection	Banking Systems	Anomaly Detection Algorithms
Text Predictions	Keyboard Apps (e.g., SwiftKey)	Recurrent Neural Networks
Personalized Marketing	E-commerce Websites	Data Mining, Predictive Analysis
Chatbots	Customer Service Platforms	Natural Language Understanding
Virtual Try-on Technology	Online Retail (e.g., Warby Parker)	Augmented Reality, AI Algorithms
Smart Home Devices	Home Automation Systems	Machine Learning, IoT Integration



The primary aim of this project is to harness artificial intelligence (AI) for modeling and discovering new catalysts. These efforts are geared towards addressing the challenges of energy storage in the context of climate change.



AlphaFold is an AI system developed by DeepMind that predicts a protein's 3D structure from its amino acid sequence. It regularly achieves accuracy competitive with experiment.

Predicting the 3D structure of proteins is one of the fundamental grand challenges in biology. By solving this challenge, we can dramatically deepen our understanding of human health, disease, and our environment, especially within areas like drug design and sustainability.

Figure announces commercial agreement with BMW Manufacturing

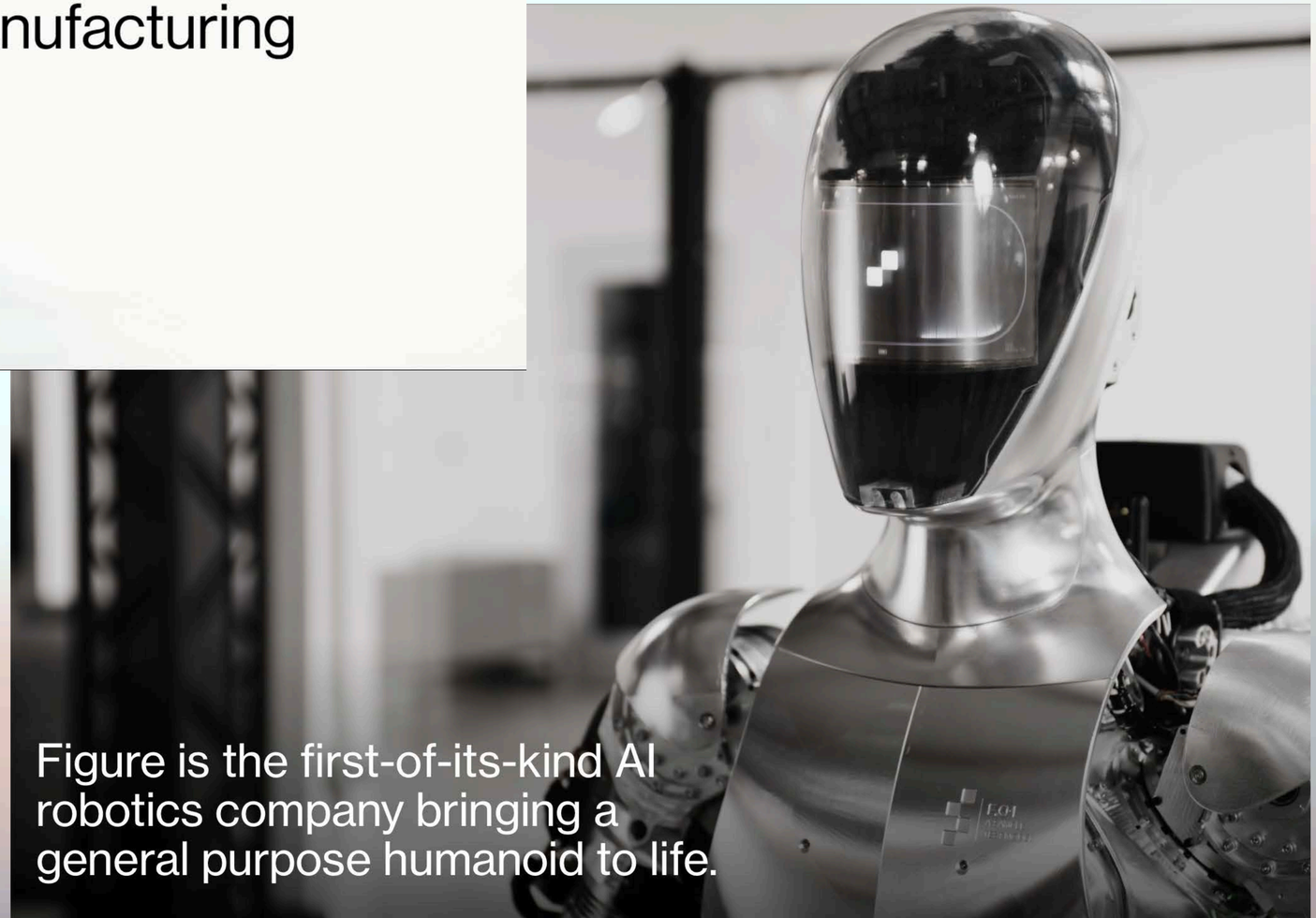
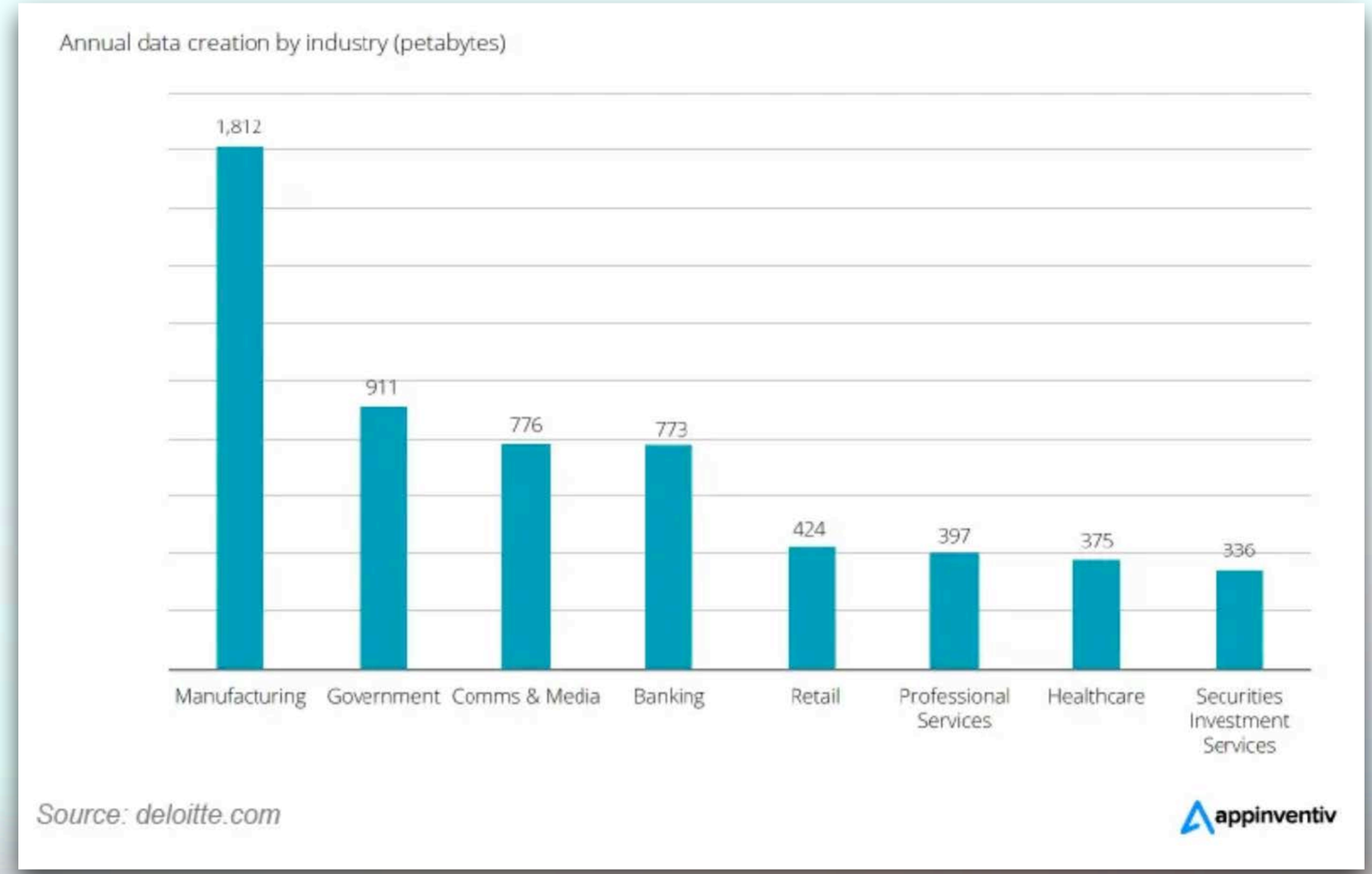


