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Joint Master in Manufacturing 4.0

Norwegian University of Science and Technology

Department of Manufacturing and Civil Engineering

COURSE NAME

TØL4204 - Flexible Automation and Artificial Intelligence

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MODULE 1 - 3

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MODULE 1

AUTOMATION, MODEL ESTIMATION AND MACHINE LEARNING

Comprehensive Report on Data Balancing Techniques.

1. Introduction and Objectives.

The aim of this report is to analyze the impact of different data balancing techniques applied to a given dataset and to identify which technique yields the best accuracy. The classification task involves predicting the state (a categorical variable) using numerical features.

Dataset Extraction.

To extract data from the dataset in the Excel sheet and view it in Python using Jupyter Notebook, the following code was utilized:

```
import pandas as pd
import numpy as np
```

To load the dataset into the Jupyter Notebook and preview its contents, the following code was used:

```
df = pd.read_csv ('gdp_1960_2020.csv')
df.head()
```

After executing the code, the data with all the variables appeared as shown in **Table 1**:

Table 1 - Dataset Extraction.

	YEAR	RANK	COUNTRY	STATE	GDP	GDP_PERCENT
0	1960	1	The United States	America	543300000000	0.468483
1	1960	2	United Kingdom	Europe	73233967692	0.063149
2	1960	3	France	Europe	62225478000	0.053656
3	1960	4	China	Asia	59716467625	0.051493
4	1960	5	Japan	Asia	44307342950	0.038206

2. Points Considered.

- *Dataset Description:* Is a description of the dataset provided?
- *Source Code:* Is the complete source code present?
- *Code Explanation:* Are all steps in the code explained?
- *Data Pre-processing:* Are data pre-processing steps described?
- *Model Parameters/Architecture:* Are the chosen model and parameter settings justified?

3. Dataset Description.

The dataset contains global GDP data from 1960 to 2020, with key columns as shown in **Table 2**:

Table 2 - Dataset Description.

THE VARIABLES	SHORT EXPLANATION
year	The year of the GDP measurement.
rank	The country's GDP rank in that year.
country	The name of the country.
state	The region/continent (like America, Asia, Europe).
gdp	The gross domestic product of the country.
gdp_percent	The percentage contribution of GDP to the global total.

The task involves predicting the **state** column, which has a significant *class imbalance*. For example: America has the most data points, while Oceania is severely underrepresented. This imbalance necessitates the application of balancing techniques to ensure that the model performs fairly across all classes.

4. Source Code.

Below is the Python code used to implement and evaluate the data balancing techniques:

```python
# Import libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Load your dataset
file_path = 'gdp_1960_2020.csv'  # Replace with the correct file path
data = pd.read_csv(file_path)

# Prepare features (X) and target (y)
X = data[['year', 'rank', 'gdp', 'gdp_percent']]  # Features
y = data['state']  # Target

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Baseline (No Balancing)
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
y_pred_baseline = model.predict(X_test)
accuracy_baseline = accuracy_score(y_test, y_pred_baseline)
print(f"Baseline Accuracy: {accuracy_baseline:.4f}")

# Oversampling (Manual Duplication)
minority_class = y_train.value_counts().idxmin()  # Identify the minority class
minority_class_data = X_train[y_train == minority_class]
minority_class_labels = y_train[y_train == minority_class]
```

```
# Duplicate minority class data
X_train_oversampled = pd.concat([X_train] + [minority_class_data] * 4, ignore_index=True)
y_train_oversampled = pd.concat([y_train] + [minority_class_labels] * 4, ignore_index=True)

# Train and test
model.fit(X_train_oversampled, y_train_oversampled)
y_pred_oversampling = model.predict(X_test)
accuracy_oversampling = accuracy_score(y_test, y_pred_oversampling)
print(f"Oversampling Accuracy: {accuracy_oversampling:.4f}")

# Undersampling
majority_class = y_train.value_counts().idxmax()  # Identify the majority class
majority_class_data = X_train[y_train == majority_class]
majority_class_labels = y_train[y_train == majority_class]

# Reduce majority class data
X_train_undersampled = pd.concat([majority_class_data[:len(minority_class_data)], minority_class_data], ignore_index=True)
y_train_undersampled = pd.concat([majority_class_labels[:len(minority_class_data)], minority_class_labels],
ignore_index=True)

# Train and test
model.fit(X_train_undersampled, y_train_undersampled)
y_pred_undersampling = model.predict(X_test)
accuracy_undersampling = accuracy_score(y_test, y_pred_undersampling)
print(f"Undersampling Accuracy: {accuracy_undersampling:.4f}")

# Class-Weight Adjustment
model = RandomForestClassifier(class_weight='balanced', random_state=42)
model.fit(X_train, y_train)
y_pred_weighted = model.predict(X_test)
accuracy_weighted = accuracy_score(y_test, y_pred_weighted)
print(f"Class-Weight Adjustment Accuracy: {accuracy_weighted:.4f}")
```

5. Code Explanation.

Each section of the code addresses a specific balancing technique. **Table 3** provides a brief explanation of the balancing techniques.

Table 3 - Code Explanation.

BALANCING TECHNIQUE	SHORT EXPLANATION
Baseline (No Balancing)	• Trains the model on the imbalanced dataset without any intervention. • Accuracy here provides a reference point to evaluate the impact of balancing techniques.
Oversampling (Manual Duplication)	• Identifies the minority class. • Duplicates minority class samples multiple times to balance the dataset. • Helps the model to learn more about the underrepresented class.
Undersampling	• Reduces the number of majority class samples to match the size of the minority class. • Risks losing information but ensures class balance.
Class-Weight Adjustment	• Assigns weights to classes inversely proportional to their frequency. • Allows the model to penalize misclassifications in minority classes.

6. Data Pre-processing.

- The dataset was split into training and testing sets using *train_test_split* (70% training, 30% testing).
- Only numeric columns (*year, rank, gdp, gdp_percent*) were used as features.
- Categorical target variable (*state*) was handled directly since Random Forest supports classification on categorical targets.

---

7. Model and Parameter Justification.

Random Forest Classifier was chosen due to its robustness and ability to handle imbalanced data with *class_weight* adjustments.

Parameters:

- *random_state = 42*: Ensures reproducibility.
- *class_weight = 'balanced'*: Corrects for class imbalance in one of the techniques.

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8. Results.

Table 4 summarizes the results.

Table 4 - Results.

TECHNIQUE	ACCURACY
Baseline (No Balancing)	0.4272
Oversampling (Manual Duplication)	0.4226
Undersampling	0.2696
Class-Weight Adjustment	0.4295

---

9. Analysis.

Table 5 - Analysis of the Results.

TECHNIQUE	ACCURACY
Baseline Accuracy (0.4272):	The **Baseline Accuracy** of 0.4272 provides a reference point for comparing other techniques. It highlights the model's struggle to classify minority classes effectively and serves as the initial benchmark for improvement.
Oversampling Accuracy (0.4226):	The **Oversampling Accuracy** of 0.4226 is slightly lower than the baseline, primarily due to overfitting on duplicated samples. Oversampling improved the representation of minority classes but failed to enhance overall accuracy and revealed limitations in addressing class imbalances.
Undersampling Accuracy (0.2696):	The **Undersampling Accuracy** of 0.2696 represents a significant drop in performance, as it led to the loss of valuable majority class data. This technique demonstrates that undersampling can be detrimental for small datasets and should generally be avoided in such contexts.
Class-Weight Adjustment Accuracy (0.4295):	The **Class-Weight Adjustment Accuracy** of 0.4295 outperformed other techniques by penalizing the model for misclassifying minority classes. It effectively balanced

	learning without altering the dataset and proved to be the most efficient method for addressing imbalances.

