STATE-OF-THE-ART SYSTEMS FOR PREDICTIVE MAINTENANCE IN INDUSTRIAL MACHINERY

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Abstract:

This project revolves around the development of an avant-garde machine learning-driven predictive maintenance system tailored for industrial machinery. Leveraging in-depth analysis of historical sensor data encompassing parameters like Air Temperature [K], Process Temperature [K], Rotational Speed [rpm], Torque [Nm], and Tool Wear [min], the system adeptly anticipates potential equipment failures. The overarching goal is to endow enterprises with proactive maintenance strategies, culminating in diminished downtime and judiciously optimized maintenance expenditures. Facilitated through the implementation of an intuitive Flask application, this innovative solution aspires to elevate operational efficiency, with the potential to catalyse augmented revenue streams for industrial entities.

1. Problem Statement:

The overarching goal of this initiative is to develop a sophisticated machine learning solution capable of accurately forecasting potential malfunctions in industrial machinery. Leveraging critical sensor data such as Air temperature [K], Process temperature [K], Rotational speed [rpm], Torque [Nm], and Tool wear [min], the system will deploy advanced algorithms to anticipate impending failures. This predictive maintenance solution seeks to furnish enterprises with invaluable insights, empowering them to strategically plan maintenance activities, mitigate downtime, and optimize associated costs. By pre-emptively identifying and addressing potential issues, industrial entities can markedly elevate their operational efficiency, steering clear of disruptive and costly downtimes.

The implementation of this state-of-the-art predictive maintenance tool not only grants businesses the ability to make informed, data-driven decisions but also positions them to enhance productivity while concurrently reducing operational risks. The assimilation of this machine learning solution allows industries to adopt a proactive approach to machine upkeep, ensuring uninterrupted operations and delivering substantial long-term cost savings. As the product facilitates the efficient allocation of resources and streamlines maintenance protocols, it emerges as an indispensable asset in the relentless pursuit of operational excellence within the industrial sector.

2. Prototype Selection:

For the prototype selection process, our team evaluated several ideas based on the following criteria:

- **2.1. Feasibility**: The product should be achievable within a short-term timeframe of 2-3 years. This ensures that development efforts are practical and realistic.
- **2.2. Viability**: The chosen prototype idea should have the potential to remain relevant and sustainable in the long-term future, spanning 20-30 years. This criterion ensures that the product/service addresses enduring needs or trends.

2.3. **Monetization**: The product should be directly monetizable, meaning it should have clear pathways for generating revenue. Indirectly monetizable idea were excluded from consideration for this project.

After careful evaluation, our team selected the **prototype idea**.

- **Feasibility**: With AI and machine learning advancements, developing an AI-powered predictive maintenance assistant is viable in 2-3 years. Leveraging existing algorithms and machine health data analytics, it predicts equipment failures.
- **Viability**: As industries adopt smart manufacturing, the demand for predictive maintenance solutions grows, making this assistant relevant and viable long-term.
- **Monetization**: Offered through subscription models to industrial enterprises, with premium features for real-time monitoring. Partnerships with equipment manufacturers and data sales to research institutions provide additional revenue streams.

3. Prototype Development:

To validate our prototype idea, we initiated small-scale code implementation and model building focused on developing a rudimentary AI model for predictive maintenance.

- **Data Collection**: We gathered a limited dataset of anonymized machine health records, including operational parameters like temperature, vibration, and performance history.
- **Model Building**: Employing machine learning algorithms, we crafted a prototype AI model capable of analyzing machine data and predicting potential failures. The model considered factors such as operational conditions, historical trends, and maintenance records to anticipate issues.
- **Validation**: The prototype AI model underwent testing using simulated machine scenarios and feedback loops to evaluate its accuracy in predicting failures. Iterative enhancements were applied based on feedback to improve the model's predictive capabilities.
- **Prototype Demonstration**: While not mandatory, we developed a basic interface to showcase the functionality of the AI-powered predictive maintenance assistant. This interface allowed users to input machine data and receive real-time predictions regarding potential equipment failures.