Figure is the first-of-its-kind AI robotics company bringing a general purpose humanoid to life.


Annual data creation by industry (petabytes)
1,812
911
776
773
424
397
375
336
Manufacturing
Government
Comms & Media
Banking
Retail
Professional Services
Healthcare
Securities Investment Services
Source: deloitte.com
appinventiv

“At a compound annual growth rate (CAGR) of 47.9% from 2022 to 2027, the worldwide artificial intelligence in the manufacturing market is expected to be worth $16.3 billion, as per a report from Markets and Markets.”

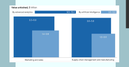
https://appinventiv.com/blog/ai-in-manufacturing/

“Organizations that adopt and integrate AI technology are better positioned to double their cash flow by 2030”

Driving Efficiency With AI in Manufacturing, ebook, www.dataiku.com

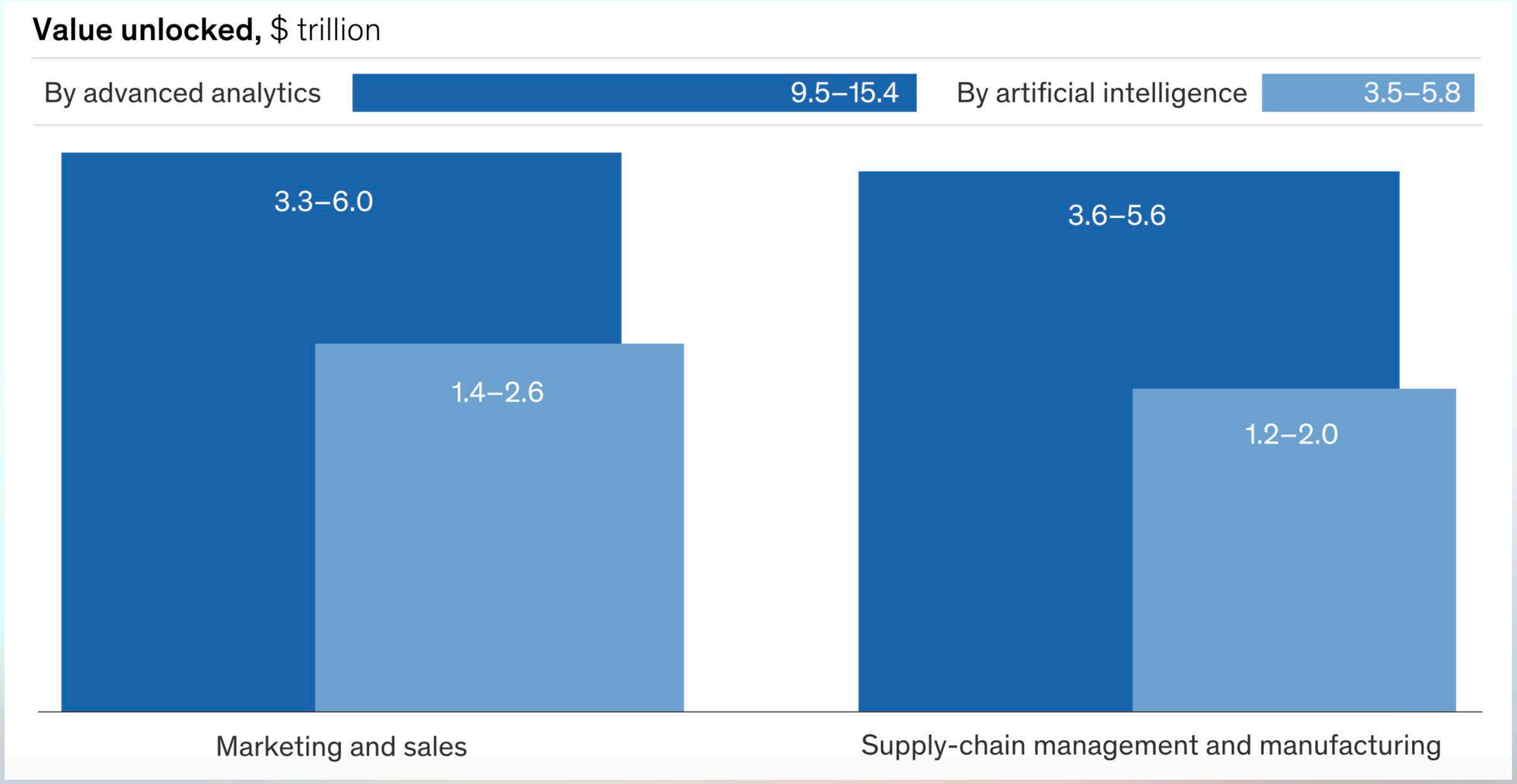
“AI on customer data to personalize promotions can lead to a 1 to 2 percent increase in incremental sales for brick-and-mortar retailers alone.”

“In advanced manufacturing, by contrast, operations often drive the most value. Here, AI can enable forecasting based on underlying causal drivers of demand rather than prior outcomes, improving forecasting accuracy by 10 to 20 percent. This translates into a potential 5 percent reduction in inventory costs and revenue increases of 2 to 3 percent.”



“In manufacturing, the greatest value from AI can be created by using it for predictive maintenance (about $0.5 trillion to $0.7 trillion across the world’s businesses). AI’s ability to process massive amounts of data, including audio and video, means it can quickly identify anomalies to prevent breakdowns, whether that be an odd sound in an aircraft engine or a malfunction on an assembly line detected by a sensor.”

An examination of more than 400 AI use cases —two areas where AI can have the greatest impact, *Harvard Business Review, 2018*.



Source: https://www.mckinsey.com/capabilities/quantumblack/our-insights/most-of-ais-business-uses-will-be-in-two-areas

“Organizations that leverage product defect detection and quality testing powered by AI and machine learning can increase manufacturing productivity by up to 50%”

Driving Efficiency With AI in Manufacturing, ebook, www.dataiku.com

“Now we can augment a lot of these AI and machine learning models with generative AI, and that can make adoption faster and change management easier.”

Manoj Kothiyal, a partner at Boston Consulting Group and the tech lead for the company’s digital in AI manufacturing platform

Continuous operations, such as helping plant floor personnel quickly identify a particular machine that is operating outside of its preferred boundaries. This would allow for real-time adjustments to prevent downtime or quality issues.

A maintenance companion, which helps shop floor personnel with maintenance tasks by digitizing paper instruction manuals and using AI to provide step-by-step, real-time instructions based on the problem at hand.