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10. Conclusion.

- **Class-Weight Adjustment** is the best technique for balancing this dataset, as it achieved the highest accuracy (0.4295).
- Oversampling and Undersampling were *less effective*, highlighting the limitations of manipulating dataset sizes.
- Baseline performance was close to Class-Weight Adjustment but remained *biased* towards majority classes.

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11. Recommendations.

- Use **Class-Weight Adjustment** for similar datasets.
- Avoid *Undersampling*, especially with small datasets.
- Explore more advanced techniques like *SMOTE* or *ADASYN* for oversampling in future analyses.

MODULE 2

ROBOTICS

Project Report: Movement and Stacking of Wooden Blocks Using the P-rob 2 Robot.

1. Abstract.

This project explores the use of the P-rob 2 robot to perform a structured task involving the movement and stacking of wooden blocks. The operation is divided into two major tasks: first, transferring three blocks from one side of a divider to an inclined ramp on the other side, and second, returning the blocks to their original side and stacking them vertically on top of one another. The project emphasizes minimizing unnecessary movements, optimizing joint rotations, and implementing smooth, safe, and efficient robotic operations. Using Python-based code, the robot was successfully programmed to complete the task with high precision and reliability, showcasing its potential for industrial applications.

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2. Introduction.

Robots are transforming the way industrial tasks are performed, especially in environments where precision, speed, and safety are paramount. This project utilizes the P-rob 2, a state-of-the-art robotic manipulator known for its user-friendly interface, teach-in functionality, and reliable sensors. The primary objective of this project is to move three wooden blocks from one side of a divider to an inclined ramp and then stack them back on the other side in a precise vertical arrangement. Efficiency, safety, and smooth operation were the key focus areas.

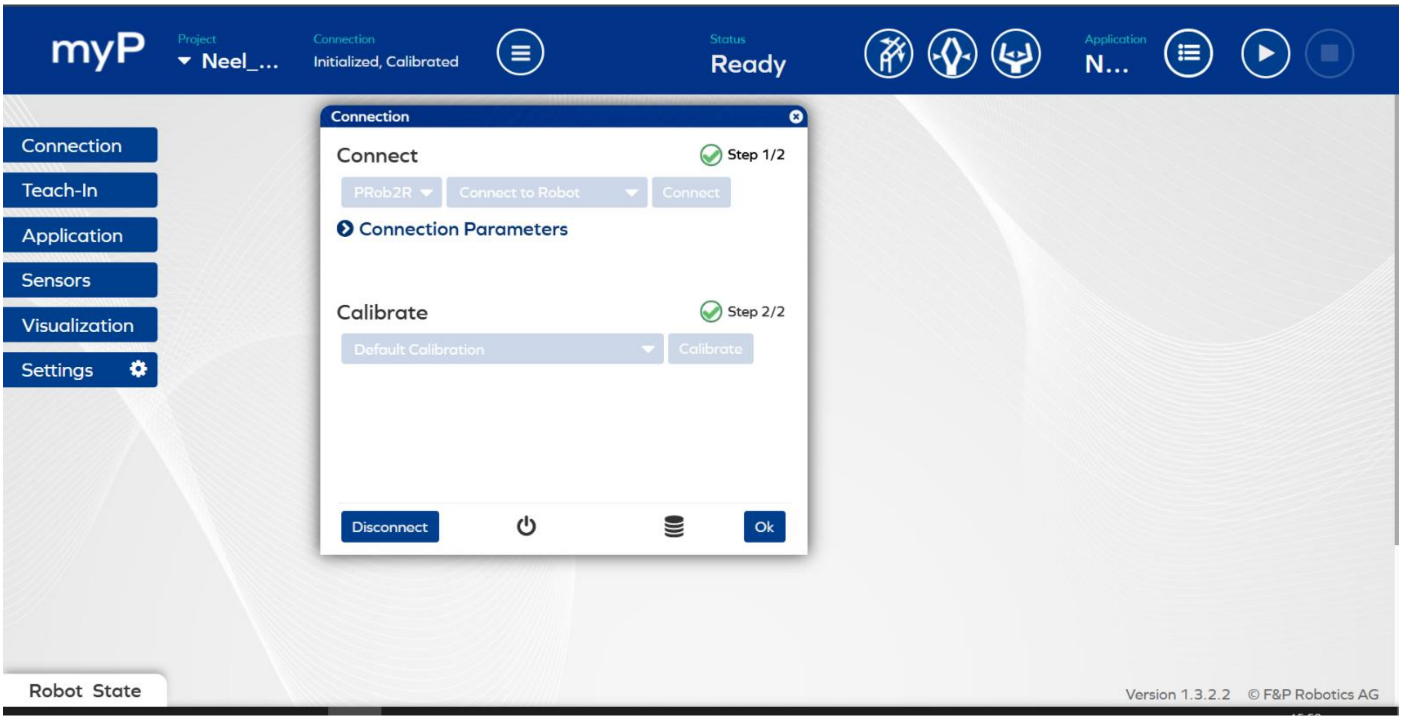

Figure 1 - Full robot interface with connection, teach-in, sensors, visualization, and settings modules.

3. Problem Description.

3.1 Initial Setup.

The blocks were placed in a horizontal line on one side of a divider as shown in **Figure 2**.

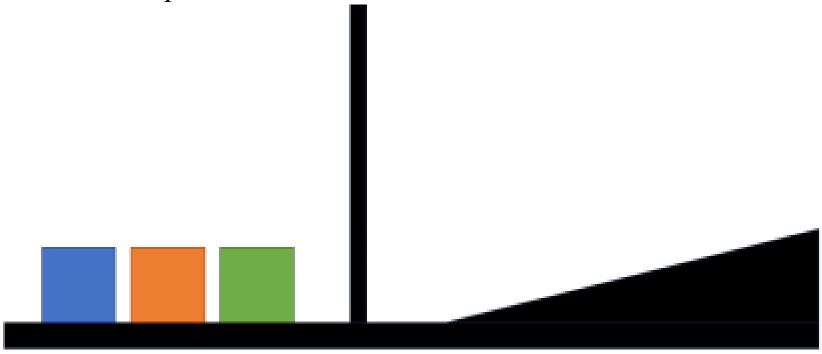

Figure 2 - Initial Position

The task was to transfer the blocks to the inclined ramp on the opposite side, ensuring stability as shown in **Figure 3**.

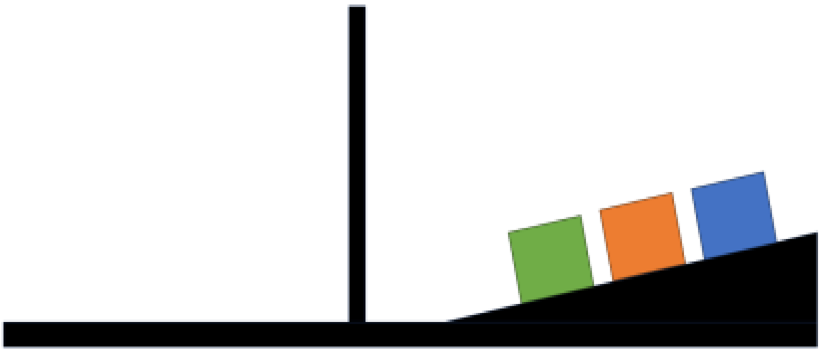

Figure 3 - Intermediate Position.