This prototype development process serves as an initial step in validating the feasibility and effectiveness of predictive maintenance in machine health monitoring systems.

4. Business Model:

The backbone of any business lies in its business model. Spending time on defining a solid business model is a strategic move compared to direct door sales. In our scenario, a subscription-based business model can be highly effective. Many businesses use such a strategy with fixed costs and additional requirement-based services. For our Smart Industrial Predictive Solutions (SIPS) Predictive Maintenance (PDM) service business, we offer three subscription plans:

- **Subscription Plan 1**: Personalized web-based monitoring system, valid for 6 months, at a fixed charge of $20,000.
- **Subscription Plan 2**: Personalized predictive system, valid for 1 year, at a fixed charge of $35,000.
- **Subscription Plan 3**: Personalized predictive system with optional IoT-based services, valid for 3 years, at a fixed charge of $80,000. (Note: Modification charges and IoT-based services are not included in the fixed charges.)

Real-Time Web-Based Monitoring and Predictive Maintenance App: How It Works:

Step 1: Approaching Clients:

- Approaching potential clients as a predictive maintenance service provider involves a strategic process utilizing various marketing channels and direct sales through affiliations. Here's a step-by-step approach to effectively approach clients in this industry:
    - **Market Research and Segmentation**: Begin by conducting thorough market research to understand the target audience. Identify industries and businesses that can benefit from predictive maintenance services, such as manufacturing, energy, healthcare, and transportation.
    - **Compelling Value Proposition**: Develop a compelling value proposition of subscription service to attract customers from different segments. Our solution can help clients reduce downtime, lower maintenance costs, and improve overall equipment efficiency.
- **Marketing**:
    - Develop a website for predictive maintenance services, including case studies, client testimonials, and industry expertise.
    - Implement search engine optimization (SEO) strategies and social media marketing to ensure the website ranks well on search engines for relevant keywords.
- Create informative and educational content related to predictive maintenance, such as blog posts, whitepapers, infographics, and videos. Share industry insights, news, and success stories to engage the audience and build relationships.
- Build an email list of potential clients who have expressed interest in the services. Send personalized and informative emails that address their pain points and offer solutions.

- **Future Development**: Showcase success stories and case studies on the website to demonstrate the real-world benefits our predictive maintenance services have delivered to clients.
- Regularly assess the effectiveness of marketing and sales strategies and make adjustments as needed. Stay up-to-date with industry trends and technologies to ensure the services remain competitive.

Step 2: Identifying Needs:

- Actively communicate to understand the needs and wants of the client.
- Observe and analyze their operations, processes, and any existing systems or equipment.
- Engage the client in collaborative problem-solving discussions, offer expertise and insights, and comprehensively document the discussions.

Step 3: Physical Installation:

- Physical installation will be handled by a third-party IoT service-based company with a focus on data security and integration.

Step 4: Offering Solutions:

- Prioritize needs and offer customized solutions to meet the specific needs and goals of the client. Offer customer support and ensure data security.

In summary, our business model emphasizes subscription-based services and a comprehensive go-to-market strategy for approaching clients and offering tailored solutions in the predictive maintenance sector.

5. Model Building:

A multifaceted business model maximizes revenue generation potential. We envision a **Software-as-a-Service (SaaS) approach** with tiered subscription plans based on data volume and features. Additionally, anonymized usage data analysis can be offered to equipment manufacturers or insurers for research and risk assessment. We also explore collaborative opportunities with industrial service providers to integrate our predictive insights into their maintenance solutions. This diversified model fosters scalability and strategic partnerships within the industrial ecosystem.