Defect detection and inspection. This means augmenting or, in some cases, replacing human inspectors with AI-enabled visual inspection. This increases accuracy and shortens the time for inspections, reducing recalls and rework and resulting in significant cost savings.

Source: https://mitsloan.mit.edu/ideas-made-to-matter/ai-manufacturing-start-data

“It’s about bringing knowledge into the organization about how to use and implement AI.”

MIT Sloan professor John Hauser

Artificial Intelligence In Manufacturing: Four Use Cases You Need To Know In 2023

Cobots

—perform tasks including gluing and welding, greasing camshafts, injecting oil into engines, and performing quality control inspections.

Additive manufacturing

— use AI to compare product designs with actual finished products and automate fine-tuning of the manufacturing process in order to bring them more closely into line.

Generative design

— enter parameters such as what materials should be used, the size and weight of the desired product, what manufacturing methods will be used, and how much it should cost, and the generative design algorithms spit out blueprints and instructions.

Predictive maintenance

— Data from vibrations, thermal imaging, operating efficiency, and analysis of oils and liquids in machinery can all be processed via machine learning algorithms for vital insights into the health of manufacturing machinery.

Source: https://www.forbes.com/sites/bernardmarr/2023/07/07/artificial-intelligence-in-manufacturing-four-use-cases-you-need-to-know-in-2023/?sh=76719e403bd8


NVIDIA

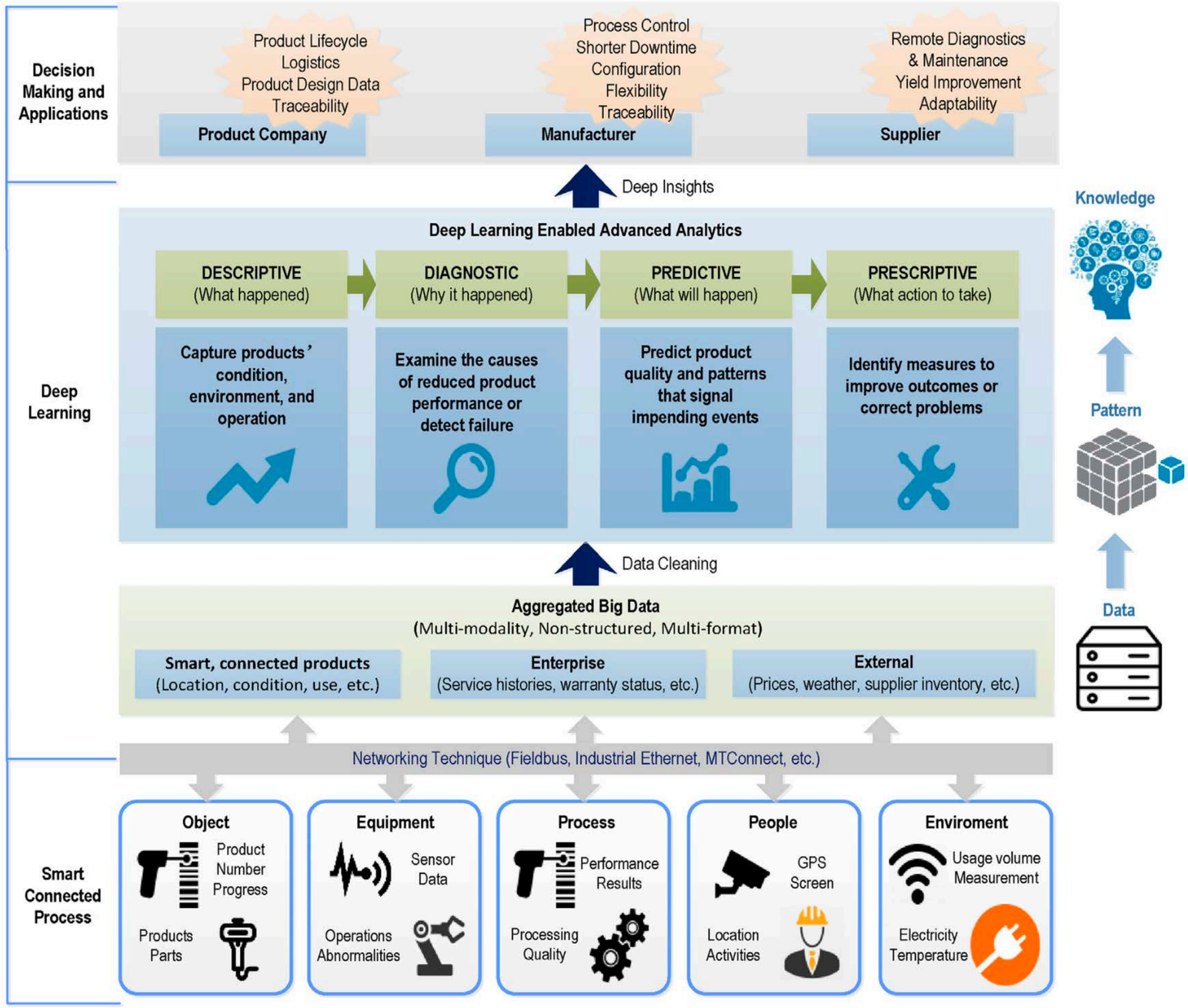
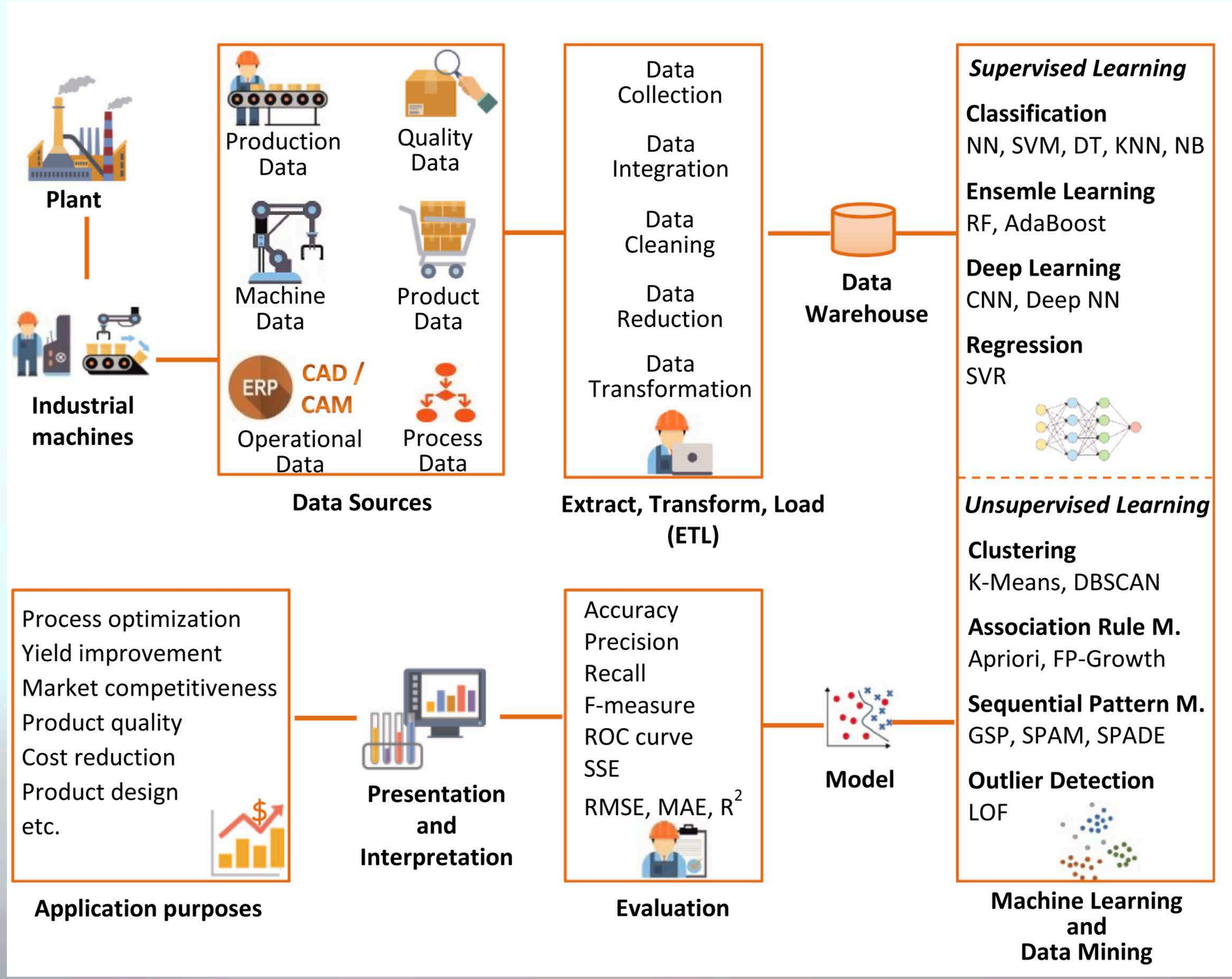
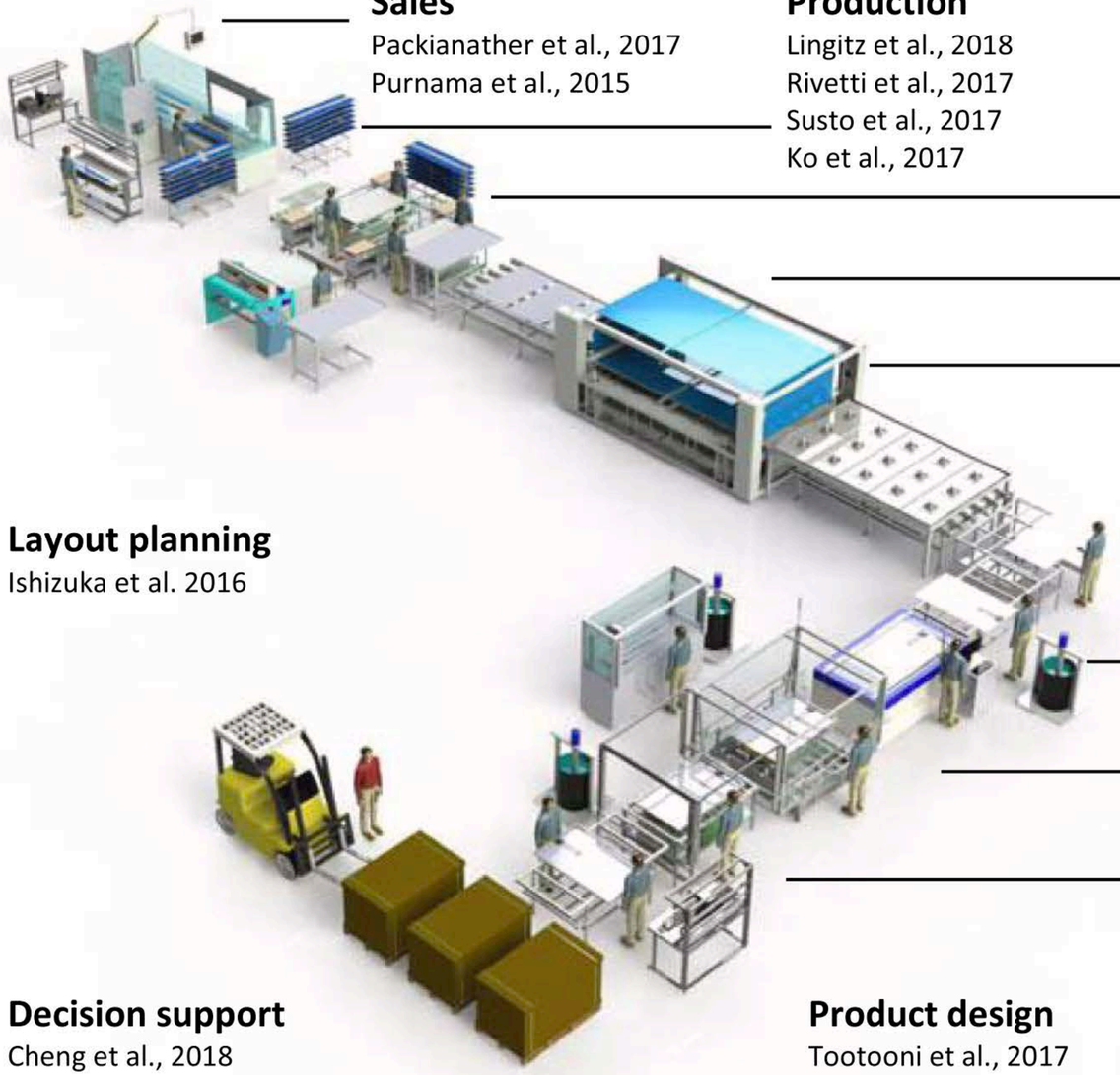


