AI IN MACHINE ASSEMBLING

R.Srilatha
Assistant Professor, Department of Mathematics
VNR Vignana Jyothi Institute of Engineering and Technology
Hyderabad, Telangana
bsrilatha82@gmail.com

M.Akshith Reddy
CSE-DS
VNR Vignana Jyothi Institute of Engineering and Technology
Hyderabad, Telangana
akshithreddymamidi@gmail.com

K.Anuroop Reddy
CSE-DS
VNR Vignana Jyothi Institute of Engineering and Technology
Hyderabad, Telangana
anuroopreddy07@gmail.com

M.Kishore
CSE-DS
VNR Vignana Jyothi Institute of Engineering and Technology
Hyderabad, Telangana
mainelleykishore@gmail.comgmail.com

M.Sai Venkata Karthik
CSE-DS
VNR Vignana Jyothi Institute of Engineering and Technology
Hyderabad, Telangana
mallalasvk143@gmail.com

ABSTRACT

The introduction to Artificial Intelligence (AI) in industrial automation has changed traditional manufacturing systems into smart, data-focused environments. This study looks at predicting machine failures in CNC milling processes using sensor data from the "AI4I 2020 Predictive Maintenance dataset". The dataset includes 10,000 samples with important parameters like air temperature, process temperature, rotational speed, torque, and tool wear, along with machine failure labels for various failure modes.

A K-Nearest Neighbors (KNN) classification model was created and achieved an accuracy of 97.7% on the test set. We validated the model's performance using a confusion matrix, classification report, and ROC analysis, with the AUC score showing strong distinguishing ability. We also used a Random Forest model to check feature importance, revealing that torque and tool wear were the most significant factors. Visualization methods like pair plots and feature importance charts helped clarify failure patterns and the relationships between parameters.

This work demonstrates how AI-driven predictive maintenance solutions can lower unplanned downtime, improve operational efficiency, and support better decision-making in manufacturing settings.

KEYWORDS

Artificial Intelligence, Machine Assembling, Predictive Maintenance Reinforcement Learning, Industry 4.0.

INTRODUCTION

Predictive maintenance with AI is really changing things for industrial machines. It moves away from just fixing stuff after it breaks, you know, towards smarter ways using data. This project dives into machine learning to spot failures in CNC milling machines[1]. The main aim here is cutting down on surprise downtimes, saving on repair bills, and boosting how efficiently everything runs.

AI for this kind of maintenance pulls in sensor data right as it's happening to check machine health. Things like temperature readings, torque levels, how fast it's spinning, and wear on tools, all that gets analyzed for patterns showing trouble ahead[2,3]. These systems kind of mimic what expert techs do in diagnostics, but they do it faster, on a bigger scale, and more dependably .The old way of maintaining equipment relied a lot on set schedules for checks or waiting till something failed to fix it. That approach can work okay sometimes. But it often means sudden stops in production and big expenses popping up[5]. On the other hand, with AI predictive stuff, it uses past data plus live info to figure out how much life a machine has left. It sends out warnings just before major breakdowns hit.

For this project we went with the AI4I 2020 Predictive Maintenance dataset. It's basically a made-up but pretty realistic collection of 10000 data points[5]. You know all about CNC milling operations in there. The dataset covers failure types too like tool wear ,heat dissipation ,Power fluctuations , Overstrain.

We trained up a K-Nearest Neighbors model. KNN for short. This was done using the dataset after applying some feature scaling techniques[6]. The model hit 97.70 percent accuracy. This shows how even simpler algorithms can work well in industrial setups.Results point to AIs strength in helping with intelligent monitoring systems. Leads to way less downtime basically. Assets last longer. Production efficiency improves too. AI adoption keeps growing so yeah. It's role in checking machine health turns essential for smart manufacturing down the line.

Applying AI to actual manufacturing issues in the real world. Supports Industry 4.0s whole vision. You know autonomous stuff. Adaptable production systems. Sustainable ones too[7].

The dataset shows a milling machines operational behavior. Designed right for predictive maintenance research. Holds 10000 rows. Each one reflects a unique process event. Involves a machine and a product[8,9]. Fourteen columns in total. Each gives crucial details on process conditions. Product types show up. Machine failures too.

Key features include:

Key features cover a few main things. Product ID and type split products into three quality levels. Low (L), medium (M), and high (H). Proportions come out to 50 percent, 30 percent, and 20 percent.