State-of-the-Art Enhancements in Predictive Analytics:

Predictive Analytics for predictive maintenance of machines health encompasses diverse approaches, such as:

- **Decision Trees**: Supervised learning for continuous value prediction.
- **Random Forests**: Ensemble learning combining multiple decision trees for heightened prediction accuracy.
- **Gradient Boosting**: Ensemble learning technique that builds a series of weak learners (typically Decision Trees) sequentially.
- **XGBoost (Extreme Gradient Boosting)**: Ensemble learning algorithm that enhances predictive accuracy by sequentially boosting decision trees, optimizing model performance in identifying potential failures and their impacts.
- **Support Vector Machine**: Supervised learning for classification or regression tasks.
- **K-Means Clustering**: Unsupervised learning algorithm, aiding in identifying patterns or anomalies in predictive maintenance datasets.
- **Naïve Bayes**: Probabilistic Algorithm utilizing Bayes' Theorem for classification, particularly useful in predicting failure modes and assessing their likelihood.
- **Neural Networks**: Deep learning algorithms for intricate tasks like image recognition and natural language processing.
- **Recurrent Neural Networks (RNN)**: Deep learning algorithm designed for sequential data analysis, making it suitable for predicting time-series patterns in industrial machine behavior for proactive maintenance planning.

Groundbreaking Strategies in the Industry:

Adhering to best practices in handling predictive maintenance datasets involves key steps:

- **Data Acquisition**: Gathering comprehensive machine data, including sensor readings, vibration, and operational metrics.
- **Data Preprocessing**: Improve data accuracy by eliminating noise and outliers during preprocessing.
- **Feature Extraction**: Identify relevant data characteristics, known as features, for predictive maintenance tasks.
- **Model Selection**: Choose an appropriate predictive analytics model for training, predicting failure probabilities.
- **Model Training and Evaluation**: Train and evaluate the model for accuracy on separate datasets before deployment.
- **Deployment and Monitoring**: Deploy the model in production and monitor its ongoing accuracy, retraining as needed.

Fine-tuning Predictive Maintenance for Maximum Efficiency:

Critical areas for fine-tuning predictive maintenance systems include:

- **Data Quality**: Ensuring high-quality data is paramount for accurate predictions, mitigating the impact of noisy or incomplete datasets.
- **Model Complexity**: Striking a balance between model complexity and interoperability is crucial to optimize prediction accuracy.
- **Deployment Costs**: Addressing the high deployment costs entails managing data collection, storage, model training and ongoing monitoring expenses.

6. Final Product Prototype:

An iterative development approach minimizes risk and maximizes learning. Our plan is to develop a minimum viable product (MVP) with core functionalities for early user testing and feedback. Initial focus will be on real-time data visualization, basic anomaly detection, and integration with common industrial sensors. Conducting pilot deployments with diverse industries will gather real-world data and refine the system based on user experience. This approach ensures market fit and user satisfaction before full-scale product launch.