Fig. 3. Deep learning enabled advanced analytics for smart manufacturing.



Source: A Dogan, Machine learning and data mining in manufacturing, Expert Systems with Applications, Review Paper, 2021



Sales
Packianather et al., 2017
Purnama et al., 2015

Production
Lingitz et al., 2018
Rivetti et al., 2017
Susto et al., 2017
Ko et al., 2017

Monitoring
Zhao et al., 2019
Ren et al., 2018
Syafrudin et al., 2018
Lei et al., 2017
Nakata et al., 2017

Quality
Bustillo et al., 2018
Lee et al., 2018
Bai et al., 2018
Kao et al., 2017
Lee et al., 2017
Mohammadi et al., 2016
Djatnaa et al., 2015

Layout planning
Ishizuka et al. 2016

Failure / Fault
Djelloul et al., 2018
Lim et al., 2017
Lee et al., 2017
Shao et al., 2017
Kim et al., 2017
Pavlyshenko, 2016

Defect
Liukkonen et al., 2018
Huang et al., 2018
Hu et al., 2018
Das et al., 2017
Zidek et al., 2016
Wang, 2013
Lee et al., 2013

Energy
Cupek et al., 2018
Wang et al., 2018

Process
Kim et al., 2018
Moldovan et al., 2017
Zhang et al., 2017
Ge et al., 2017
Zhou et al., 2017
Sand et al., 2016
Pospisil et al., 2016

Scheduling
Dolgui et al., 2018
Priore et al., 2018
Jong et al., 2017
Bergmann et al., 2017

Decision support
Cheng et al., 2018
Gandhi et al., 2018

Product design
Tootooni et al., 2017
Wang et al., 2007

Fig. 3. ML and DM studies grouped under manufacturing tasks.

