

PREDICTIVE MAINTENANCE OF SENSOR-BASED WATER PUMP USING MACHINE LEARNING

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DOI : <https://www.doi.org/10.56726/IRJMETS49090>

ABSTRACT

Predictive maintenance is used along with the Internet of Things and Machine Learning to help the industry recognize critical flaws in production or maintenance equipment. Based on data gathered by monitored controlled devices with the help of sensors, we present a system architecture model for identifying early water pump system failures in this work. In the preliminary phase, we worked on actual measured statistics, occurrences, and failures from the water pumps industry. To retain the efficiency of the machine, several preventive methods or techniques are being undertaken. In order to avoid getting production loss or later break down of machine, maintenance processes should be structured such that the maintenance work is both cost and time efficient. This research paper describes the implementation of a keen and Machine Learning architecture system for Predictive Maintenance(PdM), based one of the accurate algorithms after performing comparative analysis of algorithms and choosing the best suitable one to implement in an Industry sector, which considers the Internet of Things and Machine Learning (ML) technologies to support real-time statistics, an online collection of data, and analysis for detecting machine breakdowns sooner, allowing real-time monitoring of the data, and visualization of the data.

I. INTRODUCTION

Machine learning is a subtype of an Artificial intelligence which helps machines to learn from the data provided, improve performance based on previous experiences, and make predictions. ML is a subset of AI which includes variety of algorithms to deal with enormous amount of data. Collected data is fed into these algorithms to train them, and the model is built and the predictions are made based on the training. In today's competitive market, every company is focusing on reducing machinery downtime and thereby increasing the efficiency of the machines thus increasing the profit of the company. To put it into operation by considering the practical problems faced in the modern organizations we are proposing a system which uses machine learning techniques and IoT sensors to understand the behavioral pattern of the system and predict the breakdown of the machinery, which will eventually help overcome all the drawbacks which companies are facing with the breakdown of the machines. The proposed system aims to achieve a significant increase in the range of the accuracy of the predictions of the machinery predicted by the machine learning algorithms and predict the accurate breakdown of the machine. Typically, it was done by Maintenance Engineers in the industries, although it was beneficial up to certain extent for predicting the breakdown, however many times, it is quite demanding to predict the exact failure of the machine. This concept is based on the extraction, transformation, and analysis of the data in order to perform the condition-based monitoring of the machine. On one hand, it estimates the conditions for observation of parts at machine level; on the other hand, it demands the combination of the collected information with other management information systems. Digitization, and specifical the development of massive information science, brings on plethora of opportunities to form effective as well as sensible monitoring and prognostication maintenance applications for machineries. The aim of this analysis is to look at the probability of the breakdown of the system by using the principles of industry such as distributed computing, big data, and machine learning. It introduces various auxiliary technologies such as the industrial internet of things, data analysis, and cloud computing.

II. LITERATURE REVIEW

[1] Proposed a deep learning ANN model which was applied to a packaging robot to predict the failure of the system, it had an accuracy of 97%. [2] In a Cutting Machine, the IIOT technology was used to collect the data, which has an accuracy of 90%, which had a limitation that different classifiers led to increased complexity. [3] In this study, a thermochemical plant's system for gathering data from 30 industrial pumps is described. This data is gathered and analyzed using the Random Forest Algorithm to determine relevance. The research described the issues that occur during the implementation of machine learning algorithms on data and the performance of the system. Durbhaka et al. [4] presented the combination technique also found in the Wind Turbine that applied the predictive maintenance to predict the failure of bearings from vibration signals. K-Nearest Neighbor, k-means, and SVM were able to provide 78.8% - 87.0% accuracy. The Collaborative Recommendation Approach (CRA) is also applied on each technique, with this CRA model can achieved 93% accuracy. It is shown by Diego Andrés Moreno Salinas [3] With the rapid development and adoption of IoT in smart factories, the amount of data collected is rapidly increasing and with it the demand for effective data-driven methods. They examined methods of predictive maintenance and fault diagnosis using various techniques based on deep learning data that can integrate feature selection and diagnosis in a single step, eliminating the need for domain-specific expert knowledge. Deep learning methods can leverage the use of historical data and sensor-collected data in smart industries, enabling predictive models using raw data without requiring industry-specific knowledge or feature engineering. The autoencoder anomaly detection method provides a good solution for manufacturers who do not have historical data on device failures. Emil Cazacu, Lucian Gabriel Petrescu and Valentin Ionut [5-6-7] show that, the article proposed an advanced predictive maintenance tool for critical equipment in modern electrical installations. An intelligent and minimally invasive predictive maintenance system is thus designed. The developed maintenance system signals in advance the possibility of a defect and suggests its causes and possible remedies (if the incorrect operation is found in the database of causes of defects, a database that is always updated in the event of a new error, it is subsequently addressed). The system continuously creates an operational report of the analyzed devices, showing the trend of performance quality indicators, surface temperature variations of the tested devices, as well as their vibration levels. The novel device is also an alternative solution to the use of numerous large-scale measuring instruments that do not allow immediate and integrative analysis of the measured parameters on site. The simple architecture of the system ensures its high robustness and reliability. In addition, its high technical performance combined with low manufacturing costs make it a competitive commercial product. In addition, the device enables remote transmission of examination results.