3.2 Final Objective.

Once on the inclined ramp, the blocks were moved back to their original side and stacked vertically as shown in **Figure 4** below. The task required smooth movement paths and minimal rotation to ensure precision and safety while handling the blocks.

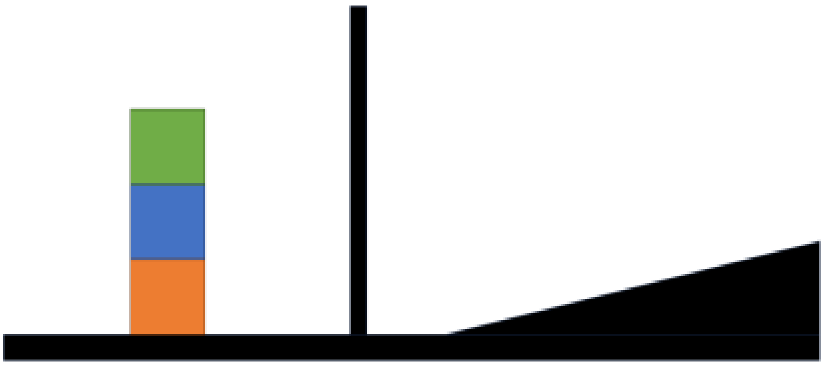

Figure 4 - Final Position.

4. Methodology.

4.1 Robot Overview.

The P-rob 2 robot is a six-axis robotic arm equipped with:

- ***Sensors***, which allow precise detection of block position and secure gripping.
- ***Grippers***, which are capable of opening, closing, and securely handling objects.
- ***Visualization Module***, which helps monitor robot movements in real-time.
- ***Teach-in Programming,*** which allows easy programming of custom tasks.

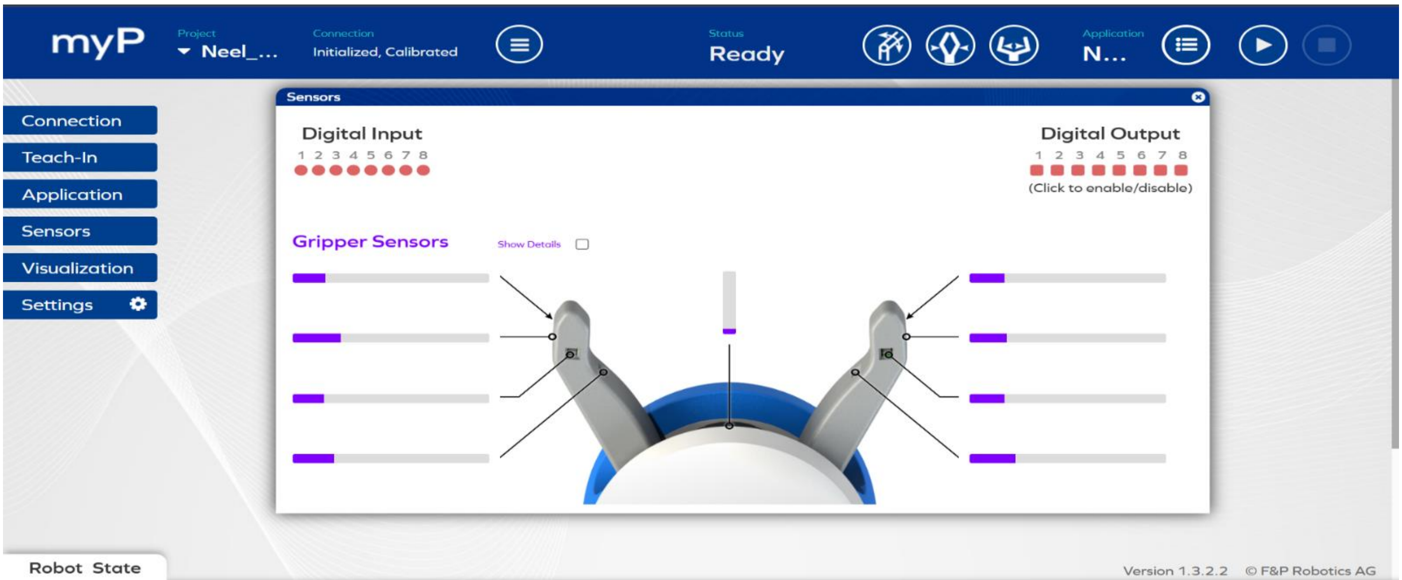

Figure 5 - Robot sensors.

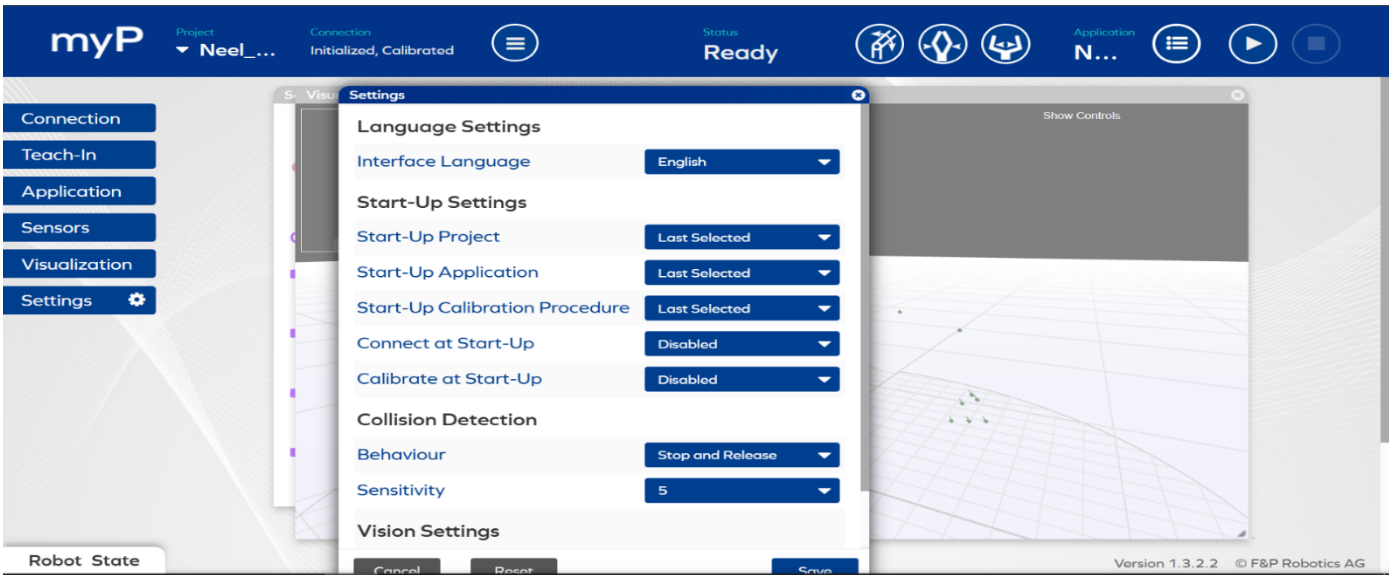

Figure 6 - Robot settings interface.