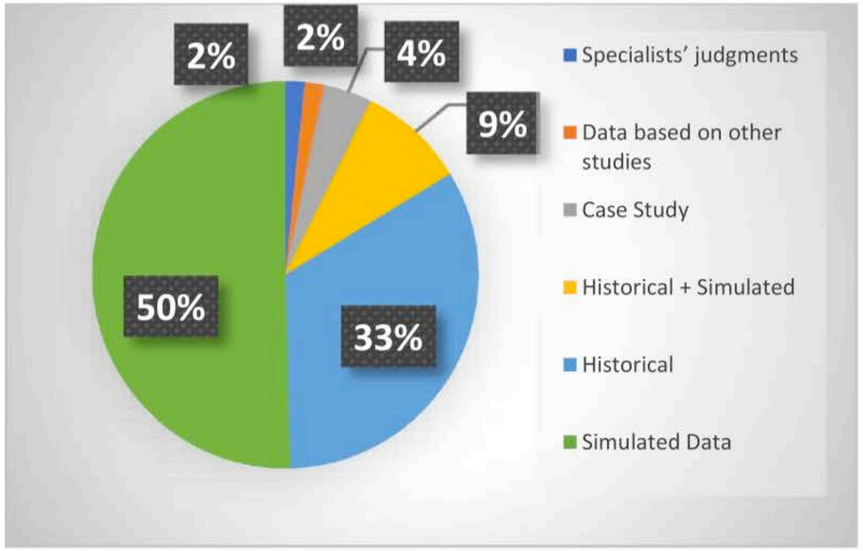
Source: A Dogan, Machine learning and data mining in manufacturing, Expert Systems with Applications, Review Paper, 2021

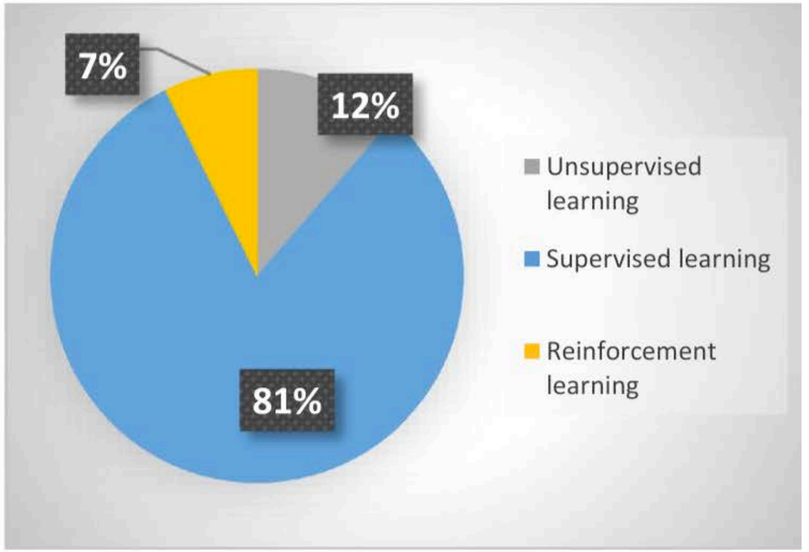
International Journal of Machine Learning and Cybernetics (2020) 11:1463–1482
https://doi.org/10.1007/s13042-019-01050-0

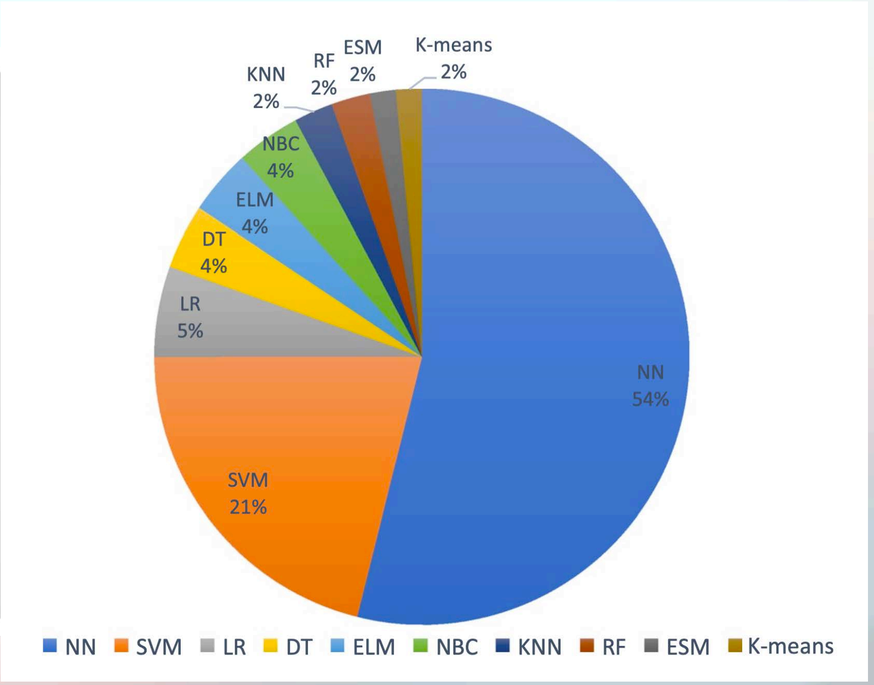
ORIGINAL ARTICLE

A systematic review of the research trends of machine learning in supply chain management

Du Ni[1] · Zhi Xiao[1] · Ming K. Lim[2,3]







ML applications in SCM

“...the past 100 years, automation in manufacturing has been about procedural automation of tasks (doing),

ML is now ushering in an era in which decision making (thinking) is progressively getting automated”

Ajit Sharma, Zhibo Zhang & Rahul Rai (2021) The interpretive model of manufacturing: a theoretical framework and research agenda for machine learning in manufacturing, International Journal of Production Research, 59:16, 4960-4994, DOI: 10.1080/00207543.2021.1930234

“Most manufacturing firm’s worldview of data is still limited to data generated from enterprise systems such as Enterprise Resource Planning Systems and Customer Relationship Management Systems.

They are not oriented towards generating and storing unstructured, big data sets such as images, acoustics, and machine log data.”

Ajit Sharma, Zhibo Zhang & Rahul Rai (2021) The interpretive model of manufacturing: a theoretical framework and research agenda for machine learning in manufacturing, International Journal of Production Research, 59:16, 4960-4994, DOI: 10.1080/00207543.2021.1930234

São Paulo Transport Powered By Google Cloud AI

Matinence Bot

Help me write a note to my manager explaining the situation. Include details on the problem, our recommendation to fix, and anticipated timing.

SPT Assistant

Sure. Here's an email you can use:

Gmail

r.moreno@sptransportation.br Cc Bcc

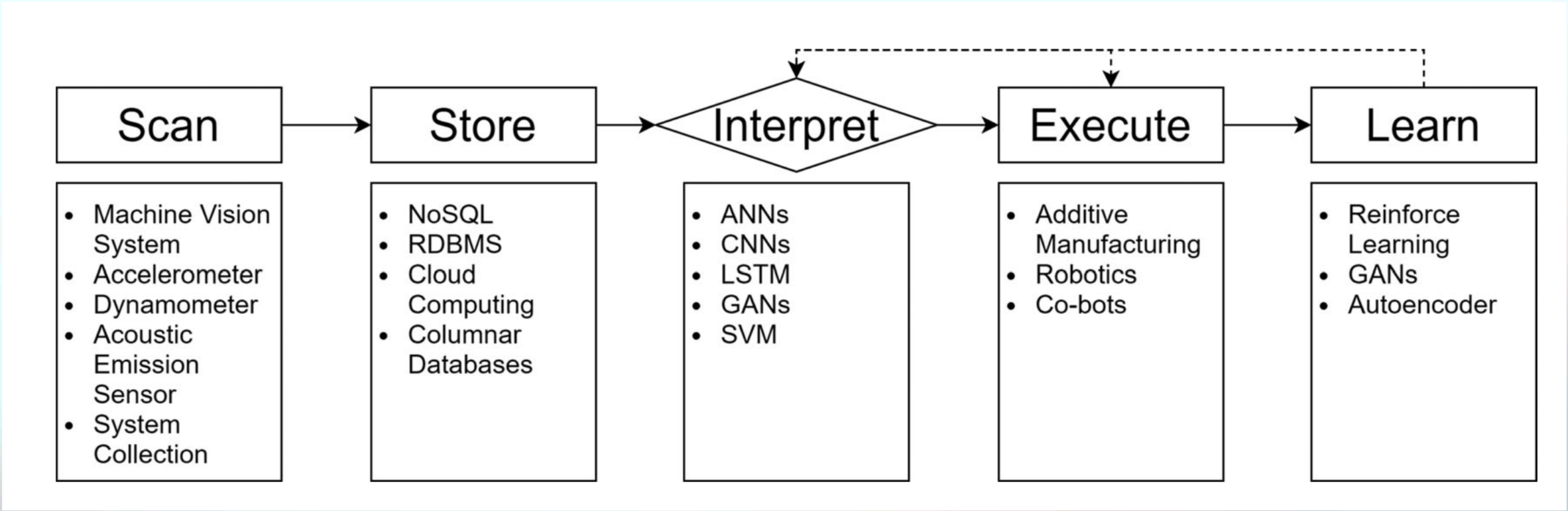
Update on locomotive K-1865

Rickson -

I've analyzed the situation with locomotive K-1865. It appears that the fuel pump is faulty, which is causing the engine to misfire. Computer assessment and manual inspection confirm the unit is not functioning correctly and will need to be replaced.

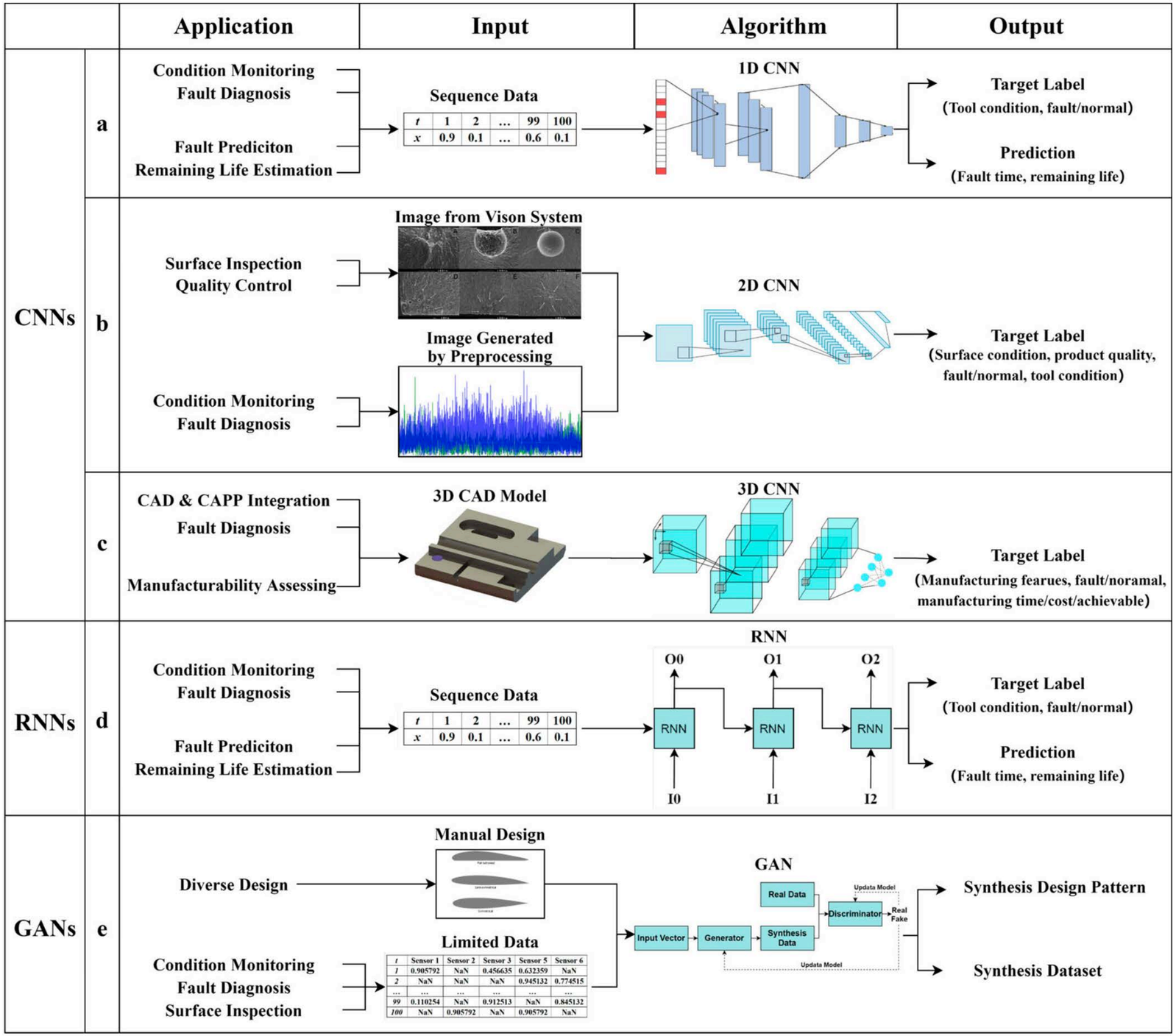
I've sourced a replacement part from IronTrack Industries, which was the supply for the original fuel pump. This is covered under warranty so there is no cost to us. Delivery is expected by tomorrow. I should be able to have the new unit installed by day's end.