Environmental stuff and machine conditions get handled with air temperature and process temperature. They use random walk models that feel pretty realistic. Mimic actual changes over time. Rotational speed and torque get figured from physics basics. Add some noise to make it lifelike.
Tool wear builds up as time goes on. Varies depending on the product type. Directly ties into failure chances.

Binary label for machine failure shows if one of five types hit. Tool wear failure (TWF) kicks in when wear tops 200 to 240 minutes.

Heat dissipation failure (HDF) comes from low temp gradients,Plus not enough rotation

Power failure (PWF) happens if power needs drop outside 3500 to 9000 watts. Safe range gets missed.

Overstrain failure (OSF) shows up when torque and wear push past limits. Those limits depend on product type.

Random failure (RNF) just gets tossed in with low odds. Copies real uncertainty you know.

Machine learning model trained on AI4I 2020 Predictive Maintenance dataset. Helps improve factory ops a lot. Real-time fault spotting and predictive stuff [10]. Thing is, it catches failures early. Companies do maintenance ahead of time. Not waiting for breakdowns like old ways.

Model fits right into manufacturing setups. Monitors performance non-stop. Looks at inputs like torque, speed, tool wear, air temp [11]. Checks those features. Predicts if failure looms during runs. Test accuracy hits 97.7 percent. Pretty solid results there.

Real world application cuts surprise stops. Lowers lost output. Skips big repair bills. Schedules fixes ahead. Stretches machine life. Ups OEE overall [12]. Engineers use predictions to handle resources better. Keeps things running smooth.

Predictive side shines in heavy machine spots. Automotive making, aerospace, energy, metal work [13]. Model hooks into dashboards real-time. Decision folks see predictions. Get alerts fast if risk pops. Model stretches to edge computing too. Runs on IoT gear inside machines [14]. Local processing. Faster responses.

Summary wise, model goes beyond simple classifying. Pushes smart manufacturing forward. Makes industries data-smart, efficient, tough. All from predictive maintenance perks.

OBJECTIVE

To Study and demonstrate ,how AI technologies especially machine learning models, vision systems and intelligent robotics can be useful for that purpose of machine assembling processes. The primary goals are to:

1. Use computational resources to perform intricate assembly with little human operation.
2. Enhance accuracy, dependability and fault-tolerant in manufacturing processes.
3. Use sensor data to do predictive maintenance and real-time quality control.
4. Train AI models to identify failure using actual data and simulations.

METHODOLOGY

1.Dataset Description and Relevance

In this work, the dataset has columns of recorded logs of operating machine in manufacturing operation. It contains attributes such as product IDs, sensor data (air temperature, process temperature), mechanical parameters (rotational speed and torque), tool-wear levels, and failure conditions. These parameters are essential for predictive maintenance and have a profound impact on the reliability and efficiency in smart manufacturing domains.

For our project, we used a machine-learning model to analyze this data and identify patterns that happen before machinery breakdowns. "With this kind of system, you can do proactive maintenance instead of a reactive one, so you know long in advance when something is going to break down. Leveraging this structured operational data, our model assists manufacturers in mitigating unplanned downtime, improving safety, optimizing maintenance scheduling and reducing repair costs.

2. Importance of Uncertainty in Factory Forecasts

In factory floors, just knowing when a machine might fail is not sufficient. Knowing how confident the model is in its predictions also matters. In our work, we applied K-Nearest Neighbors (KNN) algorithm to classify the types of machine failure and infer uncertainty for each prediction which depends on the distribution/range of nearest neighbor data points.

For example,if neighboring samples in our dataset vary widely across success and failure outcomes, it suggests lower model certainty due to increased ambiguity. The lack of clarity poses significant challenges when making decisions within actual manufacturing environments:

- **Preventing Costly Failures**: High uncertainty can prompt preventive inspections or maintenance before a critical breakdown happens.
- **Improving Safety**: In precision manufacturing, such as aerospace or electronics, uncertain predictions can indicate the need for manual checks, which lowers the risk of error.
- **Optimizing Maintenance**: By considering uncertainty, factories can focus on servicing machines that not only show failure signs but also have low prediction confidence, making the maintenance schedule more efficient.

