IOT based Predictive Maintenance for Manufacturing Machines

BECE 352E - IOT Domain Analyst

Project Report

Submitted by

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Introduction

Predictive maintenance is a technique that uses data analysis tools and techniques to detect anomalies in your operation and possible defects in equipment and processes so you can fix them before they result in failure. It allows the maintenance frequency to be as low as possible to prevent unplanned reactive maintenance, without incurring costs associated with doing too much preventive maintenance.

The top 4 causes of big losses in manufacturing machines are – breakdowns, setup and adjustments, small stops (due to blocks or precision issues) and reduced speed. All 4 of these can be handled better if predictive maintenance is implemented.

All the crucial and fallible parts of a machinery can be monitored with various sensors already in place or then deployed and using this real time data we can predict when and how a part is going to fail to function properly and hence inform the administrator in advance about the need of maintenance. Additionally, the problem is also simultaneously identified.

Any kind of reduced speed or short breaks to refill things or deal with any blockages can also be avoided using this technique.

Predictive maintenance programs have also been shown to lead to a tenfold increase in ROI by:

- 25%-30% reduction in maintenance costs
- 70%-75% decrease of breakdowns
- 35%-45% reduction in downtime

It also:

- Reduce Maintenance Costs
- Increase Asset Utilization
- Extend Asset Life
- Improve Field Crew Efficiency
- Improve Safety and Compliance
- Avoid Costly Downtime

- Prevent Industrial accidents by component failure
- Save lives by preventing catastrophic equipment failure

For all of these tasks we outsourced a dataset from kaggle, i.e. sensor readings were already available that were captured using sensors by a third person who thus made the dataset used. We customized it according to the machine problems and behaviors for a far greater accuracy.

For instance, taking the example of a simple conveyor belt, some sensors like vibrational sensor and acceleration sensor can be implemented to check the proper functioning of the belt. If there are signs of a breakdown like slowing down of the belt or an increase in vibrations, the same can be easily reported back to the administrator. Thus, the conveyor belt or its motor can be repaired or replaced as required.

In contrast, if only periodic checks and preventive maintenance is done, it's a scheduled process that might not be able to work well in all scenarios. It might take up too many resources and too much time when it isn't required. It also requires machine downtime.

How can we leverage predictive maintenance techniques to optimize maintenance scheduling and minimize downtime for manufacturing equipment, thereby reducing costs and improving operational efficiency?

This report will explore the use of sensor data and data analysis tools to:

1. Identify potential equipment failures before they occur.
2. Schedule maintenance interventions only when necessary.
3. Reduce unplanned downtime and associated production losses.
4. Optimize resource allocation for maintenance activities.
5. Extend the lifespan of critical equipment.

Methodology

1. Literature Review and Dataset Analysis:

- Extensive research papers, open-source datasets, and industry reports related to manufacturing processes and machinery are reviewed.
- Existing datasets, such as those focusing on hydraulic systems and milling activities, are analyzed to identify key features, operational parameters, and failure modes relevant to manufacturing machines.

2. Algorithmic Synthesis and Data Integration:

- Advanced algorithms and statistical models are employed to simulate real-world data characteristics and generate synthetic datasets.
- The synthesis process incorporates insights from literature review and dataset analysis to ensure the representation of various operating conditions and failure scenarios encountered in manufacturing environments.
- Datasets from different sources are integrated to enrich the dataset with diverse features and scenarios.

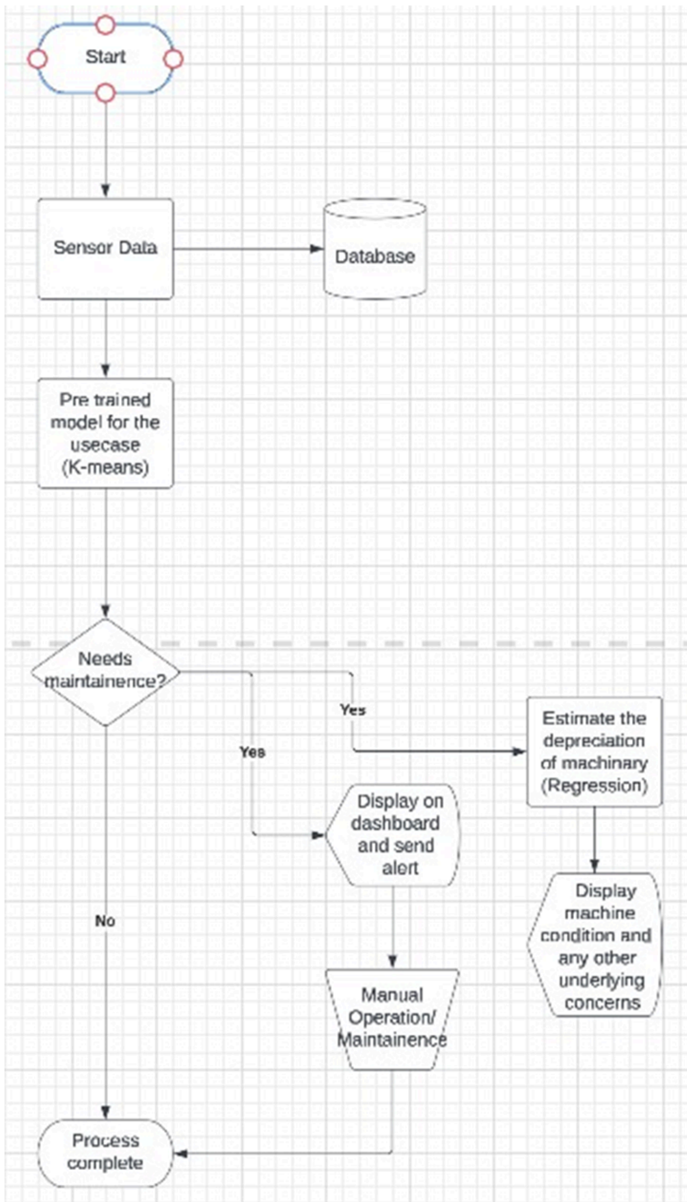
3. Feature Representation and Scaling:

- The synthetic dataset encompasses a wide range of features specific to manufacturing machines, including parameters such as temperature, vibration, pressure, motor current, and acoustic emission.
- Feature scaling and normalization techniques are applied to standardize the representation of variables and ensure compatibility across different types of manufacturing machines and sensor readings.

4. Quality Assurance and Validation:

- Rigorous validation procedures are implemented to assess the fidelity, accuracy, and reliability of the synthetic dataset.
- Statistical tests, comparison with existing datasets, and expert domain knowledge are leveraged to validate the consistency and relevance of the generated data.

Methodology -– Flowchart:



Methodology—Data Generation:

- The Data is synthesized based on research papers that resemble real-world data using algorithms and statistical models . Existing datasets were analyzed, patterns and trends were identified. Using this information we created our dataset with characteristics similar to the original data. The synthetic data includes information on vibration, temperature, and other factors that affect the condition of the conveyor belt.

- The Dataset contained variables such as Acceleration along the X,Y and Z axes, Vibration along the X, Y and Z axes, and temperature sensor readings.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Acceleron	Temperatu	freq_x	a_x	freq_y	a_y	freq_z	a_z	vib_x	vib_y	vib_z	AnomalyD	AnomalyType	
2	62.99	123.27	99.36	0.0054	62.92	0.0022	52.98	0.0069	18400	28600	7678.261	0	0	
3	61.4	125.86	86.42	0.0059	67.33	0.0028	50.14	0.0066	14647.46	24046.43	7596.97	0	0	
4	63.16	139.13	90.46	0.0045	68.2	0.002	46.1	0.007	20102.22	34100	6585.714	0	0	
5	50	131.37	90.84	0.0044	75.7	0.0029	51.93	0.006	20645.45	26103.45	8655	1	1	
6	62.78	139.62	92.04	0.0058	74.15	0.0021	56.81	0.0066	15868.97	35309.52	8607.576	0	0	
7	60.53	133.77	95.3	0.0044	66.59	0.0023	59.02	0.0066	21659.09	28952.17	8942.424	0	0	
8	61.16	121.36	183	0.0042	68.71	0.0023	53.4	0.0068	43571.43	29873.91	7852.941	1	3	
9	60.16	122.15	81.28	0.005	63.72	0.001	49.43	0.0061	16256	63720	8103.279	0	0	
10	63.77	125.41	82.14	0.0059	79.83	0.0022	58.5	0.0074	13922.03	36286.36	7905.405	0	0	
11	61.44	123.08	90.39	0.0056	60.7	0.0018	51.48	0.0064	16141.07	33722.22	8043.75	0	0	
12	63.84	122.19	83.77	0.0057	65.88	0.0022	55.03	0.0077	14696.49	29945.45	7146.753	0	0	
13	63.69	132.34	95.64	0.0044	65.31	0.0021	52.6	0.007	21736.36	31100	7514.286	0	0	
14	64.02	121.82	96.53	0.0055	60.69	0.0012	54.71	0.0073	17550.91	50575	7494.521	0	0	
15	64.27	122.04	90.52	0.005	79.33	0.0028	59.84	0.0066	18104	28332.14	9066.667	0	0	
16	62.3	122.13	82.48	0.0044	79.5	0.0015	45.89	0.0067	18745.45	53000	6849.254	0	0	
17	64.75	136.69	81.61	0.0041	61.38	0.0026	46.25	0.007	19904.88	23607.69	6607.143	0	0	
18	60.13	137.29	87.83	0.0055	76.22	0.0012	52.74	0.0068	15969.09	63516.67	7755.882	0	0	
19	60.05	135.45	95.26	0.0053	79	0.0029	55.88	0.0067	17973.58	27241.38	8340.299	0	0	
20	63.01	123.87	84.83	0.0056	70.15	0.0021	80	0.0078	15148.21	33404.76	10256.41	1	5	

Methodology – Algorithm:

- Take data from sensors (Here we have considered an already existing dataset.)