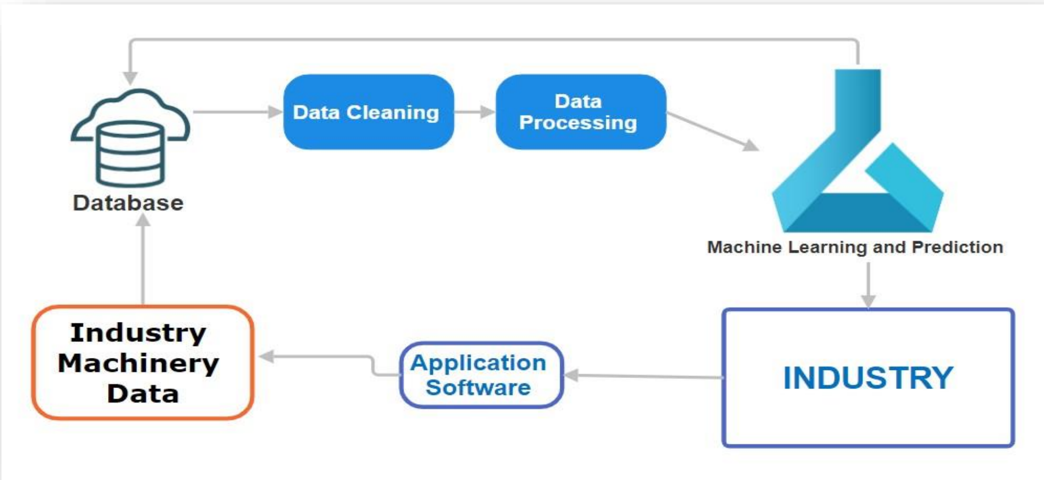


Figure 1: Predictive Maintenance System Design

7. Product Details:

Our system leverages sensor data (temperature, vibration, etc.) to predict potential equipment failures. Data sources encompass industrial sensors, historical maintenance records, and external databases. Advanced algorithms like **XGBoost and LSTM networks** analyze data for anomaly detection and failure prediction. Utilizing frameworks such as TensorFlow or PyTorch provides flexibility and scalability for model development and deployment. A team of data scientists, software engineers, and domain experts will be assembled to drive development and implementation. Cost will be determined by factors such as features, data volume, and deployment model (SaaS vs. on-premise)

8. Code Implementation/Validation on Small Scale:

A phased approach minimizes development risks. We plan to utilize readily available machine learning libraries for initial prototype development. Focus will be on a specific type of machinery with relevant sensor data collection. Basic anomaly detection algorithms will be implemented, with results visualized for user feedback. This initial stage validates feasibility and refines the approach before full-scale development commences.

Code: GitHub Repository

Objective:

The goal of this predictive maintenance project is to develop a machine learning model that can effectively predict machine failures based on a synthetic dataset provided. The dataset contains information about various features related to the manufacturing process, and the target variable includes two aspects: whether a machine failure occurred (binary classification) and the type of failure if it occurred (multi-class classification).

Figure 2: Objective of the Business Model Prototype

Dataset Description

The dataset consists of 10,000 data points with 14 features for each observation. The features include:

1. UID: Unique identifier ranging from 1 to 10,000.
2. ProductID: Categorized as low (L), medium (M), or high (H) quality variants with variant-specific serial numbers.
3. Air Temperature [K]: Generated using a random walk process, later normalized to a standard deviation of 2 K around 300 K.
4. Process Temperature [K]: Generated using a random walk process, normalized to a standard deviation of 1 K, added to the air temperature plus 10 K.
5. Rotational Speed [rpm]: Calculated from power of 2860 W, overlaid with normally distributed noise.
6. Torque [Nm]: Normally distributed around 40 Nm with a standard deviation of 10 Nm and no negative values.
7. Tool Wear [min]: Tool wear values added based on the quality variants H/M/L (5/3/2 minutes).
8. Machine Failure Label: Indicates whether the machine failed in a particular data point for any of the specified failure modes.

Figure 3: Description of Dataset

```
# Read the CSV file into a pandas DataFrame
df = pd.read_csv("D:\\Feynn-Labs-Project-1\\project1\\predictive_maintenance.csv")

# Display the first few rows of the DataFrame
df.head()
```

	UDI	Product ID	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Target	Failure Type
0	1	M14860	M	298.1	308.6	1551	42.8	0	0	No Failure
1	2	L47181	L	298.2	308.7	1408	46.3	3	0	No Failure
2	3	L47182	L	298.1	308.5	1498	49.4	5	0	No Failure
3	4	L47183	L	298.2	308.6	1433	39.5	7	0	No Failure
4	5	L47184	L	298.2	308.7	1408	40.0	9	0	No Failure

Figure 4: Data Acquisition

```
# List of machine learning models to be evaluated
models = [LinearRegression, LogisticRegression,
          DecisionTreeClassifier, RandomForestClassifier,
          KNeighborsClassifier, GaussianNB,
          MultinomialNB, SVC]

# Corresponding names for the models
names = ['LinearRegression', 'LogisticRegression',
         'DecisionTreeClassifier', 'RandomForestClassifier',
         'KNeighborsClassifier', 'GaussianNB',
         'MultinomialNB', 'SVC']

# List to store model names and their corresponding accuracy scores
data = []

# Loop through each model and evaluate its performance
for name, model in zip(names, models):
    # Display the current model being processed
    print(name)

    # Initialize the model
    m = model()

    # Train the model on the training data
    m.fit(x_train, y_train)

    # Evaluate the model's performance on the test data and calculat
    score = m.score(x_test, y_test)

    # Append model name and accuracy score to the data list
    data.append([name, score])
```