Thanks,
Marcos

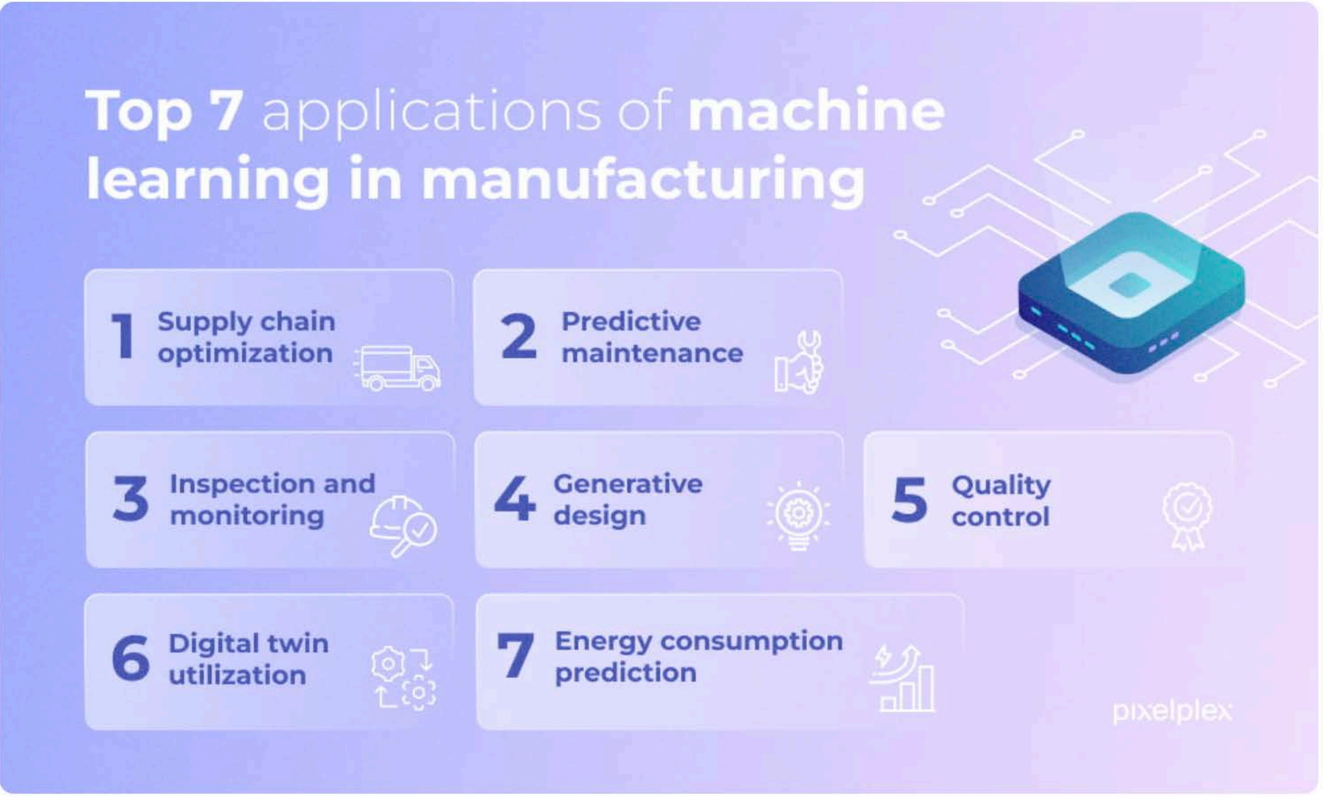


interpretive model of technology

Ajit Sharma, Zhibo Zhang & Rahul Rai (2021) The interpretive model of manufacturing: a theoretical framework and research agenda for machine learning in manufacturing, International Journal of Production Research, 59:16, 4960-4994, DOI: 10.1080/00207543.2021.1930234



Ajit Sharma, Zhibo Zhang & Rahul Rai (2021) The interpretive model of manufacturing: a theoretical framework and research agenda for machine learning in manufacturing, International Journal of Production Research, 59:16, 4960-4994, DOI: 10.1080/00207543.2021.1930234



Supply chain optimization

Demand forecasting

—clients' behaviors and preferences utilizing time series analysis, feature engineering, and NLP.

Warehouse control

—rapid replenishment of goods by facilitating stock control with deep learning-based computer vision systems.

Logistics and transport

—optimization machine learning algorithms assess and allocate the most optimal routes for shipping and transportation solutions.

Predictive maintenance

—algorithms to forecast the next failure of a component, piece of equipment, or system.

Digital twin utilization

—manufacturing companies can create a virtual representation of their products and processes, testing and optimizing them before they are built.

Energy consumption prediction

—DL, autoregressive models, RNN, LSTM

Inspection and monitoring

—examination of integrated circuit (IC) wire bonding problems X-ray images, computer vision

Generative design

—develop new designs for specific products

Quality control

—machine learning-enabled Root Cause Analysis (RCA).

AI Anomaly Assistant App

Aligns your processes with your business goals and provides intelligent insight into your production processes

In an initial proof-of-concept project, GM and Autodesk engineers applied generative design technology to reconceive a small but essential vehicle component, the seat bracket where seat belts are fastened.

The software produced more than 150 valid design options based on parameters the engineers set, such as required connection points, strength, and mass, with an organic structure no human could have imagined.

As a result, the new seat bracket is 40 percent lighter and 20 percent stronger than the original, consolidating eight different components into one 3D-printed part, another significant benefit of generative design.

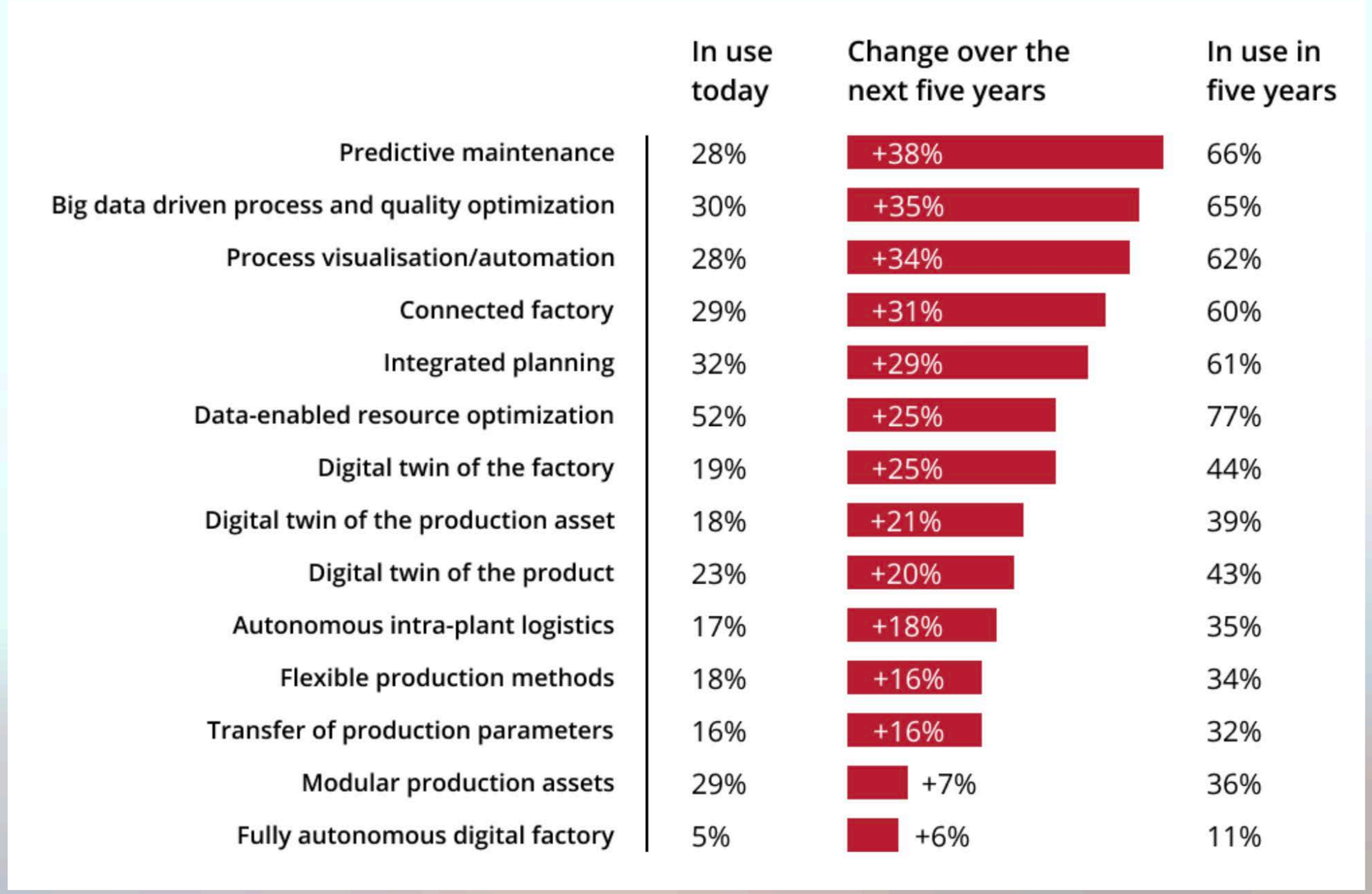
Rolls-Royce is now incorporating ML into its processes to a much greater extent. This technology allows a jet engine to communicate with and be aware of other engines, the support ecosystem, and the customer airline.