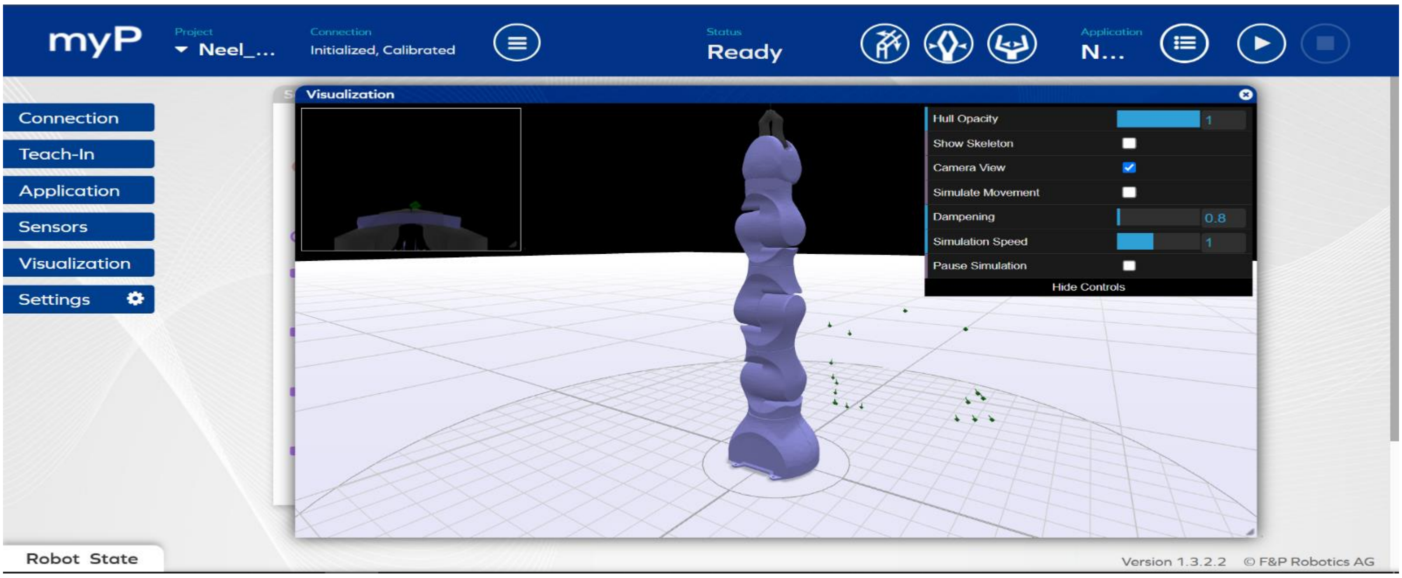

Figure 7 - Robot visualization module.

4.2. Task Execution Steps.

The task was divided into three stages:

Table 6 - Task Execution Steps

STAGES	SHORT EXPLANATION
Stage 1: Initial Pickup	• The robot was programmed to move to the starting position and pick up the first block. • The gripper opened and closed to securely grip each block.
Stage 2: Transfer to the Ramp	• Blocks were moved to the ramp on the opposite side of the divider via predefined paths.
Stage 3: Restacking	• The robot moved back to the original side, stacking the blocks in a vertical arrangement.

5. Implementation.

The task was implemented using the following Python-based control code for the P-rob 2 robot. The code efficiently controlled the robot's movements and gripper actions:

```
# Open the gripper to ensure it is ready for gripping the first block
open_gripper(position=None, velocity=None, acceleration=None)

# Move to the first block's position using Path 1
play_path("Path 1", velocity=None, acceleration=None)

# Close the gripper to securely grip the first block
close_gripper(velocity=None, acceleration=None, current=None)

# Move the first block to the inclined ramp using Path 2
play_path("Path 2", velocity=None, acceleration=None)
```

```
# Open the gripper to release the first block onto the ramp
open_gripper(position=None, velocity=None, acceleration=None)

# Move to an intermediate position to prepare for the next block
move_to_pose("Extra Pose for 1", velocity=None, acceleration=None, block=True, offset=None, mode='trapezoidal')

# Move to the second block's position using Path 3
play_path("Path 3", velocity=None, acceleration=None)

# Close the gripper to grip the second block
close_gripper(velocity=None, acceleration=None, current=None)

# Move the second block to the inclined ramp using Path 4
play_path("Path 4", velocity=None, acceleration=None)

# Open the gripper to release the second block onto the ramp
open_gripper(position=None, velocity=None, acceleration=None)

# Move to another intermediate position to align for the third block
move_to_pose("Extra Pose for 2", velocity=None, acceleration=None, block=True, offset=None, mode='trapezoidal')

# Move to the third block's position using Path 5
play_path("Path 5", velocity=None, acceleration=None)

# Close the gripper to grip the third block
close_gripper(velocity=None, acceleration=None, current=None)

# Move the third block to the inclined ramp using Path 6
play_path("Path 6", velocity=None, acceleration=None)

# Open the gripper to release the third block onto the ramp
open_gripper(position=None, velocity=None, acceleration=None)

# Close the gripper to prepare for transitioning to restacking
close_gripper(velocity=None, acceleration=None, current=None)

# Move back to the original side with the blocks using Path 7
play_path("Path 7", velocity=None, acceleration=None)

# Open the gripper to prepare for the stacking process
open_gripper(position=None, velocity=None, acceleration=None)

# Move to the first block's stacking position using Path 8
play_path("Path 8", velocity=None, acceleration=None)

# Close the gripper to grip the first block again for stacking
close_gripper(velocity=None, acceleration=None, current=None)

# Move to the stacking position of the first block using Path 9
play_path("Path 9", velocity=None, acceleration=None)

# Open the gripper to release the first block in the stacked position
open_gripper(position=None, velocity=None, acceleration=None)

# Move to the second block's stacking position using Path 10
play_path("Path 10", velocity=None, acceleration=None)
```

```
# Close the gripper to grip the second block for stacking
close_gripper(velocity=None, acceleration=None, current=None)

# Move to the stacking position of the second block using Path 11
play_path("Path 11", velocity=None, acceleration=None)

# Open the gripper to release the second block in the stacked position
open_gripper(position=None, velocity=None, acceleration=None)

# Move to the final intermediate position to finish the task
move_to_pose("Extra Pose last", velocity=None, acceleration=None, block=True, offset=None, mode='trapezoidal')

# Move the robot to the neutral resting position
move_to_pose("NR Pose 1", velocity=None, acceleration=None, block=True, offset=None, mode='trapezoidal')

# Close the gripper to signify the completion of the operation
close_gripper(velocity=None, acceleration=None, current=None)
```

This code was designed to:

- Ensure smooth, efficient movements.
- Minimize unnecessary joint rotations.
- Securely grip and release the blocks at each stage.

Figure 8 - Robot picking up blocks.

