Prototype development and Buisness/ Financial Modelling
for
Predictive Maintenance
as an
AI Product

Submitted By -

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Prototype Selection

The prototype selected for this project is predictive maintenance implementaion for industries. It was chosen based on 3 important factors -

I. **Feasibility** – The product can be developed by a good team of data scientists in a very short term. As there are already available products on the market which they can refer as a resource. Then time required will be for finetuning it for particular industry usecase.

II. **Viability** – Predictive Maintenance is the future for industry. As Industry 4.0 revolution is nearby, different companies are opting for AI assisted forecasting for their component failure. As time goes more and more companies will go for predicitive maintenance and then it will become a core part of their daily operation. Following are some major factors which will contribute greatly to the success of predictive maitenance in industry.

- **Increasing Industrial Automation:** The ongoing trend of industrial automation across various sectors increases the need for reliable and efficient maintenance practices. As more machinery and equipment become automated, predictive maintenance becomes crucial to ensure optimal performance, reduce breakdowns, and maximize productivity.
- **Growing Data Availability:** With the proliferation of connected devices, sensors, and data collection systems, there is an abundance of data available for predictive maintenance. The availability of large and diverse datasets allows for more accurate predictive models and better-informed decision-making. Additionally, advancements in data storage, processing power, and cloud computing make it easier to manage and analyze vast amounts of data in real-time.

III. **Monetization** – This is a product which can be monetized directly. Following are some ways which can be used for revenue.

- **Subscription Model**: Offer the predictive maintenance solution as a subscription-based service. Customers pay a recurring fee to access and utilize the product. Subscription models can be structured based on factors such as the number of assets monitored, frequency of data analysis, or the level of support provided.
- **Licensing or Software-as-a-Service (SaaS):** Provide the predictive maintenance software as a licensed product or a cloud-based SaaS solution. Customers pay an upfront fee or a regular subscription to use the software, which may include features such as real-time monitoring, data analytics, and predictive algorithms.
- **Pay-per-Use:** Implement a pay-per-use or pay-per-insight model where customers are charged based on the number of predictive maintenance analyses performed or the value derived from actionable insights provided. This approach allows customers to pay for the specific results or benefits they obtain from the product.
- **Partnerships and OEM Integration:** Collaboration can be done with original equipment manufacturers (OEMs) or industry partners to integrate our predictive maintenance solution into their products or services. By leveraging existing industry networks and customer bases, we can expand our market reach and monetize through partnerships.

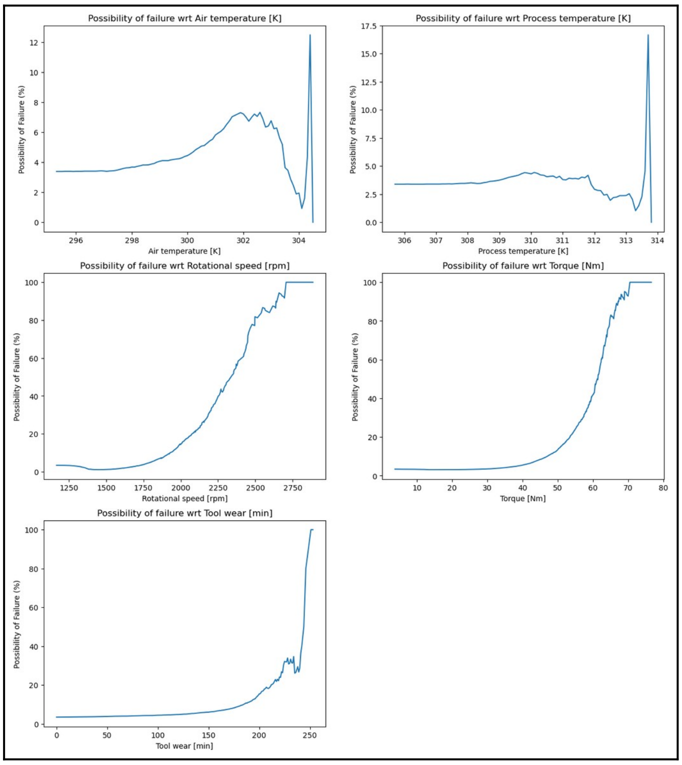
Prototype Development

Dataset

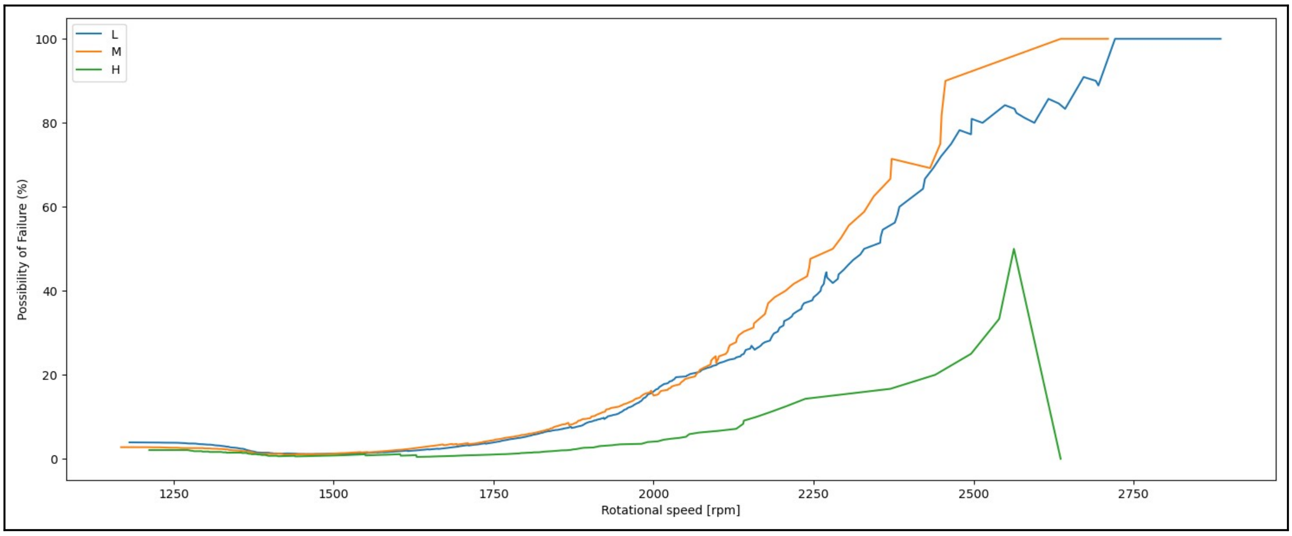
There are already available datasets on the internet for differnt industry equipments or parts. These datasets can be used to build a basic working product. For future differnt usecases of different company, team can add new models to the existing plateform. For our demonstration we have chosen a dataset which is a part of the paper, S. Matzka, "Explainable Artificial Intelligence for Predictive Maintenance Applications," 2020 Third International Conference on Artificial Intelligence for Industries (AI4I), 2020, pp. 69-74, doi: 10.1109/AI4I49448.2020.00023.