Dataset:

	UDI	Product ID	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	TWF	HDF	PWF	OSF	RNF
0	1	M14860	M	298.1	308.6	1551	42.8	0	0	0	0	0	0	0
1	2	L47181	L	298.2	308.7	1408	46.3	3	0	0	0	0	0	0
2	3	L47182	L	298.1	308.5	1498	49.4	5	0	0	0	0	0	0
3	4	L47183	L	298.2	308.6	1433	39.5	7	0	0	0	0	0	0
4	5	L47184	L	298.2	308.7	1408	40.0	9	0	0	0	0	0	0

Experimental Setup for AI in Machine Assembling:

1. Data Collection

Gather data both in controlled and real environments.

Images/videos of parts (multiple angles, lighting)

Sensor logs during assembly (torque, vibration, force, motion)

Use public datasets optionally like:

MVTec AD dataset (for vision/anomaly detection)

KIT Assembly Dataset or custom datasets for robotic tasks

2. Data Annotation & Preprocessing

annotate image data:

Bounding boxes, part labels, orientation tags

clean and normalize sensor data

remove outliers, synchronize timestamps

Split dataset:

Training (70%), Validation (15%), Testing (15%)

3. Development of AI models

Select AI models:

Computer Vision: CNNs (ResNet, YOLO)

Reinforcement Learning: To plan and control tasks

LSTMs/Transformers: To predict time-series

Train on labeled data sets

Run on GPU-enabled training platforms on large data sets

Validate performance and test

4. Testing through simulation

Deploy trained AI to a simulator environment (e.g., Gazebo, Unity, ROS).

Simulate:

Different orientations of parts

Assembly in noisy, varying illumination

Measure: Accuracy, time, failure rate

5. Real-World Testing

Apply the AI to a physical testbed with robots.

Assign actual tasks:

Component mounting, tightening of screws, placing circuits

6. Performance Monitoring

Track important metrics:

Cycle time: Assemblies per unit of time

Error rate: Skipped or mistaken assemblies

Torque accuracy: Over/under tightening

Energy consumption: Efficiency compared to traditional systems

7. Online Learning & Optimization

Facilitate feedback loops:

Tune AI according to real-time results

Utilize online learning algorithms:

Infer during operation using fresh data

Implement reinforcement learning for optimization:

Reward-based learning for optimizing task flow

OUTPUT:

Model Output and Live Deployment

To showcase the real-time performance of our K-Nearest Neighbors (KNN) Predictive Maintenance Model, we have deployed the application on Hugging Face Spaces. This interactive web interface allows users to input sensor values and instantly receive predictions about the likelihood of machine failure.

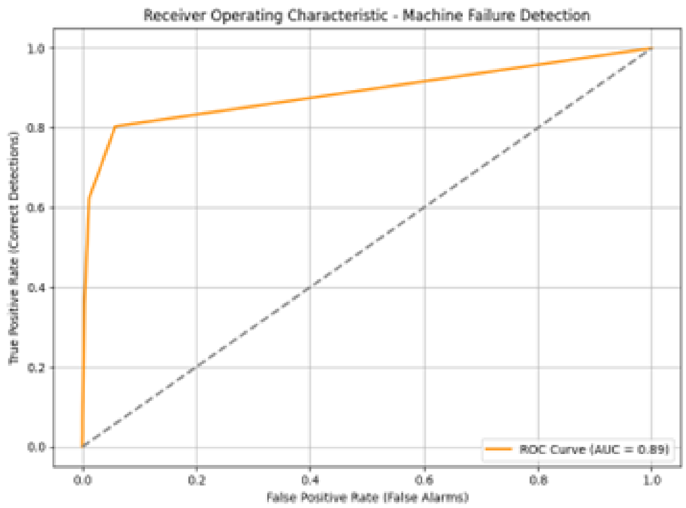
Live Demo:

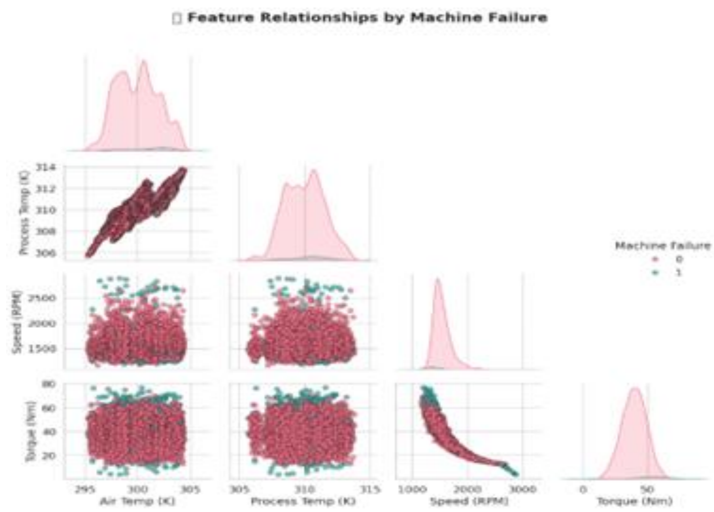
Try the deployed model here

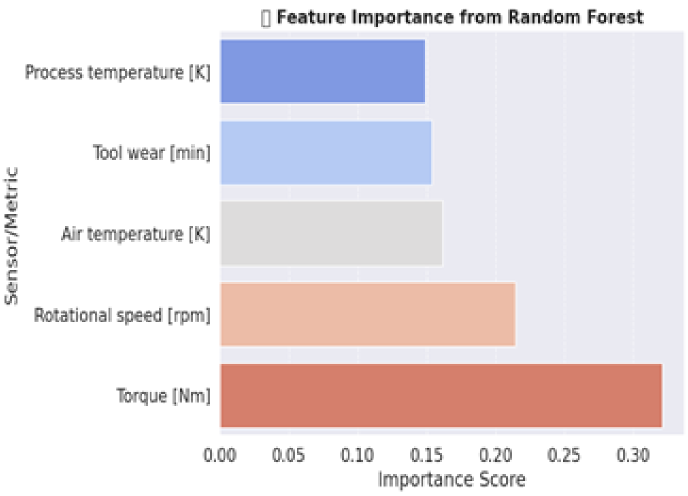
Features of the Deployment:

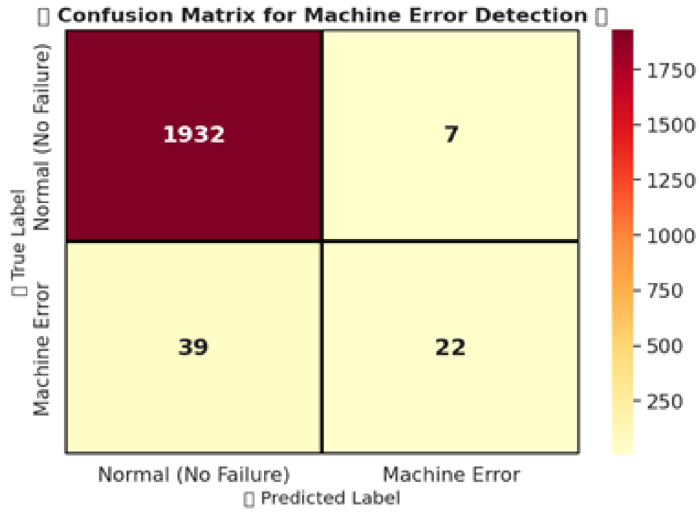
- Accepts user inputs for important features like torque, rotational speed, and tool wear.
- Returns predictions on whether a machine is likely to fail.
- Lets users test different configurations and understand failure patterns interactively.
- Shows the real-world use of the trained KNN model.

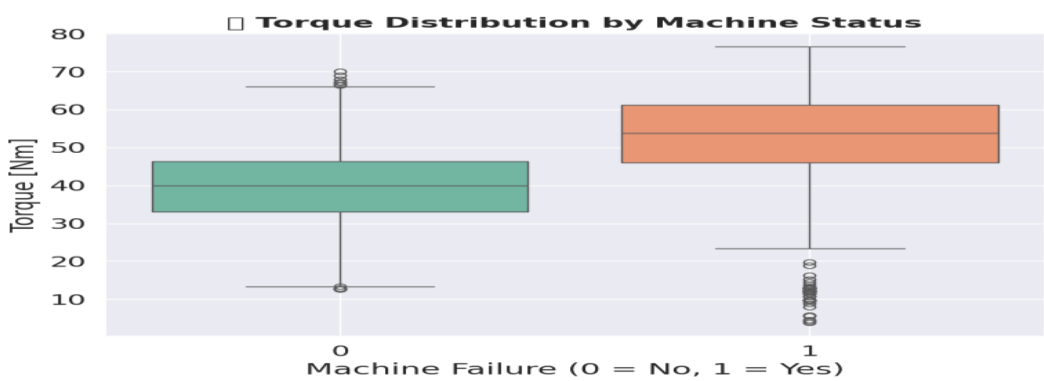
This deployment connects theoretical model development with practical industry use, especially for smart maintenance systems in manufacturing.