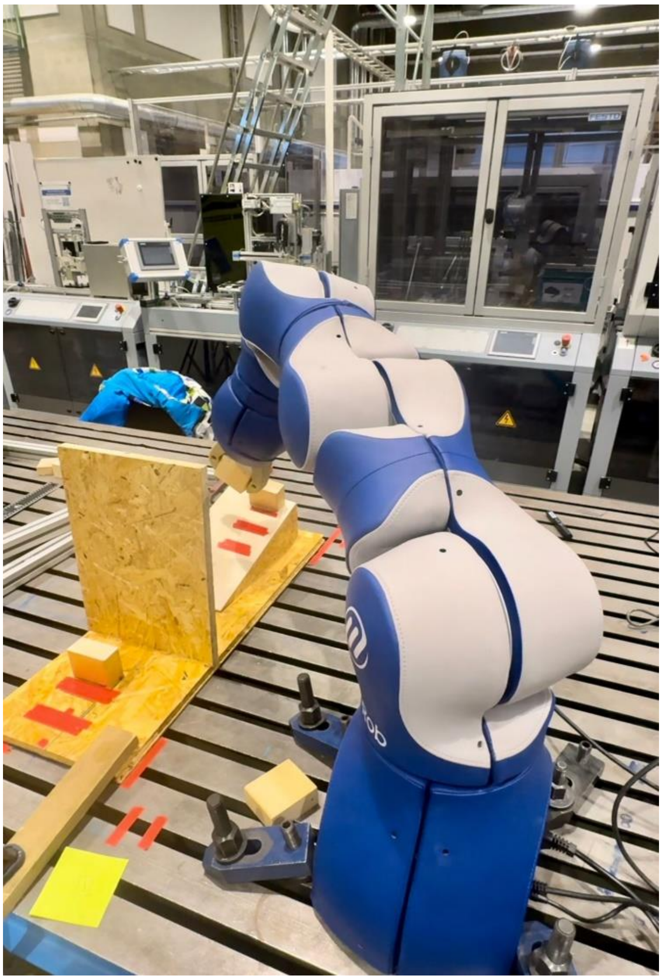

Figure 9 - Robot transferring blocks to the ramp.

Figure 10 - Robot stacking blocks vertically.

6. Results.

6.1 Execution.

The robot successfully completed the task in three stages:

1. Transferring blocks to the inclined ramp.
2. Returning blocks to the original side.
3. Stacking blocks vertically without misalignment.

The code provided proved effective, achieving smooth and reliable execution.

6.2 Observations.

- *Precision:* The robot maintained accuracy in placing and stacking the blocks.
- *Efficiency:* The paths minimized unnecessary movements.
- *Safety:* The robot operated without collisions or dropped blocks.

7. Discussion.

The project showcased the P-rob 2 robot's ability to handle structured, repetitive tasks with high reliability. Key highlights include:

- *Efficiency in Motion Planning:* The use of predefined paths reduced execution time and joint stress.
- *Safety Mechanisms:* The robot's sensors and calibrated motions ensured safe operation.
- *User-Friendly Interface:* The robot's teach-in programming made task implementation straightforward.

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8. Conclusion.

This project successfully demonstrates the capability of the P-rob 2 robot in performing precise object manipulation tasks. By using efficient coding and the robot's advanced features, the task was executed with a high degree of reliability. The results validate the use of robotics for industrial applications where precision and safety are critical.

MODULE 3

ARTIFICIAL INTELLIGENCE IN MANUFACTURING ENGINEERING

Summary Report on Advancing Manufacturing Through Artificial Intelligence: Current Landscape, Perspectives, Best Practices, Challenges, and Future Direction.

1. AI Evolution in Manufacturing Organizations.

AI has fundamentally changed the manufacturing industry by replacing conventional techniques with intelligent, automated, and adaptable technologies. By beginning with simple process automation, it developed over time as machine learning (ML) and data analytics advances made predictive capabilities and operational insights possible.

The evolution of AI in manufacturing organizations is evident when factories began to leverage AI to streamline operations, improve product quality, reduce expenses, and enhance output efficiency **[7], [8].** AI played a central role in facilitating smart factories (Industry 4.0) **[2],** where interconnected systems, IoT devices, and AI algorithms create a highly automated and intelligent manufacturing environment **[3].**

AI-based predictive maintenance systems had the ability to process real-time data from sensors and equipment using machine learning algorithms to forecast failures or maintenance needs **[11].** These systems detect trends and abnormalities, issuing alerts to operators for proactive maintenance thus reducing unscheduled downtime **[12].**

Another critical application is the control of the quality of products, where AI algorithms analyze vast datasets (for example images, sensor readings, historical records) to detect defects or deviations from specifications **[13].** This real-time monitoring helps manufacturers to address quality issues promptly, minimizing errors and waste while achieving significant cost savings and improved customer satisfaction **[14].**

The evolution towards Industry 5.0 (sustainable, human-centric, and resilient industry) and Society 5.0 (economic advancement balanced with social problem resolution) reflects the broadening applications of AI in manufacturing **[35].** Robotics and production process automation are further advancing, driven by AI technologies **[15].**

Emerging paradigms like Edge AI, which enables real-time decision-making on devices without relying on centralized data processing, are becoming essential for scenarios where continuous network access is impractical **[38].** The need for interpretable AI models, avoiding the "black-box" nature of machine learning, has become crucial for achieving regulatory compliance and AI trustworthiness **[40].**

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2. AI Evolvement Progression in Manufacturing Organizations.

AI has progressed through distinct phases of development in manufacturing:

Early Adoption: Because AI can process and analyze large datasets, make intelligent decisions, and adjust in real-time, it is driving this revolution and bringing about important and lasting improvements. AI integration in manufacturing is the process of integrating cutting-edge technologies and algorithms that enable machines and systems to perform jobs that have traditionally been performed by people, leading to increased automation, efficiency, and precision. **[9].** Factories streamline their operations, raise the bar on product quality while cutting down on expenses, and boost their output using the power of AI **[7], [8].**

Advanced Analytics: The field of predictive maintenance is one of the most notable areas where AI is revolutionizing the industrial sector **[10].** The traditional maintenance procedures often adhere to a fixed schedule, resulting in unnecessary downtime and inefficient resource allocation. On the other hand, AI-based predictive maintenance systems evaluate real-time data from sensors and equipment using machine learning algorithms to predict impending failures or maintenance requirements **[11].** AI systems may detect trends and abnormalities and provide alerts to operators, allowing for proactive maintenance and reducing unscheduled downtime **[12],** thus making them perfect in advanced analytics.

Quality control is another important way AI is being used in manufacturing. AI systems are able to examine vast amounts of data, including pictures, sensor readings, and historical data, in order to find flaws or departures from the required standards **[21].** This enables manufacturers to identify and rectify quality concerns in real-time, ensuring that only items with desired standards are released on the market. Quality control solutions driven by AI reduces errors and waste **[14],** resulting in significant savings.