Model name	Score
RandomForestClassifier	0.980854
DecisionTreeClassifier	0.974386
KNeighborsClassifier	0.941785
LogisticRegression	0.885640
SVC	0.832083
GaussianNB	0.763519
MultinomialNB	0.642432
LinearRegression	0.596257

Figure 5: Building a Machine Learning Model and Evaluation of Model

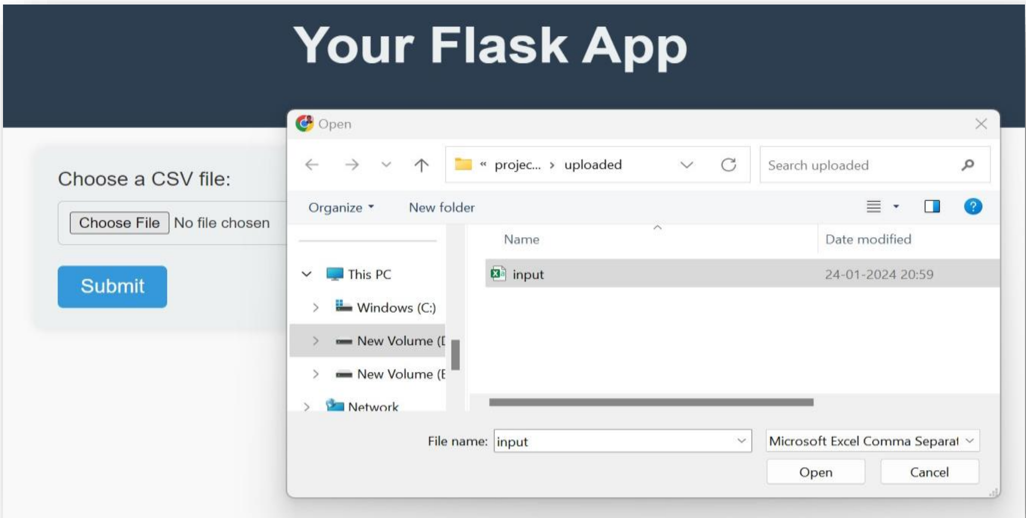
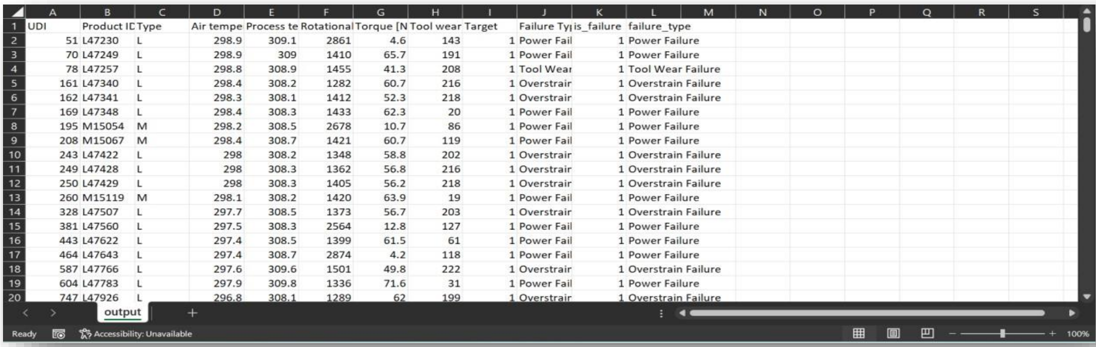