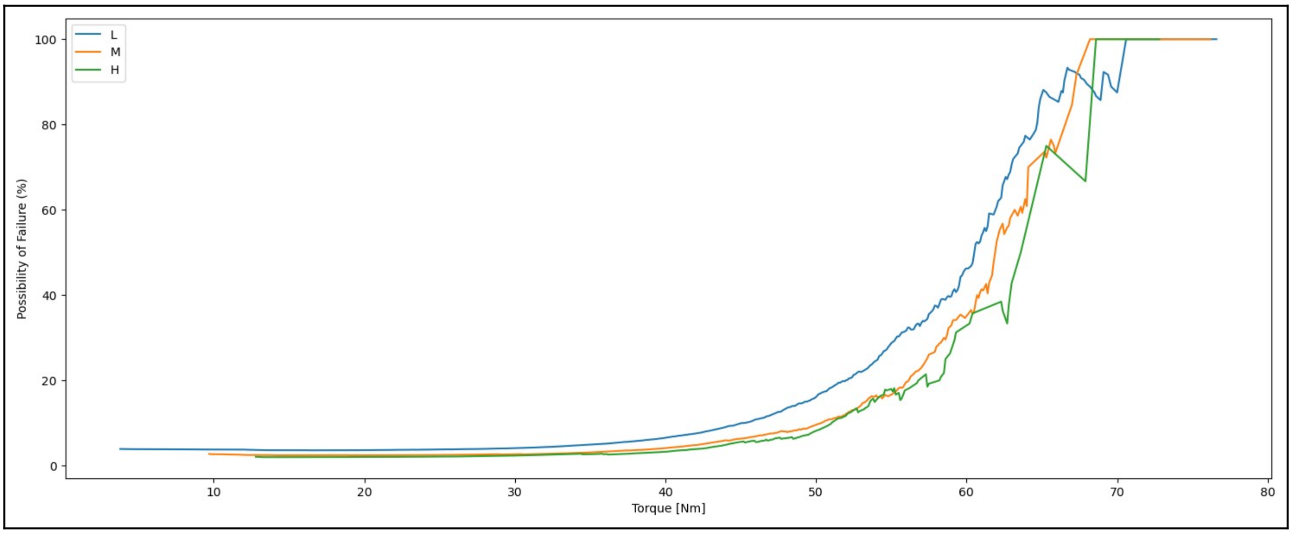
EDA on the features

The dataset contained various parameters recorded by sensors like, air temperature, rotational speed, torque etc. Before training the model, by doing EDA we could find some insights to the data. Following are some insights expressed in various plots -



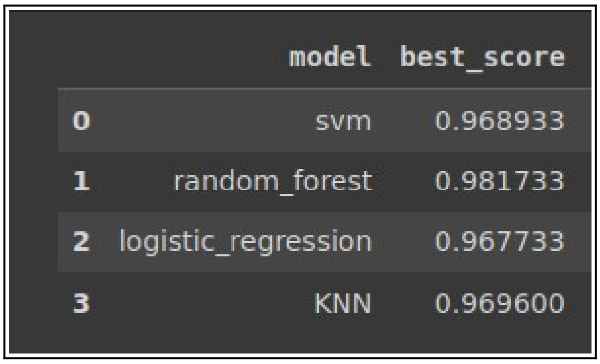
Here, we can see that probability of tool failure is highly dependent on input parameters. So combining these one can build a model with good accuracy/precision.
We also did a extensive analysis on how the tool type can affect dependency of various parameters on failure. So here are the results -





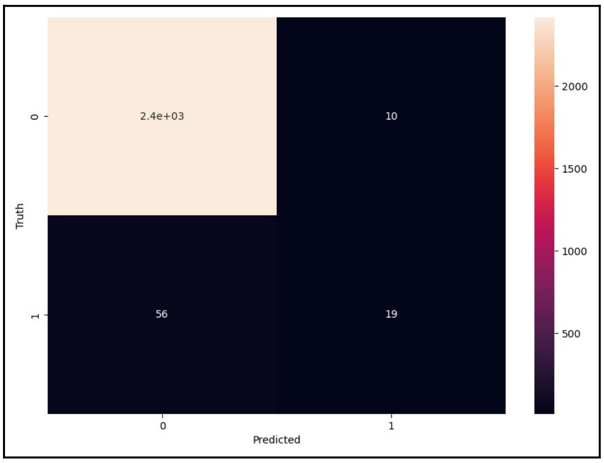
Model Performance

Finally various classification models were trained after doing feature engineering. Models were tuned for hyperparameter giving best results. Following are the best performing models -