Furthermore, AI is leading to developments in robotics and the automation of production processes **[15].** AI-enabled collaborative robots operate alongside human operators to perform routine tasks with remarkable accuracy and speed **[16].** These robots can adapt to new environments, gain knowledge from their experiences, and improve over time. AI-powered automation **[17]** also makes integrating various industrial components and systems easier, enhancing workflow efficiency and overall productivity. Intelligent robotics has the potential to revolutionize various industries by amplifying output, streamlining operations, and enriching customer interactions **[18].**

For example, the biotechnology industry is rapidly evolving, driven by advancements in manufacturing technology **[19].** The integration of artificial intelligence (AI) in bioprocessing, automation, and data integration within biotechnological engineering enhances industrial operations through predictive maintenance, process optimization, and quality control, significantly improving supply chain management **[19], [20].**

Moreover, AI's influence in manufacturing extends beyond the factory environment, encompassing various dimensions of supply chain management **[21].** AI algorithms can analyze vast amounts of data related to inventory levels, demand forecasts, and logistical constraints to find the best strategies for planning production **[22],** managing inventories, and distributing goods. Streamlining these operations could enhance customer satisfaction, reduce stockouts, and shorten production times for manufacturers.

Modern Innovations - Deep Learning and Neural Networks: AI evolvement progression in manufacturing organizations involves the issue of deep learning which provides a diverse range of techniques that leverage the capabilities of neural networks to address complex tasks effectively. Convolutional Neural Networks excel in analyzing images **[25],** while Recurrent Neural Networks are skilled at processing sequential data **[26],** and Long Short-Term Memory Networks overcome challenges with long-term dependencies. These techniques are driving revolutions across various domains. Generative Adversarial Networks facilitate the generation of realistic synthetic data **[27],** while Autoencoders and Variational Autoencoders are powerful tools for unsupervised learning and data reconstruction **[28].** Initially it was designed for natural language processing, transforming model architectures and demonstrate broad adaptability **[29],** Deep Reinforcement Learning enables intelligent decision-making in dynamic environments **[30].**

Moreover, other techniques such as Siamese Networks, Zero or Few-Shot Learning, Meta-Learning, and Capsule Networks **[31], [32]** are just a few examples of innovative techniques driving the frontiers of artificial intelligence and machine learning. Deep learning excels at automatically learning hierarchical features from raw data, reducing the need for extensive manual feature engineering. Additionally, its adeptness in handling large and complex datasets empowers it to achieve state-of-the-art performance in various domains. The extensive adoption of libraries such as TensorFlow, Keras, and PyTorch **[33]** has expedited the deployment of deep learning models, exerting a lasting influence across a wide array of domains. Moreover, these libraries seamlessly integrate with platforms such as Google Cloud, Azure, Amazon SageMaker, and IBM Watson **[34],** enabling the development of cloud-based solutions.

Digital Twins: AI evolvement progression in manufacturing organizations involves the concept of digital twins which holds the promise of playing a crucial role in realizing the vision of smart manufacturing **[62].** Digital twins in manufacturing provide an advanced simulation platform that enables organizations to digitally test and enhance their processes, reducing the need for physical prototypes and minimizing costly errors **[63].** Recent technology breakthroughs, such as smart sensors, cloud computing, AI, and the rise of Industry 4.0, have opened the path for digitizing manufacturing processes and the creation of digital twins. In the manufacturing workflow, cyber-physical systems use sensors to collect data from the actual world. This data is then used as input for the digital twin. The Digital Twin then evaluates and analyzes this data, providing outputs via virtual simulations **[63].** This approach enables the assessment of possible outcomes and the early identification of issues before initiating the manufacturing process, all without incurring additional costs.

Explainability and Trust: Explainable AI: The complexity of features learned by various machine learning techniques often results in models acting as black-box solutions, making it challenging to interpret their decisions intuitively. This has recently become a regulatory must-have to achieve AI trustworthiness **[40].** Thus, in the field of Explainable AI (XAI), methods like Local Interpretable Model-Agnostic Explanations (LIME), Shapley Additive explanations (SHAP), PDP, feature importance methods, rule-based models, Layer-wise Relevance Propagation (LRP), counterfactual explanations, and anchors have emerged to try to overcome this difficulty by allowing users to comprehend and interpret the model's features and methodology **[44].** This approach aims to empower stakeholders to justify actions taken based on algorithm recommendations, thereby increasing trust in the model's results **[41].** Libraries like ELI5, Skater, SHAP, Tensorflow What-if Tool, and other tools provided by Google and Fiddler Labs have emerged as a result of the XAI field's impetus. Customers can use these tools to create machine learning systems that emphasize high transparency by describing the learnt elements of the model and how they affect predictions. Consequently, this promotes more openness and confidence in AI-driven decision-making processes. Furthermore, for explainable AI projects, platforms such as AI4EU offer algorithms like SHAP-Tree-MCDA, LioNets, and LORE.

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3. AI from Conceptual Formulation to Implementation Stage in Manufacturing Organizations.

The path from conceptualizing AI to its implementation involves the following steps:

- ***Objective Definition:***

  Manufacturers identify specific goals such as reducing downtime, enhancing quality, or optimizing resources **[11].** Traditional maintenance procedures often adhere to a fixed schedule, resulting in unnecessary downtime and inefficient resource allocation. On the other hand, AI-based predictive maintenance systems evaluate real-time data from sensors and equipment using machine learning algorithms to predict impending failures or maintenance requirements **[11].**

- ***Data Collection:***

  1. Internet of Things (IoT) Sensors

  In manufacturing settings, Internet of Things (IoT) sensors play a pivotal role in data collection, revolutionizing production process monitoring and optimization **[45].** These smart sensors are strategically deployed throughout the manufacturing unit to gather real-time data from machines, equipment, and various production parameters. They continuously collect information on factors such as temperature, pressure, humidity, machine performance, energy consumption, and more. This wealth of data gives manufacturers valuable insights into their operations, enabling them to make informed decisions for process improvement, predictive maintenance, and quality control. With IoT sensors, manufacturers can achieve enhanced efficiency, reduced downtime, and improved product quality, ultimately leading to cost savings and a competitive edge in the industry **[46].** While FIWARE makes it easier to manage and connect IoT devices, a direct connection is still required to retrieve the data they generate **[47].** This connection must adhere to the standard for semantic interoperability (ISO 21823-3). Various libraries have been created to interact with devices using widely-used programming languages like Python. Examples include aws/aws-iot-device-sdk-python, ibm-watson-iot/iot-python, Iotc, and the Python Client for Cloud IoT API.

  Lampropoulos et al. **[48]** reviewed how augmented reality (AR) can be enhanced by integrating deep learning, semantic web, and knowledge graphs. The study focuses on the exponential growth of data and the demand for real-time, adaptive, and tailored information. By merging augmented reality with deep learning, systems can gain intelligence and improve computer vision. Semantic web technologies and knowledge graphs provide semantically interconnected information, which improves data retrieval and interpretation. This connection can result in the creation of intelligent, user-friendly applications.

2. Supervisory Control and Data Acquisition (SCADA) Systems.

SCADA systems are essential in manufacturing as they collect, monitor, and control data effectively. They continuously gather real-time data from diverse sensors and devices **[49],** enabling swift issue identification and production optimization. SCADA systems also preserve historical data, which can be used to analyze trends. Configurable alarms and event notifications enable quick reactions to anomalous situations. SCADA systems also ensure compliance in industries with stringent standards by simplifying data collecting and reporting for audits. Furthermore, SCADA systems are critical in modern production because they provide complete data collection capabilities that increase productivity, quality, and efficiency while assuring safety and compliance. Python can communicate with SCADA systems using libraries such as Ignition, which typically store data in a database for simple extraction.