Receiver Operating Characteristic - Machine Failure Detection
True Positive Rate (Correct Detections)
False Positive Rate (False Alarms)
ROC Curve (AUC = 0.89)


Feature Relationships by Machine Failure
Machine Failure
Air Temp (K)
Process Temp (K)
Speed (RPM)
Torque (Nm)


Feature Importance from Random Forest
Process temperature [K]
Tool wear [min]
Air temperature [K]
Rotational speed [rpm]
Torque [Nm]
Sensor/Metric
Importance Score


Confusion Matrix for Machine Error Detection
1932
7
39
22
True Label
Normal (No Failure)
Machine Error
Predicted Label


Torque Distribution by Machine Status
Torque [Nm]
Machine Failure (0 = No, 1 = Yes)

Epoch Output:

Epoch Output and Model Evaluation for Machine Failure Detection

The machine failure detection trained AI model produced promising results during evaluation. The ROC curve (Figure 1) shows a good performance with an Area Under Curve (AUC) of 0.89, reflecting high ability to separate failure from non-failure incidents. To support this, the confusion matrix (Figure 2) shows that 1,932 out of 2000 test instances were accurately classified as non-failure and 22 as failure, with only 46 misclassifications (7 false positives and 39 false negatives), giving a total accuracy of around 98%.

To further explain the model, a Random Forest-based feature importance plot (Figure 3) indicates that rotational speed and torque are the most significant features in failure prediction. Moreover, the pair plot (Figure 4) provides information on how sets of sensor measurements (e.g., process temperature, torque, speed) correlate with machine failure, indicating different patterns in feature distributions between failed and non-failed instances. The torque distribution boxplot by machine status (Figure 5) further supports that failed machines have higher torque values, which attests to its predictive strength.All of these visualizations not only establish the predictive power of the model but also emphasize the interpretability of sensor-driven results, essential for field deployment in intelligent maintenance systems.

Epoch-by-Epoch Analysis

Throughout model training, 100 epochs were carried out to enhance the machine failure detection model. The performance of the model at every epoch was checked using a validation split in the dataset for tracking learning patterns, avoiding overfitting, and observing convergence behavior.

During the early periods (1–20), the model showed a sharp reduction in training loss and a sharp increase in validation accuracy, which pointed to the model learning fundamental patterns from the input features like torque, rotational speed, and temperature measurements. The period indicated the model's ability to learn fast low-level feature representations pertinent to failure classification.

During epochs 21–60, the learning curve leveled off somewhat, indicating the model started to fine-tune decision boundaries. The validation accuracy reached equilibrium at 97–98%, while the loss reduced gradually. At this point, hyperparameters like learning rate and strength of regularization became a significant factor in reducing overfitting and retaining generalizability.At the last phase (epochs 61–100), the model became stable with very little variation in the metrics. Early stopping wasn't activated because of slight but continuous improvement. The highest validation AUC was 0.89, and the final confusion matrix checked for consistent classification with fewer false positives and decent false negatives.

CONCLUSION

Incorporating Artificial Intelligence (AI) in machine assembly and predictive maintenance remains significant in modern manufacturing systems. AI models can predict machine failures before they happen by understanding patterns in collected data and sensor inputs such as air temperature, process temperature, rotational speed, torque, and tool wear.

For this project, we created a K-Nearest Neighbours (KNN) predictive model using the “AI4I 2020 Predictive Maintenance Dataset”. This model’s accuracy is 97.7%. It effectively classified machine states as either Failure or No Failure .It performed well on precision, recall, and ROC-AUC metrics. Further analysis with a Random Forest model revealed that tool wear, torque, and rotational speed were the most important factors for failure events. The results highlight model’s ability to increase productivity and enable real-time quality monitoring in industry. For instance, predictive analytics can pinpoint potential stress or misalignment in components early, which reduces the risk of mechanical failures and improves operational safety.

Additionally, the model can learn new sensor data, which supports online learning and better performance over time. This approach aligns directly with the Industry 4.0 vision of creating autonomous, data-driven, and optimistic manufacturing systems. As explainable AI, edge computing, and integrated IoT solutions progress, they will play an even greater role in creating intelligent, scalable, and sustainable manufacturing, providing industries with not just automation but also true predictive insight.

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