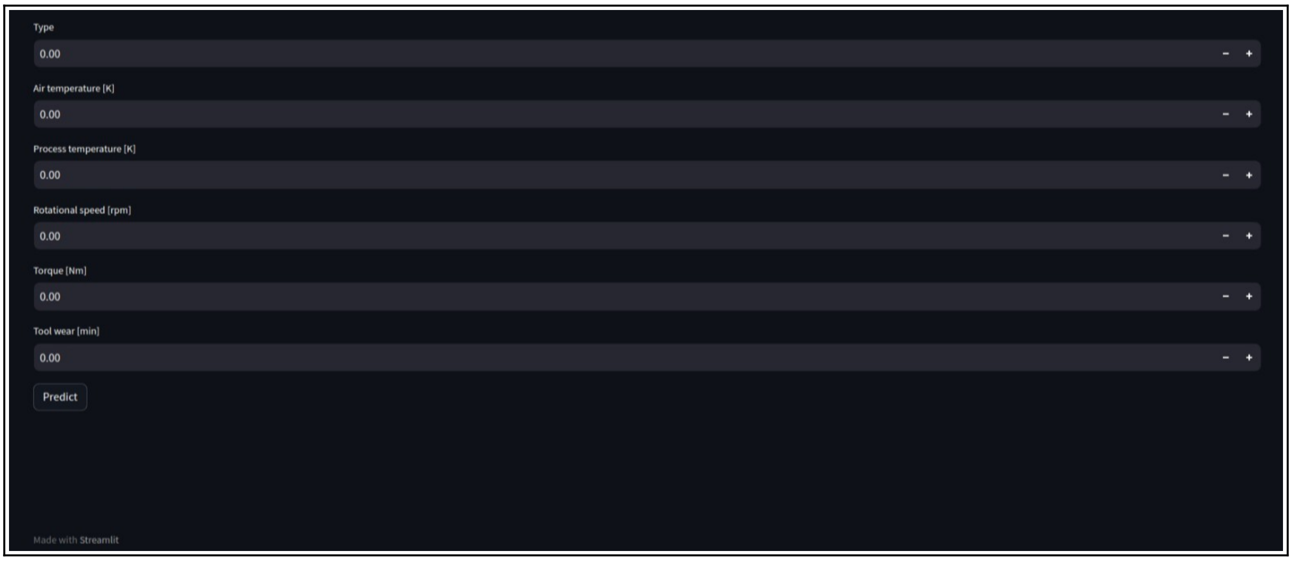
	model	best_score
0	svm	0.968933
1	random_forest	0.981733
2	logistic_regression	0.967733
3	KNN	0.969600

After plotting the confusion matrix, we can see that the model is not making too much error on False Positives or False Negatives.



UI of the webapp

Finally, we have a made a web app with steamlit to better realize our product. Following is a glimse of UI for the web app. There is room for imrpovement for the final product where the sensor data will be continuously fetched into the model and it will make predictions, which can bee again show to the front user in the web app.



The complete project is on the following github repository - https://github.com/ko-rudy001/Feynn_Labs_Project/blob/main/3rd%20Project.ipynb

Business Modelling

The value of money

Predictive maintenance technologies enable an organization to take proactive actions, such as performing targeted maintenance, clustering maintenance activities, and adjusting asset usage. Few of these actions can be performed instantaneously, however (preparing a maintenance activity, for example,takes time), nor can they be initiated at every moment in time. In reality, most organizations have a response time—thetime required to respond to a request for action—which depends on the action to betaken, the organizational context, and the timing of the request. The consequence is logical, yet important: the earlier you know an asset is going to fail, the bigger the range of proactive actions you can take. In fact, for many actions, organizations have both a minimum response time and an optimal response time. Let's take the overhaul of an electric motor as an example- The minimum response time is based on an emergency scenario. If you find out right now that the motor is about to break down, how long will it take you to start the maintenance activity? That might require that you stop the production process (wasting product), hire a skilled maintenance technician from a contractor (at a premium), or obtain a spare electric motor (with emergency shipping). If the consequences of breakdown are great enough, it's possible to save money. with such an emergency approach But the motor's overhaul would be much less costly if the organization had more time to react The optimal response time denotes how long an organization needs to optimally perform an action. In this example, the optimal response time depends on the time between planned production stops, the scheduling horizon for maintenance technicians, and the standard delivery time for electric motors. If production is stopped once every month, for example, and the scheduling horizon and delivery time are three weeks, the optimal value of preventive overhaul can be derived if the organization knows more than a month in advance that the motor is about to break down. The technology's prediction horizon—how far in advance a prediction system produces a correct prediction— therefore determines the value that can be derived. This idea is visualized in figure 1

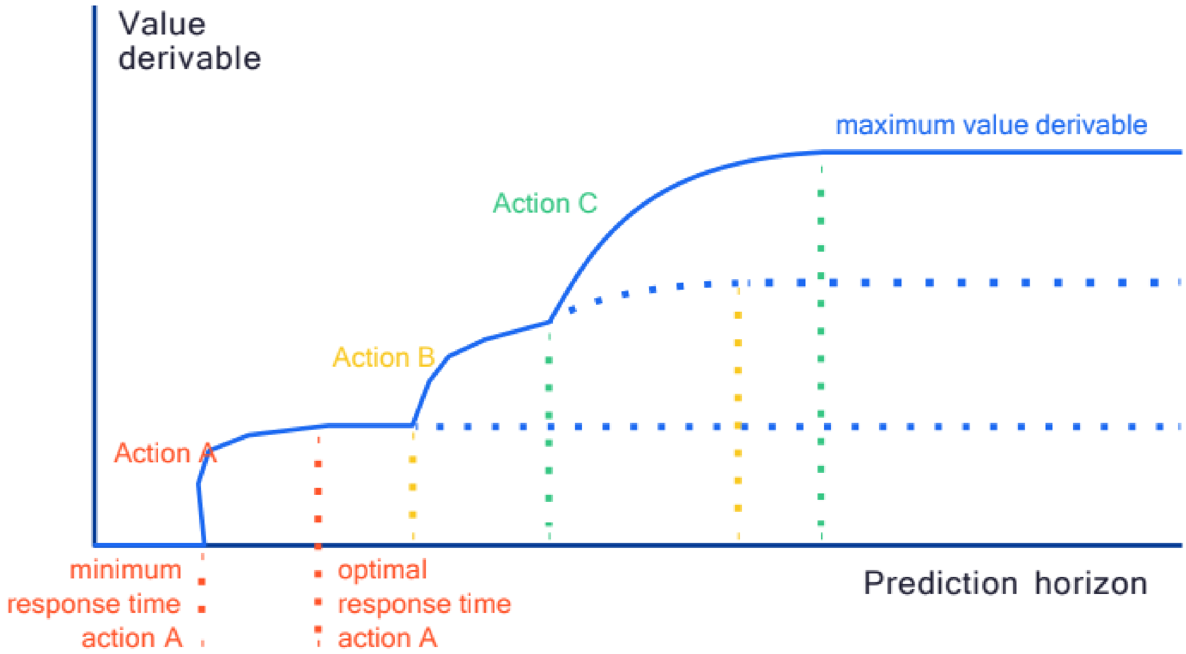


Figure 1: The value of time: an example of a relationship between a condition monitoring technology's prediction horizon and the potential value you can derive