Figure 6: Data Ingestion from Local Directory to Machine Learning Model



UDI	Product ID	Type	Air tempe	Process te	Rotational	Torque [N	Tool wear	Target	Failure Ty	is_failure	failure_type
51	L47230	L	298.9	309.1	2861	4.6	143	1	Power Fail	1	Power Failure
70	L47249	L	298.9	309	1410	65.7	191	1	Power Fail	1	Power Failure
78	L47257	L	298.8	308.9	1455	41.3	208	1	Tool Wear	1	Tool Wear Failure
161	L47340	L	298.4	308.2	1282	60.7	216	1	Overstrair	1	Overstrain Failure
162	L47341	L	298.3	308.1	1412	52.3	218	1	Overstrair	1	Overstrain Failure
169	L47348	L	298.4	308.3	1433	62.3	20	1	Power Fail	1	Power Failure
195	M15054	M	298.2	308.5	2678	10.7	86	1	Power Fail	1	Power Failure
208	M15067	M	298.4	308.7	1421	60.7	119	1	Power Fail	1	Power Failure
243	L47422	L	298	308.2	1348	58.8	202	1	Overstrair	1	Overstrain Failure
249	L47428	L	298	308.3	1362	56.8	216	1	Overstrair	1	Overstrain Failure
250	L47429	L	298	308.3	1405	56.2	218	1	Overstrair	1	Overstrain Failure
260	M15119	M	298.1	308.2	1420	63.9	19	1	Power Fail	1	Power Failure
328	L47507	L	297.7	308.5	1373	56.7	203	1	Overstrair	1	Overstrain Failure
381	L47560	L	297.5	308.3	2564	12.8	127	1	Power Fail	1	Power Failure
443	L47622	L	297.4	308.5	1399	61.5	61	1	Power Fail	1	Power Failure
464	L47643	L	297.4	308.7	2874	4.2	118	1	Power Fail	1	Power Failure
587	L47766	L	297.6	309.6	1501	49.8	222	1	Overstrair	1	Overstrain Failure
604	L47783	L	297.9	309.8	1336	71.6	31	1	Power Fail	1	Power Failure
747	L47926	L	296.8	308.1	1289	62	199	1	Overstrair	1	Overstrain Failure

Figure 7: Output Extraction from the built Machine Learning Model

9. Financial Modelling:

One of the best methods for calculating profit is by using the following linear equation, where each term holds its own significance:

Total profit (y) equals the product of the cost of subscription services or expected total sales divided by the number of customers (m), multiplied by the market variable x, plus a constant (c) that encompasses other costs including primary and secondary expenses.

Therefore, this formula can be expressed as:

$$y = m * x + c$$

- y: total profit
- m: cost incurred on subscription services
- x: market
- c: constant, it depends on others costs, that includes primary and secondary

Therefore, the formula can be written as:

$$Total\ Profit = \frac{Expected\ Total\ Sales}{Number\ of\ Customers} \times market + cost\ (constant)$$

Total profit equals the expected total sales divided by the number of customers, multiplied by the market variable, plus a constant.

Justifying value of each variable:

1. **Value of c**: The value of c represents the fixed costs associated with primary and supportive structures of the business. This cost encompasses various elements such as supportive infrastructure, human resource expenses, technology investments, firm infrastructure, procurement costs, and primary structure expenses including cloud infrastructure, product development, distribution and reliability channels, as well as marketing, sales, and services.

Supportive Activities	Cost (INR)	Justification
Technology Development	100000	Software applications, design and building hardware components for a product
Human Resource	1200000	Hiring and training employees for various roles, managing employe benefits and payroll
Firm Infrastructure	300000	Setting up and maintaining physical office spaces including rent, utilities, and office equipment
Procurement	500000	Purchasing raw materials or components needed for product manufacturing
Total Cost	2100000	
Primary Activities	**Cost (INR)**	**Justification**
Cloud Infrastructure	100000	Renting server space and computing resources from AWS, Azure, or Google Cloud
Product Development	50000	Designing new software applications or physical products. Conducting research to improve existing products
Distribution and Reliability	200000	Partnering with logistics companies for warehousing and shipping
Marketing and Sales	100000	Conducting market research to identify customer preferences
Services	100000	Offering maintenance and repair services post-purchase
Total Cost	550000	

Table 9.1: Cost Analysis of SIPS (Smart Industrial Predictive Solutions) Value Chain

Given that we are currently in the ideation stage, we can assume the cost of the supportive structure to be zero. However, the estimated cost of the primary structure for the business is approximately $5\ to\ 6\ lakh\ rupees$. Therefore, let's consider the $value\ of\ c$ to be $6\ lakhs$. Importantly, the value of c is independent of market dynamics.