- ***Manufacturing Execution Systems (MES):*** The implementation of Manufacturing Execution Systems (MES) has become widespread **[50].** These systems facilitate bi-directional communication throughout the enterprise, connecting data from all production facilities. Studies have explored optimal methods for extracting data from MES, such as research by **[51], [52].** Implementing MES provides a centralized and comprehensive platform for continuous improvement initiatives and operational excellence in modern manufacturing **[53].** MES integrates with other enterprise systems, such as Enterprise Resource Planning (ERP) and Supply Chain Management (SCM), enabling seamless information flow and better decision-making. MES are critical in aspects such as production planning and scheduling, real-time production monitoring, quality management, inventory control, traceability, equipment maintenance, workforce optimization, and data analytics **[54].**

- ***Computer Vision Systems (CVS):*** Computer Vision Systems (CVS) are valuable tools for data collection, particularly in industries that require capturing information from images and videos **[1].** In manufacturing, CVS enhances data collection by identifying and classifying defects in real-time. CVS empowers manufacturers to address root causes, improve production efficiency, and minimize waste **[55].** Real-time monitoring through CVS ensures worker safety **[56]** by detecting unsafe actions and fostering a safer work environment. Additionally, CVS automates visual inspections of products, ensuring compliance with quality standards and providing valuable data on product quality.

- ***Model Development:*** Within this dynamic landscape, the AI4EU platform **[42]** emerged as a collaborative hub housing advanced algorithms such as IoT data analysis models and the Markov Decision Process, driving transformative advancements in machine learning applications. Chen et al. **[43]** investigated the crucial role of Machine Learning (ML) in the digitalization of manufacturing operations as part of Industry 4.0. To categorize ML jobs and assess development trends, the study introduces a framework known as the 'Four-Know' (Know-what, Know-why, Know-when, Know-how) and 'Four-Level' (Product, Process, Machine, System). The paper also provides an implementation pipeline for ML solutions, outlining the phases from data gathering to model deployment. It also addressed several ML methods (supervised, semi-supervised, unsupervised, and reinforcement learning) and their applications in manufacturing, emphasizing obstacles and future possibilities for ML in this industry.

Deep learning provides a range of techniques that leverage the capabilities of neural networks to address complex tasks effectively. Convolutional Neural Networks excel at analyzing images **[25],** while Recurrent Neural Networks process sequential data **[26].** Long Short-Term Memory Networks overcome challenges related to long-term dependencies. These techniques are driving revolutions across various domains. Generative Adversarial Networks facilitate the generation of realistic synthetic data **[27],** while Autoencoders and Variational Autoencoders are powerful tools for unsupervised learning and data reconstruction **[28].** Moreover, other techniques such as Siamese Networks, Zero or Few-Shot Learning, Meta-Learning, and Capsule Networks **[31], [32]** are just a few examples of innovative techniques pushing the frontiers of artificial intelligence and machine learning.

- ***Pilot Testing:*** The application of Artificial Intelligence (AI) methods for Predictive Maintenance (PdM) in the steel industry highlights its importance in Industry 4.0. This includes AI techniques like deep learning and machine learning for PdM tasks such as fault detection, production planning **[22],** inventory management, and goods distribution. Streamlining these operations enhances customer satisfaction, reduces stockouts, and shortens production times for manufacturers. However, using AI in manufacturing presents challenges **[23], [24].** Industries play an important role in validating AI concepts and implementing large-scale pilot initiatives. They provide the essential infrastructure, data, and resources for testing AI applications in real-world manufacturing scenarios, allowing researchers to solve practical difficulties and develop models. Governments and financial bodies frequently promote AI research and development in manufacturing **[67].** This financial support enables ambitious concepts and prototype development while overcoming early adoption difficulties. Governments also create legislative frameworks to assure ethical AI use, data privacy, and safety standards, fostering trust in AI technologies.

- ***Continuous Monitoring:*** As industries deploy increasing numbers of sensors and actuators in their manufacturing processes, reliance on cloud services has risen, leading to higher network traffic and potentially affecting transmission performance. To address these challenges, tools like TensorFlow Lite, uTensor, the Embedded Learning Library (EEL), CMIS NN, ARM Compute Library, and deepC have emerged as useful for implementing Edge AI solutions **[39].** Companies like NVIDIA and Advantech provide tailored Edge AI solutions to enable industries to integrate and operate Edge AI effectively, enhancing decision-making speed, ensuring data privacy, and reducing network dependency.

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4. How the Manufacturing Sector is Transforming to Intelligent and Smart Manufacturing Systems.

The integration of AI, IoT, and cyber-physical systems has redefined manufacturing by creating smart, adaptive systems. Transformative elements include:

- ***Smart Factories.***

AI is facilitating the creation of smart factories, which are a central component of Industry 4.0 **[2].** In these environments, networked systems, IoT devices, and AI algorithms combine to provide a highly automated and intelligent manufacturing setting **[3], [4].** Incorporating AI into smart factories enhances productivity, real-time monitoring of manufacturing processes, and data-driven decision-making **[5], [6].** By leveraging AI technologies, manufacturers can streamline operations, improve product quality, and optimize resource allocation, ensuring efficient production cycles with minimal waste.

- ***Digital Twins.***

The concept of a digital twin is playing an increasingly crucial role in realizing the vision of smart manufacturing **[62].** Digital twins in manufacturing provide an advanced simulation platform that enables organizations to digitally test and enhance their processes, reducing the need for physical prototypes and minimizing costly errors **[63].** Through continuous data feedback from the physical world to the digital model, digital twins help manufacturers optimize design, production, and maintenance processes. This integration contributes to better performance, cost savings, and faster product development cycles.

- ***Human-Robot Collaboration (HRC).***

AI is driving innovations in robotics and the automation of production processes, particularly in Human-Robot Collaboration (HRC) **[15].** AI-enabled collaborative robots can operate alongside human workers to perform routine tasks with remarkable accuracy and speed **[16].** This collaboration enhances production efficiency by combining the strengths of human dexterity and decision-making with the speed and precision of robotic systems. HRC systems are transforming manufacturing environments, enabling more flexible and scalable production lines that can adapt to varying demands and complex tasks.

- ***Edge Computing.***

One of the key advantages of Edge AI is speed and privacy, as computations are performed locally on devices rather than sending data to a centralized server. This eliminates the need for extensive data transfers, reducing latency and enhancing data privacy **[38].** By processing data at the source, Edge AI enables real-time decision-making, ensuring faster responses to changes in the manufacturing environment. This is especially valuable in environments where timely interventions are crucial for maintaining operational efficiency and safety.

- ***Sustainability.***

AI-driven tools play a pivotal role in promoting sustainability in manufacturing. By leveraging AI, manufacturers can minimize waste, optimize energy consumption, and adopt more environmentally friendly practices **[64], [66].** AI-powered systems can predict maintenance needs, optimize production schedules, and monitor energy use to identify areas where resources can be conserved. This integration of AI not only improves efficiency but also aligns with growing environmental regulations and the increasing demand for sustainable practices within the industry.

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5. Benefits of Smart or Intelligent Manufacturing Systems.

Intelligent manufacturing systems deliver substantial benefits across multiple dimensions:

- ***Productivity.***

  Incorporating AI into smart factories paves the way for enhanced productivity, enabling real-time monitoring of manufacturing processes and data-driven decision-making **[5], [6].** By leveraging AI technologies, manufacturers can automate repetitive tasks, optimize workflows, and address inefficiencies on the production floor. AI's ability to analyze vast amounts of data in real-time allows for immediate interventions, improving overall efficiency and throughput.