The value of accuracy

Even if you have all the time in the world, few predictive maintenance technologies are capable of perfectly predicting failures—neither from the start nor over time. Most new applications require learning—by machines, by humans, or both—while over time the predictive performance is subject to changes in the asset itself (e.g., modifications) and its operational context (e.g., process or product changes). Two important performance indicators for a predictive maintenance technology are its sensitivity and its specificity. The sensitivity, also known as the true positive rate, indicates the percentage of failures that are identified beforehand (providing the organization sufficient response time). Specificity, or the true negative rate, indicates how well the technology is able to identify that an asset is not about to fail. The higher the specificity, the lower the number of false alarms. The higher the sensitivity, the lower the number of unexpected breakdowns. Together, the sensitivity and specificity determine the technology's accuracy: the percentage of failures and non-failures that are correctly identified as such.

	Actual condition: positive (failure)	Actual condition: negative (no failure)	
Predicted condition: positive (failure)	true positive (TP)	false positive (FP) (type I error)	
Predicted condition: negative (no failure)	false negative (FN) (type II error)	true negative (TN)	
	SENSITIVITY: $\frac{TP}{TP + FN}$	*SPECIFICITY:* $\frac{TN}{FP + TN}$	*ACCURACY:* $\frac{TP + TN}{TP + TN + FP + FN}$

Figure 2: The value of accuracy: classifying predictive sensitivity and specificity

To calculate the business case for a new predictive maintenance technology, we have to take into account that its accuracy is not perfect. Especially for complex assets with multiple failure modes and degradation mechanisms, business case analyses should incorporate the probability of missing an upcoming failure and the probability of raising a false alarm. In addition, it should be noted that for many assets, the current accuracy— before implementing the new predictive maintenance technology—is rarely zero. Anomalies and upcoming failures can, for example, be detected during visual inspections, functional tests, and via production interference, although the prediction horizon of these methods is typically lower than with predictive maintenance technologies. Sound business cases therefore focus on the difference in accuracy between the old andnew situations.

The value of decisions

Almost by definition, predictive maintenance is intended to reduce the cost of maintenance, by enabling you to skip scheduled maintenance activities, prevent unexpected breakdowns, reduce the frequency of inspections, cluster maintenance activities, or perform focused maintenance. This value is generated by making decisions that are better informed. But insight into the current and future state of assets can also benefit other stakeholders in the organization, such as the production department—by reducing energy and materials usage, increasing availability, reducing slowdowns and reducing quality losses—and the project department—by extending assets' useful life. Table 1 summarizes common value drivers for predictive maintenance, including the range of realized benefits I've observed in practice (in percentages).

Value driver	Observed percentages	Beneficial for
Reduced maintenance costs	-10%-50%	Maintenance department
Reduced capital expenditure	-10%-50%	Project department
Reduce safety & environmental risk	0%-50%	Many stakeholders
Reduced operational costs	0%-50%	Production department
Increased overall equipment effectiveness	0%-50%	Production department

Table 1 Common value drivers for predictive maintenance, including benefits observed in the field

Methods for calculatingthe business case

There are many ways to calculate a business case, as well as a wide variety of outcome variables. The most dominant outcome variables are the return on investment (ROI)—the ratio between the financial gain an investment produces and its cost—and the payback period, or time it takes to recover the investment's cost. Selecting the appropriate method depends, among other things, on the technology's use case—to monitor an individual asset, a group of similar assets, or a group of dissimilar assets—and how important timing is. If it doesn't matter when costs are incurred and revenues are earned, you can simply use averages to calculate the business case (such as the mean time between failure, average cost of breakdown, and so forth). If timing does matter, such as when computing a payback period or an ROI with a discount rate, you'll need to run simulations. In this section, we'll look at three sample methods for calculating the business case for predictive maintenance.

	Individual asset	Group of similar assets	Group of dissimilar assets
Timing *does not* matter	Example 1: ROI without discount rate		Example 3: Upper limit
Timing *does* matter		Example 2: Payback period	

Table 2 Three sample methods for calculating the business case

Financial Modelling

(a) Market in which product and service will be launched into:

Predictive maintenance is a proactive maintenance strategy that uses data analysis tools to identify equipment problems before they occur. By analyzing data from sensors and other sources, predictive maintenance can identify patterns and anomalies that indicate potential equipment failures. This allows maintenance teams to take corrective action before a failure occurs, reducing downtime and maintenance costs. Machine learning for predictive maintenance can be applied in various markets and industries where equipment or assets require regular maintenance to prevent breakdowns and optimize their performance. Some of the key markets where predictive maintenance using machine learning is commonly applied include:

1. **Manufacturing:** Predictive maintenance can help manufacturing industries optimize their production processes by predicting failures or malfunctions in machinery and equipment. This ensures minimal downtime and reduces maintenance costs.
2. **Energy and Utilities:** Power plants, renewable energy facilities, and utility companies can leverage machine learning for predictive maintenance to monitor and predict the health of their infrastructure, such as turbines, generators, transformers, and transmission lines. This helps prevent costly failures and improves overall operational efficiency.
3. **Transportation and Logistics:** In the transportation sector, predictive maintenance can be applied to vehicles, aircraft, railways, and shipping fleets. By analyzing sensor data and historical maintenance records, machine learning models can predict maintenance needs, avoid unexpected breakdowns, and optimize maintenance schedules.
4. **Oil and Gas:** In the oil and gas industry, predictive maintenance can be used to monitor critical equipment like pumps, compressors, pipelines, and refineries. By identifying potential failures in advance, companies can reduce downtime, minimize safety risks, and optimize maintenance activities.
5. **Healthcare:** Predictive maintenance can be beneficial in healthcare facilities to monitor and maintain medical equipment such as MRI machines, X-ray systems, and patient monitors. Machine learning algorithms can detect anomalies and predict maintenance requirements, ensuring continuous availability of essential medical equipment.
6. **Telecommunications:** Telecommunication networks rely on various components such as routers, switches, and servers. Predictive maintenance using machine learning can help identify potential issues or degradation in network infrastructure, enabling proactive maintenance and minimizing service disruptions.
7. **Aerospace and Defence:** In the aerospace and defense sectors, predictive maintenance can be applied to aircraft, military vehicles, and defense systems. By analyzing sensor data and other relevant parameters, machine learning algorithms can predict maintenance needs, improve operational readiness, and reduce costs.

These are just a few examples of markets where machine learning for predictive maintenance can be applied. In general, any industry that relies on critical equipment or assets can benefit from predictive maintenance to optimize performance, reduce costs, and enhance overall operational efficiency.

(b) Data/statistics regarding that market online:

Top predictive maintenance companies using AI

IBM

IBM Watson IoT is at the forefront of predictive maintenance with its comprehensive suite of tools and technologies. Leveraging AI and ML, the company's solutions analyse vast amounts of data to detect anomalies and predict equipment failures, enabling businesses to implement timely maintenance strategies.

IBM Predictive Maintenance and Quality is an integrated solution that companies can use to:

- Predict the failure of an instrumented asset so that you can prevent costly unexpected downtime.
- Make adjustments to predictive maintenance schedules and tasks to reduce repair costs and minimize downtime.
- Quickly mine maintenance logs to determine the most effective repair procedures and maintenance cycles. Identify the root cause of asset failure faster so that you can take corrective actions.
- Identify quality and reliability issues definitively and in a timely way.

IBM Watson IoT's predictive maintenance capabilities have been adopted by organizations across various industries, including manufacturing, energy, and transportation.

Siemens

Siemens, a global powerhouse in engineering and technology, offers a range of predictive maintenance solutions for industries such as manufacturing, energy, and healthcare. Siemens' solutions empower businesses to detect anomalies, predict failures, and schedule maintenance activities strategically.

In 2022, Siemens announced it had acquired Senseye, a leading provider of outcome-oriented predictive maintenance solutions for manufacturing and industrial companies. Senseye Predictive Maintenance enables asset intelligence across all your plants without the need for manual analysis. Combining leading AI with human insights, the platform helps organisations to increase productivity, work more sustainably, and accelerate digital transformation.

SAP

SAP, a leading provider of enterprise software, has ventured into the predictive maintenance arena with its intelligent asset management solutions. SAP's platform utilises AI and machine learning algorithms to analyse sensor data, identify patterns, and forecast potential failures. By integrating predictive maintenance capabilities with other enterprise systems, SAP enables businesses to optimise maintenance operations and reduce costs.

General Electric

General Electric (GE) is renowned for its innovative approach to predictive maintenance. GE Digital SmartSignal has been a leading predictive maintenance software solution across industries for nearly two decades, with continuous investment in analytics breadth and innovation. Its Digital Twin solution enables industrial companies to predict, diagnose, forecast, and prevent downtime of critical equipment.

Uptake

Uptake is a leader in predictive analytics SaaS, working to translate data into smarter operations.Uptake specialises in industrial AI and analytics solutions, offering predictive maintenance capabilities for various sectors, including manufacturing, energy, and transportation. Uptake's platform combines data science, ML, and domain expertise to deliver actionable insights. By leveraging real-time data from sensors and other sources, Uptake's solutions predict equipment failures, optimise maintenance schedules, and improve asset reliability.

Statistics and achievements of companies:

U.S. industrial products manufacturer

Achievements: PdM saves millions of dollars in unplanned downtime and Mike Macsisak, a maintenance veteran, has seen it happen throughout his career. In his current role setting up a PdM program for a U.S. manufacturer of industrial products, steam trap problems such as boiler steam pipeline flaking are being caught and corrected early, and his team is consistently putting the right oil in the right machines. A mine he previously worked at had 91% uptime because of PdM. And he recently heard that a bearing solution he implemented seven years ago for a food manufacturer solved the root cause of a recurring problem and is still running “like new” today.

Tennessee snack food manufacturer

Achievements: Year-to-date equipment downtime is 0.75% and unplanned downtime is 2.88% at PepsiCo’s Fayetteville, TN, Frito-Lay plant, said Carlos Calloway, the site’s reliability engineering manager, in his presentation at the Leading Reliability 2021 conference.

San Diego energy utility

Achievements: San Diego Gas & Electric (SDG&E) Company is actively exploring a variety of AI, ML, and emerging technology opportunities to improve operations and maintenance. In one example, previously unleveraged data applied to ML algorithms predicted the failure of T-splices, a crucial underground power distribution asset, with a high degree of accuracy and sufficient time for crews to plan repairs. Due to its success, the program is being extended to other critical assets such as oil switches, load break elbows, and transformers.

Louisiana alumina refinery

Achievements: The Noranda Alumina plant in Gramercy, LA, realized a 60% decline in bearing changes in the second year of using a new lubrication solution, saving approximately $900,000 in bearing purchases and avoiding costly downtime. “Four hours of downtime is about $1 million dollars’ worth of lost production,” said Russell Goodwin, a reliability engineer and millwright instructor at Noranda Alumina in his Leading Reliability 2021 presentation. In addition, the grease completion rate reached 92% this year.