2. **Value of $\boldsymbol{x}$**: The value of x is determined by various factors affecting market performance. The factors may include:
   a. **Customer Demand**: Variables related to customer behaviour, such as the number of customers, market segments, or demographics, could significantly impact market performance.
   b. **Identify Specific Metrics**: Factors like industry growth and external influences, including geopolitical scenarios, can also affect market performance.

Give the absence of a direct formula for x, let's consider scenarios to determine its value:

- The current market size for predictive maintenance services in India is estimated at $1.5 billion by McKinsey, with a current adoption rate of 22% for Predictive Maintenance (PDM) in overall manufacturing units in India and a Compound Annual Growth Rate (CAGR) of 26.7%

3. **Value of $\boldsymbol{m}$**: The value of variable "m" can be ascertained through thorough market segmentation techniques applied to manufacturing clients, considering factors such as the size of the company, number of employees, machines (both new and old), and their operational status (whether they are closed or in operation). For the time being, let's assign it a value of 40,000. Therefore, the equation becomes:

$$y = 40{,}000 * x + 5{,}50{,}000$$

Financial Equation for Predictive Maintenance:

The subsequent financial formula can be utilized to gauge the advantages of predictive maintenance within the manufacturing sector:

$$\begin{aligned} Predictive\ Maintenance &= (downtime\ cost * downtime\ reduction) \\ &+ (repairs\ cost * reduction\ repairs) + (asset\ \ replacement\ cost \\ &* asset\ life\ extension) \end{aligned}$$

Where:

- $downtime\ cost$: Downtime costs encompass the expenses incurred from reduced production, loss of revenue, and diminished customer satisfaction resulting from machinery and equipment malfunctions
- $downtime\ reduction$: Downtime reduction represents the percentage decrease in downtime achieved through predictive maintenance
- $repairs\ cost$: The cost of repairs includes expenses related to repairing and replacing machines and equipment that have failed
- $reduction\ repairs$: Repair reduction signifies the percentage decrease in repair costs achieved through predictive maintenance
- $asset\ replacement\ cost$: The expense of asset replacement refers to the cost associated with replacing machinery and equipment that have reached the end of their useful life
- $asset\ life\ extension$: Asset life extension denotes the percentage augmentation in the lifespan of assets attained through predictive maintenance

For instance, let's consider a manufacturing company with an annual cost of downtime of \$2 million. If the company adopts predictive maintenance and realizes a 30% reduction in downtime, the annual savings from decreased downtime would amount to \$600,000. Additionally, incorporating the $Total\ Maintenance\ Cost$ (TMC) equation in the form of a linear equation with different coefficients:

$$TMC = (2.5x) + (1.8x) + (1.2x) + \$300{,}000$$

Here:

- PMC , CMC , and $PrMC$ represent Predictive Maintenance Cost, Corrective Maintenance Cost, and Preventive Maintenance Cost, respectively
- x denotes an independent variable (e.g., time or production volume)
- Coefficients 2.5, 1.8, and 1.2 represent the slopes of the respective costs
- \$300,000 is the constant term, representing fixed or baseline maintenance costs

10. Conclusion:

By meticulously addressing critical factors like intellectual property, regulatory compliance, and operational constraints, we can develop a robust and commercially viable predictive maintenance system. Prioritizing innovative concepts, user-centric design, and iterative development will ensure a successful product that revolutionizes industrial equipment management. Our system's ability to predict failures, optimize maintenance, and streamline operations creates a compelling value proposition for businesses across diverse industries. By harnessing the power of machine learning and data analytics, we are poised to usher in a new era of proactive and efficient industrial operations.

References:

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