- ***Cost Savings.***

  AI plays a significant role in cost savings through enhanced quality control. AI algorithms can process large volumes of data, including images, sensor readings, and historical data, to detect defects or deviations from the desired specifications **[13].** This enables manufacturers to quickly identify and rectify quality concerns in real-time, ensuring that only products meeting stringent quality standards are released to the market. By reducing errors and waste, AI-driven quality control not only improves product quality but also results in significant cost savings and higher customer satisfaction **[14].**

- ***Agility.***

  AI revolutionizes production planning and resource optimization, providing manufacturers with the tools to respond quickly to market demands and changes in production conditions **[59].** By accurately forecasting future demand and optimizing production schedules, AI helps manufacturers maintain cost efficiencies and smooth operations. Additionally, AI's ability to analyze patterns in resource utilization enables optimal allocation, improving inventory management, energy consumption, and overall production efficiency **[60].**

- ***Enhanced Quality.***

  AI systems are instrumental in ensuring enhanced quality by identifying defects and production issues in real-time **[13], [14].** Through continuous monitoring and automated analysis, AI enhances defect detection, leading to higher quality outputs and fewer rejections. This helps manufacturers meet rigorous quality standards while maintaining high levels of customer satisfaction.

- ***Sustainability.***

  AI contributes significantly to sustainability by optimizing resource usage and reducing waste, which supports corporate environmental goals **[66].** AI-driven solutions help manufacturers improve energy efficiency, monitor resource consumption, and minimize material waste, contributing to more environmentally friendly production practices and promoting sustainability across the entire manufacturing process.

- ***Safety.***

  AI also enhances workplace safety by monitoring hazardous environments and ensuring compliance with safety protocols **[65].** AI systems can detect potential safety hazards in real-time, alerting workers and management to risks such as unsafe actions, equipment malfunctions, or environmental hazards. This proactive approach helps maintain a safe working environment, reducing accidents and ensuring compliance with safety regulations.

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6. Costs Involved in Intelligent Manufacturing Systems.

The implementation of AI systems in manufacturing involves substantial investments across several key areas:

Infrastructure: The adoption of AI in manufacturing requires a significant upfront investment in IoT devices, sensors, and high-performance computing systems to collect and process vast amounts of data. These components are essential for enabling AI-driven systems but can be expensive to acquire and deploy **[38].**

Model Development: Developing and training AI models involves the use of specialized tools, software, and expert knowledge. This requires skilled personnel, computational resources, and time for data collection and model refinement, making it a costly endeavor for organizations aiming to leverage AI capabilities **[43].**

Integration: One of the challenges in adopting AI is integration with legacy systems. Aligning AI technologies with existing manufacturing systems often requires complex modifications, software updates, and ensuring compatibility with older equipment. This process can incur significant costs and operational disruptions **[23].**

Training: For successful AI adoption, companies must invest in workforce reskilling. Employees need to acquire the knowledge and skills required to operate and manage AI-driven systems effectively. This involves costs associated with training programs, workshops, and the potential hiring of new specialized talent to manage AI technologies **[67].**

Maintenance: AI systems require continuous updates and real-time monitoring to ensure optimal performance. Over time, models may need to be retrained with new data, and the underlying infrastructure must be maintained and upgraded. Ongoing costs for software maintenance, data management, and system monitoring are essential to keep AI systems functioning efficiently **[58].**

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7. Challenges and Constraints of AI Applications in Manufacturing.

Several significant challenges hinder the broader implementation and effective use of AI in manufacturing:

High Initial Investment: Smaller manufacturers often face financial constraints that make it difficult to invest in AI technologies. The high upfront costs of acquiring IoT devices, sensors, and advanced computing systems, as well as the expenses related to AI model development and integration, can be prohibitive for these companies **[23].**

Data Quality: AI systems rely heavily on data, and poor-quality data can significantly impair their performance. Inconsistent, incomplete, or outdated data can lead to inaccurate models, reducing the reliability and effectiveness of AI applications in manufacturing processes **[23], [24].**

Integration Complexity: Merging AI systems with existing manufacturing infrastructure presents technical challenges. Integrating AI with legacy systems often requires extensive modifications and custom solutions to ensure compatibility, which can be time-consuming and costly **[23].**

Cybersecurity Risks: The adoption of AI introduces cybersecurity risks. AI systems can become vulnerable to cyberattacks, which may result in data breaches, system compromises, or operational disruptions. Protecting AI-driven systems from cyber threats is an ongoing concern in manufacturing industries **[58].**

Resistance to Change: Employees may be resistant to adopting AI technologies due to concerns about job displacement or difficulty adapting to new workflows. The introduction of AI systems requires overcoming cultural resistance and ensuring employees are adequately trained to work alongside AI solutions **[35].**

Ethical Concerns: As AI becomes more integrated into manufacturing processes, ethical issues related to algorithmic bias, data privacy, and transparency arise. Manufacturers must implement responsible AI governance to ensure fairness, accountability, and ethical decision-making in AI systems, which can be complex and require careful attention to regulations **[40].**

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8. Future AI Applications in Manufacturing Organizations.

The future of AI in manufacturing is set to bring groundbreaking advancements that will transform industries across the globe. These developments include:

Autonomous Factories: AI-driven factories, with minimal human intervention, will redefine production processes. These fully automated facilities will optimize production lines, reduce human error, and increase overall operational efficiency, resulting in faster, more reliable manufacturing **[67].**

Advanced Predictive Maintenance: With the evolution of AI models, predictive maintenance will become more accurate and efficient. These advanced models will not only predict failures with greater precision but also suggest optimized maintenance schedules, reducing downtime and improving asset longevity **[11].**

Sustainability Initiatives: AI will play a key role in advancing sustainability within manufacturing. By optimizing energy consumption and supporting circular economic practices, AI can help reduce carbon footprints and drive environmentally friendly strategies across industries **[66].**

Personalized Manufacturing: The future of personalized manufacturing lies in AI's ability to analyze real-time customer feedback and deliver highly customized products. AI-powered analytics will allow manufacturers to adjust production in real time, meeting unique customer demands and creating personalized goods on a large scale **[61].**

Collaborative AI Systems: The synergy between human workers and AI technologies will lead to more collaborative AI systems. These partnerships will enhance operational flexibility, streamline workflows, and foster a culture of innovation by combining human creativity with AI's computational power **[15], [16].**

Edge Computing Expansion: The increasing adoption of edge computing in AI systems will allow real-time data processing at the source, enhancing efficiency and security. By processing data locally, manufacturers can achieve quicker decision-making, reduce latency, and bolster privacy without relying on centralized systems **[38].**

I firmly believe that AI will undoubtedly have a greater impact on the industrial sector as it develops further thus resulting in production environments that are more intelligent, sustainable, and flexible.

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9. Conclusion.

AI has emerged as a key component in the growth of manufacturing, offering revolutionary advantages in terms of sustainability, quality, and productivity. Notwithstanding difficulties, its integration signals a move toward intelligent and flexible systems that strike a balance between human-centered methods and technical innovation. AI has the potential to transform production and build a robust and sustainable industrial future by tackling ethical and practical issues.

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