Singapore rail operator

Achievements: A significant goal was met in August 2019 for Singapore rail operator SMRT Trains Ltd. when it achieved one million mean kilometers between failure (MKBF) across all its lines. This is the equivalent of traveling over the entire network thousands of times before seeing a service delay of five minutes or more. Hundreds of manual planning hours have been eliminated, and about 20 maintenance train deployments per year are avoided. Engineers have a better idea of the work conditions and the work crews’ maximum work capacity per shift is optimized.

Important Points to note

1. Market Size and Growth:

- The global predictive maintenance market size was estimated to be around $3.3 billion.
- The market is expected to experience significant growth, with a projected CAGR of 24.8% during the forecast period of 2021-2026.
- The manufacturing sector holds a significant share of the predictive maintenance market due to its emphasis on optimizing production processes and reducing downtime

2. Benefits of Predictive Maintenance:

- Predictive maintenance can lead to cost savings by reducing maintenance expenses by up to 30%.
- Downtime can be reduced by approximately 45% through proactive maintenance practices.
- Predictive maintenance improves asset reliability by around 25% and extends equipment lifespan by 20-30%.

3. Predictive Maintenance Technologies:

- Machine learning algorithms are widely employed for predictive maintenance in the manufacturing industry. These algorithms analyze historical data, sensor readings, and other relevant parameters to detect patterns and anomalies that indicate potential equipment failures.
- Other technologies used in predictive maintenance include artificial intelligence (AI), Internet of Things (IoT) sensors, data analytics, and condition monitoring systems.

4. Case Studies:

- Numerous case studies highlight successful implementations of predictive maintenance in manufacturing:
- A leading automotive manufacturer implemented predictive maintenance on its assembly lines, resulting in a 20% reduction in downtime and a 25% decrease in maintenance costs.
- A steel manufacturing company utilized predictive maintenance to monitor machinery health and achieved a 30% improvement in equipment reliability, leading to higher productivity and reduced maintenance expenses.

5. Key Challenges:

- Implementing predictive maintenance requires integrating and managing large volumes of data from diverse sources, including sensors, maintenance logs, and operational systems.
- The shortage of skilled personnel with expertise in data analysis and machine learning poses a challenge for organizations adopting predictive maintenance.
- Ensuring data security and integrity is crucial to maintaining the effectiveness of predictive maintenance solutions.

Top Predictive Maintenance Start-ups and Companies in India

Utvyakta:

Our solution - Kompress.AI is a predictive maintenance and energy-saving solution specifically customized for air compressors. This provides monitoring of critical parameters and analytics to derive specific performance and utilization insights.

CLAIRVIZ TECHNOLOGY SYSTEMS PVT LTD:

ClairViz Systems is a Smart Manufacturing company offering Products and Bespoke End to End solutions to help Manufacturing companies increase their Efficiencies & Profitability

We offer Enterprise, SaaS, and Mobility Products for Industry 4.0 by leveraging IIOT, Edge Computing, Machine Learning & Analytics to drive sustainable Benefits

We have two products.

1. DOMMS (Digital Operations and Maintenance Management System)- For Prescriptive, Proactive and Predictive Maintenance
2. Osprey

Starlly-Spectra:

Spectra helps companies using machines/equipment at their sites/units, and companies building machines/equipment for a certain domain, with a workflow that helps take care of monitoring/managing machines/equipment remotely.

INOVMAC PRIVATE LIMITED:

Inovmac builds smart power tools/machines to ensure reliable service, transparency in machine failure, and quick service time leading to a happy customer. Inovmac's solution of using machine modularity and IIoT (Industrial Internet of Things) with robust hardware helps to provide visibility on machine failures at a granular level, and quickly resolve the issue.

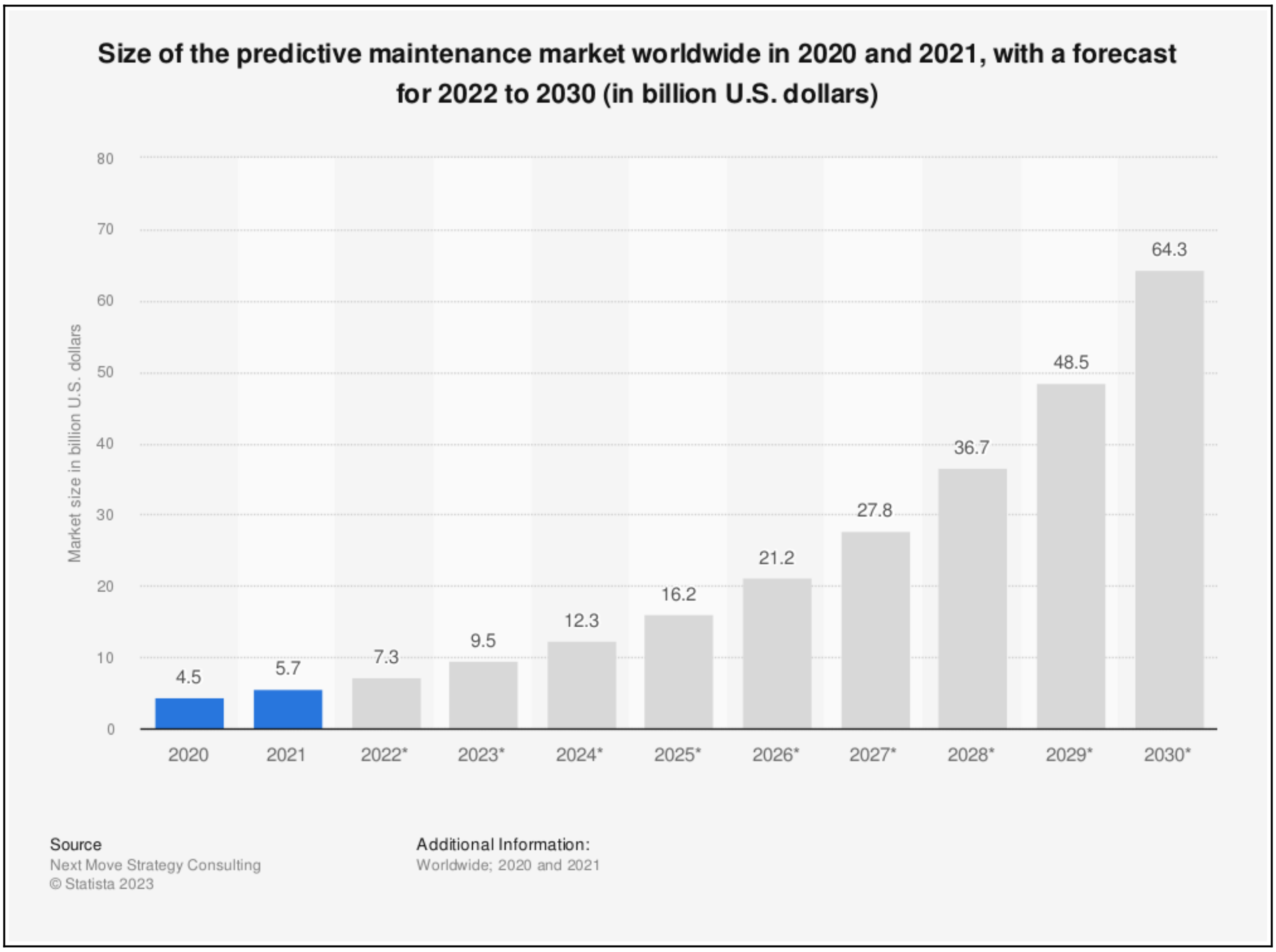
Sensiwise:

Offers solutions in the areas of Cold-Chain Logistics & Industrial Asset Tracking & Monitoring. Our solutions help enterprises become more agile, efficient, transparent & innovatives.

(c) Forecasting of market

We were unable to collect appropriate data regarding the market to perform forecasting. But there were some good statistical analysis and forecasting performed by reputed farms were available on the internet. Following are some statistics on the growth of this market -

US Market

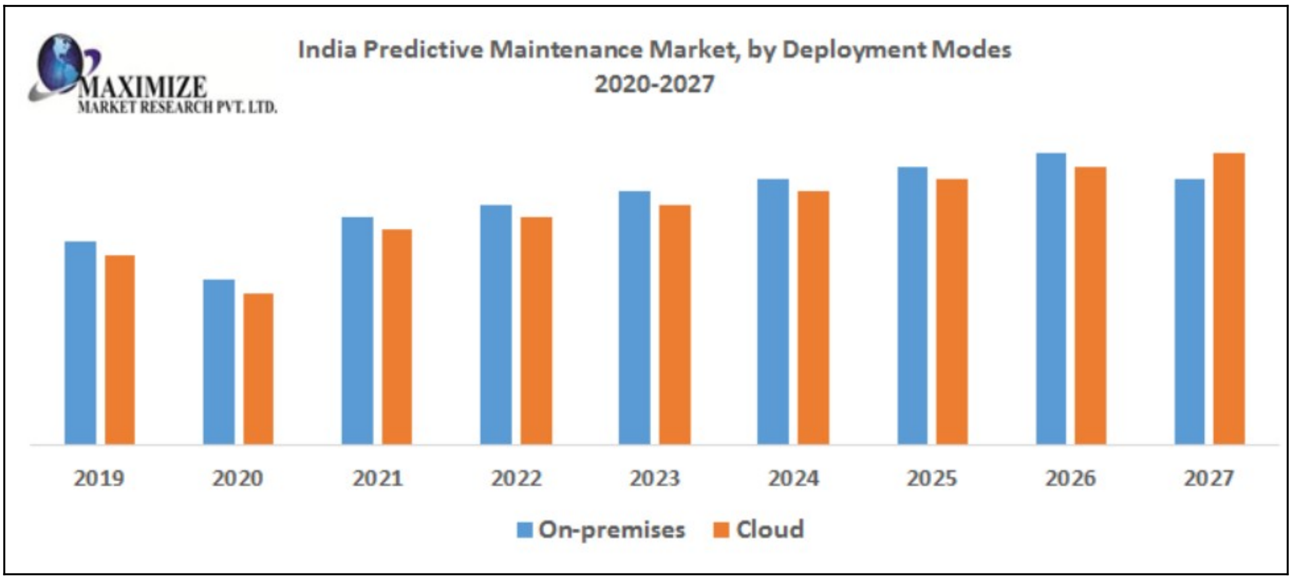


For instance, the data from the U.S. Department of Energy indicates that predictive maintenance is very cost-effective and that it helps an enterprise to gain remarkable results such as a tenfold increase in ROI, 70-75% decrease in breakdowns, 25-30% reduction in costs, and 35-45% reduction in downtime.

Indian Market

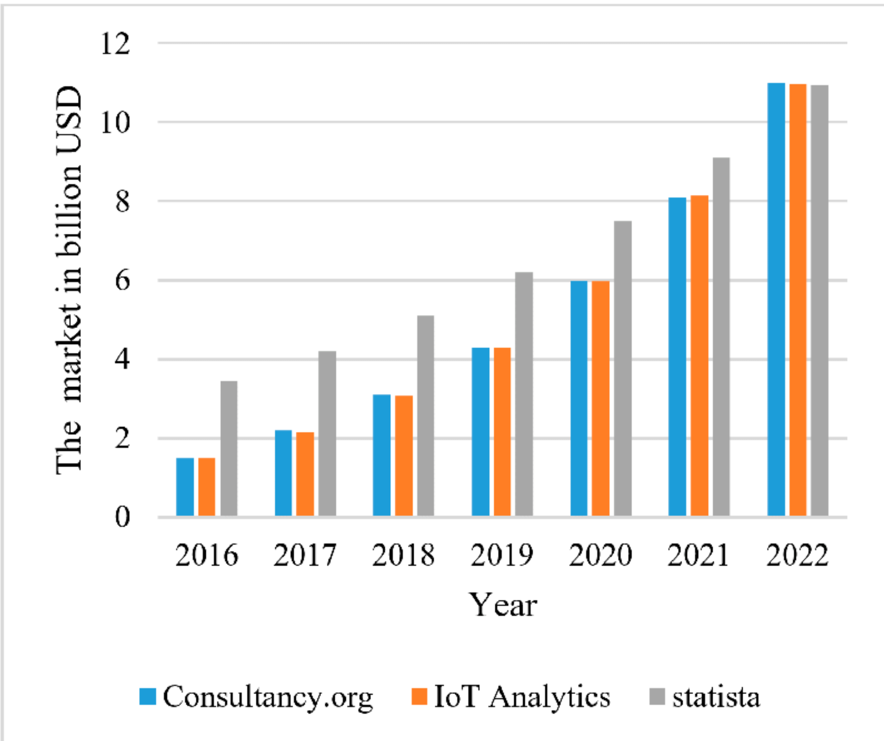
For Indian market also we collected analysis performed by the group "Maximize Market Research Pvt. Ltd.". According to the analysis **India Predictive Maintenance Market** is expected to reach