- Feed data in pre-trained model

Pre-trained model - K means – for conveyor belt:

- K=2, the number of clusters --> 0:doesn't require maintenance, 1: requires maintenance
- Select random K points or centroids. (It is based on initial dataset, historical, training).
- Assign each data point to their closest centroid, which will form the predefined K clusters.
- Calculate the variance and place a new centroid of each cluster.
- Repeat the third step, which means re-assign each datapoint to the new closest centroid of each cluster.
- If any reassignment occurs, then go to step-4 else go to FINISH.
- The model is ready.
- Send the required alert.
- Based on the frequency and type of maintenance, estimate the machine's depreciation, using regression.

Codes:

https://colab.research.google.com/drive/1rpV2kQIUxTjdmBnOCwJTr5P-C1z13pAv?usp=sharing

Dataset:

PredictiveMaintenanace

Results and Discussion

- Dataset: Synthetically generated based on industry given values.
- Algorithm: Classification method used to classify as in need of maintenance of not.
- Accuracy results:
    - Precision: 0.9922
    - Recall or Sensitivity: 0.910
    - Classification error: 0.0903


```
{"ok":true,"result":{"message_id":42,"from":{"id":5627588564,"is_bot":true,"first_name":"MaintainenceReminder","username":"MainRembot"},"chat":
{"id":1839649176,"first_name":"Helly","username":"artemis_0088","type":"private"},"date":1714670261,"text":"MaintainenceRequired"}}
```


```python
from sklearn.metrics import accuracy_score
print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_train, y_pred)))
```

```
Model accuracy score: 0.9016
```

```python
classification_error = (FP + FN) / float(TP + TN + FP + FN)
print('Classification error : {0:0.4f}'.format(classification_error))
```

```
Classification error : 0.0984
```

```python
precision = TP / float(TP + FP)
print('Precision : {0:0.4f}'.format(precision))
```

```
Precision : 0.9924
```

Benefits of Predictive Maintenance Compared to Traditional Preventive Maintenance

Traditional preventive maintenance involves scheduling maintenance tasks at predetermined intervals, regardless of the actual condition of the equipment. This approach can lead to several drawbacks:

- **Unnecessary maintenance:** Regular maintenance can be performed even when the equipment is functioning properly, which wastes time and resources.
- **Increased downtime:** Preventive maintenance often requires taking equipment out of service, which can lead to production losses.
- **Unexpected failures:** Equipment failures can still occur between scheduled maintenance intervals, leading to downtime and production losses.

  Predictive maintenance, on the other hand, uses sensor data and data analysis to monitor the health of equipment and predict when maintenance is actually needed. This approach offers several advantages over traditional preventive maintenance:

Reduced Maintenance Costs: Predictive maintenance focuses on fixing problems before they become critical, eliminating unnecessary maintenance procedures that traditional approaches require. This targeted approach saves resources and reduces overall maintenance expenditure.
Minimized Downtime: Traditional methods can lead to downtime due to scheduled maintenance, even when equipment is functioning well. Predictive maintenance identifies issues beforehand, allowing repairs to be scheduled during planned downtime or when production impact is minimal. This significantly reduces unplanned outages and keeps your operations running smoothly.
Improved Asset Life: By proactively addressing equipment concerns, predictive maintenance catches problems early on, preventing them from escalating into major failures. This reduces wear and tear, extending the lifespan of your valuable assets and maximizing their return on investment.
Enhanced Safety: Traditional methods might miss potential safety hazards until they cause problems. Predictive maintenance identifies these risks in advance, allowing you to address them before they pose a threat to personnel or the environment. This proactive approach promotes a safer work environment.
Optimized Resource Allocation: Predictive maintenance prioritizes maintenance needs based on real-time data. This eliminates wasted effort on unnecessary preventive procedures and ensures that resources are directed towards equipment that truly needs attention. This targeted approach optimizes the utilization of your maintenance team and resources.

Conclusion

Through this project we studied the common problems faced in automobile manufacturing plants and found we could come up with an industry appropriate solution to help with some of the problems faced with machinery failures, particularly, informing the administrator of an impending breakdown of a machine and scheduling a repair.This significantly reduces the down-time, saves the maintenance and machinery costs. As the accuracy of the results is high there is only a negligible chance of missing out on needed maintenance. Although this project explores multiple ways to get the most accurate prediction, the method of prediction is subject to change for each machine. Thus, it is imperative for a real-world installation that a tailor-made solution be used to ensure maximum accuracy and returns.Overall, comparing the huge cost of replacing expensive machinery or the costs incurred due to the downtime, the method of predictive maintenance gives us a much better result.

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