Schneider Electric, a global power management and industrial automation firm, employs a predictive Internet of Things (IoT) analytics solution based on Microsoft Azure Machine Learning and Azure IoT Edge to remotely monitor and configure oil pump settings in its production plants.

Vistra, power producer company built a heat-rate optimizer powered by machine intelligence, which examined hundreds of inputs and gave recommendations every 30 minutes.

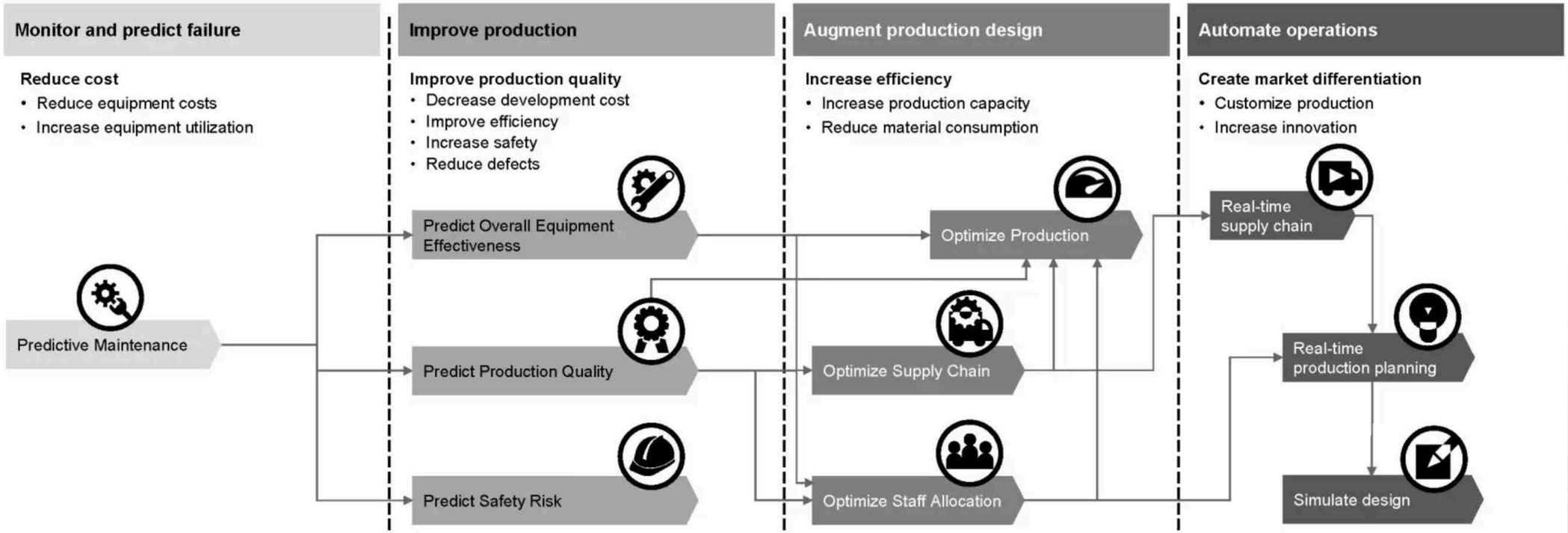
Source: https://pixelplex.io/blog/machine-learning-in-manufacturing/

PwC reported that predictive maintenance will be one of the largest growing machine learning technologies in manufacturing, having an increase of 38% in market value from 2020 to 2025.



Source: https://mobidev.biz/blog/machine-learning-application-use-cases-manufacturing-industry

Applied Industrialized AI – Manufacturing



30 percent or less of total potential data value is realized by most manufacturers

20-30 **Improve Production** percent increase in delivery reliability

80 **Augment Production Design** percent of manufacturing costs are affected by decisions made in the design stage

20-50 **Automate Operations** percent potential reduction in defects through simulation and testing

60 **Monitor and Predict Failure** percent of wasted expenses come from unnecessary operation and maintenance costs

7 **Augment Production Design** percent potential reduction in working capital

50 **Automate Operations** percent potential decrease in product development costs

This material is based on research by:
"Big Data: 20 Mind-Boggling Facts Everyone Must Read," Forbes, 2015.
"The Digital Universe In 2020: Big Data, Bigger Digital Shadows, and Biggest Growth in the Far East," EMC, 2012.
"The age of analytics: Competing in a data-driven world," McKinsey Global Institute, 2016.
"Big data: The next frontier for innovation, competition, and productivity," McKinsey Global Institute, 2011.
"Industrial Design: A Competitive Edge for U.S. Manufacturing Success in the Global Economy," National Endowment for the Arts, 2017.

Source: https://spd.tech/machine-learning/ai-and-ml-in-manufacturing-industry/

Some of the most compelling reasons to employ machine learning and artificial intelligence within manufacturing are:

- Significant process-driven loss reductions.
- Cost reductions driven by predictive maintenance.
- Consumer-driven product creation thanks to smart factories.
- Boost in capacity through process optimization.
- Ability to scale product lines by streamlining and optimizing processes.
- More efficient inventory management by using predictive analytics.
- Extended life of machinery and equipment via Predicting Remaining Useful Life (RUL).
- Better supply chain management.
- Enhanced quality control.
- Improved safety conditions on the manufacturing floor with the help of deep learning techniques implementation.

Source: https://eleks.com/blog/machine-learning-in-manufacturing/

Hands on...

What we can do...

AI in Manufacturing Workshop series

Workshop 1: hands on data analytics with python and R

- **Data Exploration Techniques:** Using Python and R for data inspection and summarization.
- **Data Visualization:** Creating interactive charts and dashboards with libraries like ggplot2 in R and Seaborn in Python.
- **Predictive Modeling:** Regression and classification techniques in both Python and R.
- **Data Integration:** Combining data from various sources and formats.

Workshop 2: hands on machine learning with python

- **Supervised Learning Techniques:** Regression and classification using scikit-learn.
- **Unsupervised Learning:** Clustering and dimensionality reduction for anomaly detection.
- **Model Evaluation:** Cross-validation and performance metrics for assessing model accuracy.
- **Feature Engineering:** Techniques for creating and selecting features that improve model performance.
- **Machine Learning Pipelines:** Automating workflows in Python for reproducibility and efficiency.
- **Deployment Strategies:** Approaches for integrating machine learning models into production.

Workshop 3: hands on deep learning and LLMs with python

- **Neural Network Foundations:** Understanding the basics of neural networks and their applications.
- **Convolutional Neural Networks (CNNs):** Deep learning for image analysis in manufacturing quality control.
- **Recurrent Neural Networks (RNNs):** Leveraging sequence data for predictive maintenance.
- **Transformer Models and LLMs:** An introduction to state-of-the-art language models and their use in predictive analytics.
- **Model Deployment:** Techniques for deploying deep learning models.

What we can do...

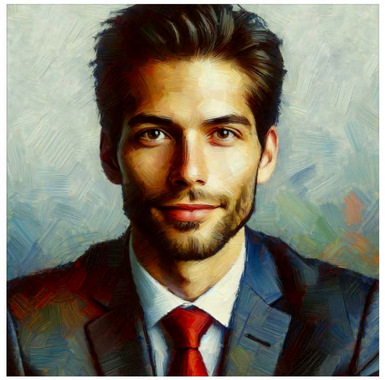
Meet AI team at the company,
Discuss possible AI application opportunities
Existing data, new data generation
Data Analytics
Network Science
ML, DL, LLM training using local data

Thanks to…

You

https://www.ndsu.edu/fileadmin/_processed_/f/1/csm_Kambiz_7ba65256c4.jpg make an artistic filter for this image

ChatGPT



Here is the image with an artistic filter applied, inspired by the impressionist style.

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