US $ 4 Bn by 2026, at a CAGR of 25.2% during the forecast period. Following are the analysis performed -

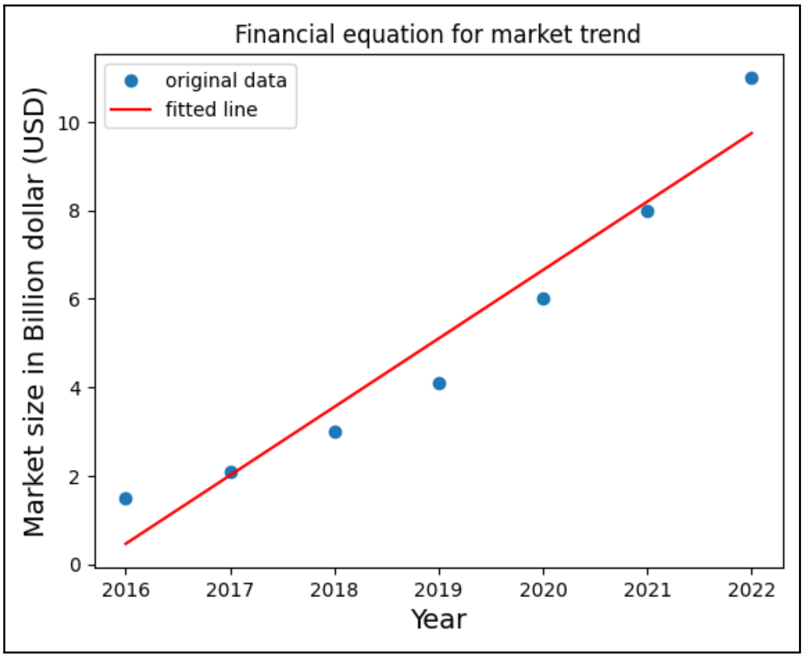


(d) Designing Financial equation based on market trend

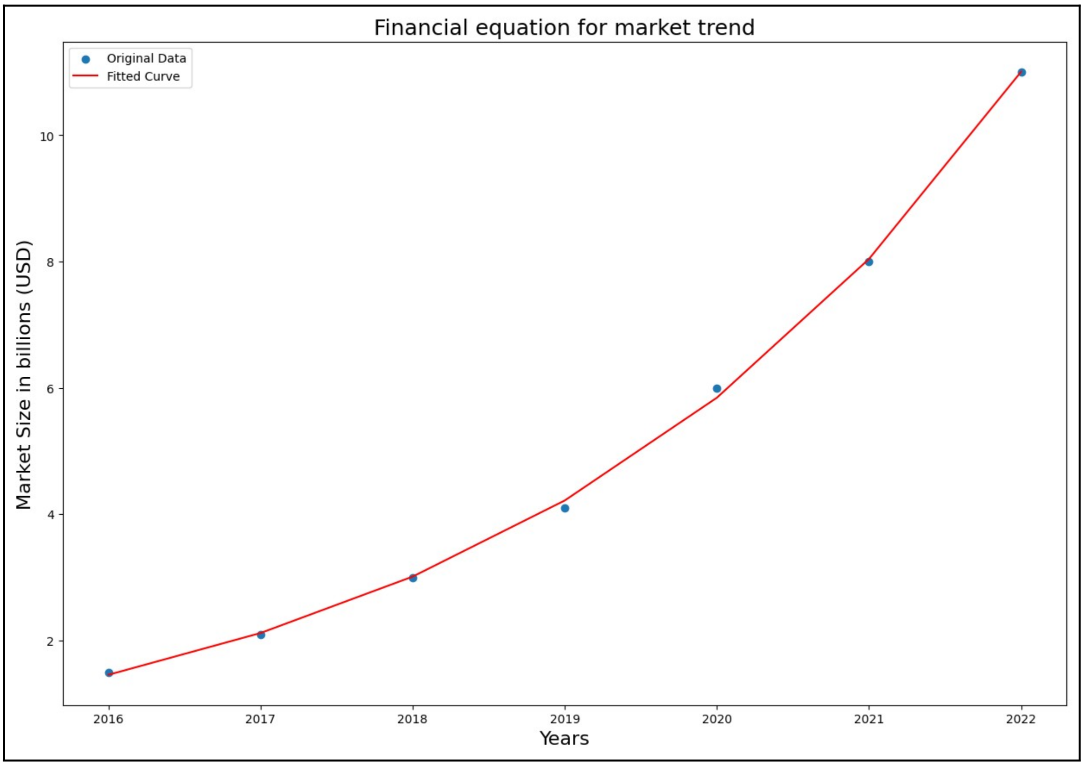
Various farms reported different market size for the past years. So we have gathered a combined plot of global market for predictive maintenance. The data from IoT Analytics was taken for deriving the financial equation.



Based on this data, we derived the financial equation for current market trend. First we tried to fit a linear equation to the data and here is the result -



We can notice that linear line, y = mx + c (m=1.55, c = -3117.14) is not able to explain the trend perfectly. So, next we tried with a exponential line here we can see that it fits the trend perfectly.



The equation is of the exponential form, $y=a\cdot e^{b\cdot x}+c$ with a = 1.89, b= 0.3 and c = -0.43.