III. METHODOLOGY PLANNED

Initially, we fetched the dataset from UCI website. After getting the dataset we analyzed the dataset and performed some pre-processing techniques (feature engineering) which gave us raw data into understandable format. Raw data contains attributes such as null values and missing values in the columns. So, we solved such kind of issues by using pre-processing techniques. Then, we came to know that the output values in the dataset are not in the same ratio. It is very imperative that the output values in the dataset should be close to equal in order to get higher accuracy of the model. So, we used some functions to get the output of the dataset in the equal ratio. After the feature engineering was performed, we fed the data to different ML models. Then, we fed this processed data to the machine learning algorithms. We used some machine learning algorithms like Random Forest, Support vector machine (SVM), Decision tree, Linear regression. The dataset was trained on respective models and based the accuracy of the model we chose logistic regression which had the highest accuracy.

A hardware containing various sensors such as temperature, voltage, sound, vibration sensors are mounted on a 5V DC water pump. The data is being collected using Arduino, which continuously collects the data.

A Machine learning model created in Jupyter notebook was deployed in Raspberry PI using Raspberry Pi OS (previously called Raspbian) and the data collected through Arduino was fed is continuously fed to the model. Based on the data generated, the output will be shown.

The visualization of the machine status will be done through the bulb of different colors such as Red, Yellow, and Green. If green bulb is ON, it can be stated the condition of machine is normal, as soon as the red bulb turns

ON, it can be concluded that the machine condition is broken i.e., machine requires maintenance to be conducted immediately before it breaks down, an immediate action must be required otherwise it may lead to breakdown of machinery and its respective consequences. The Yellow bulb indicates that the machine is recovering from the damage.

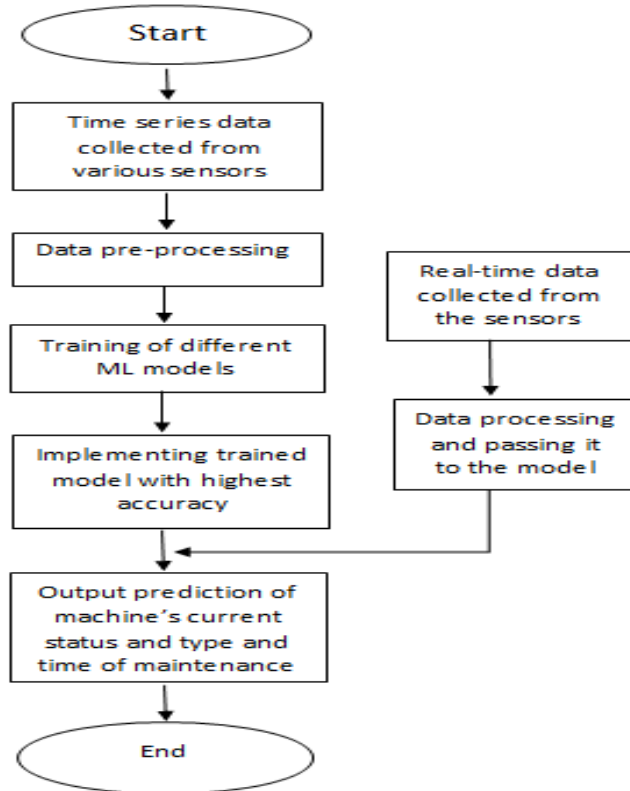


Fig 1. System architecture

IV. ALGORITHM

Random Forest is a well-known machine learning algorithm from the supervised learning approach. It may be applied to both classification and regression issues in machine learning. It is built on the notion of ensemble learning, which is a method that involves integrating several classifiers to solve a complicated issue and enhance the model's performance.

Random Forest is a classifier that comprises several decision trees on various subsets of the provided dataset and takes the average to enhance the predicted accuracy of that dataset, as the name implies. Instead of depending on a single decision tree, the random forest collects the forecasts from each tree and predicts the final output based on the majority vote of predictions.

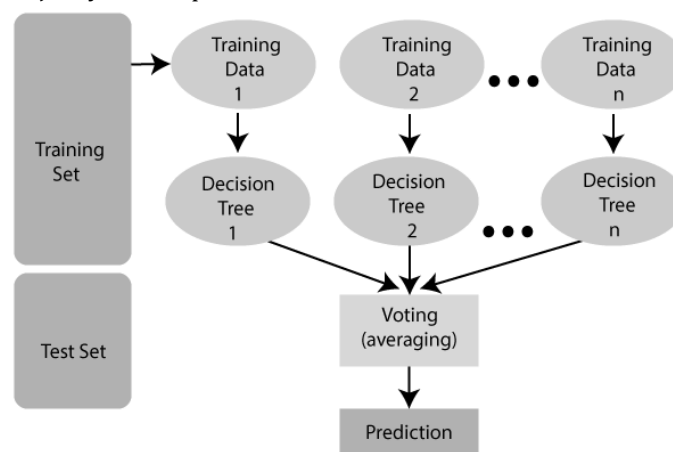


Fig 2. Working of random forest

Random Forest operates in two stages: the first is to generate the random forest by mixing N decision trees, and the second is to make predictions for each tree generated in the first phase.

The steps below illustrate the working process:

- 1: Choose K data points at random from the training set.
- 2: Create decision trees for the specified data points (Subsets).
- 3: Determine the number N for the number of decision trees you wish to construct
- 4: Reverse steps 1 and 2.
- 5: Find the forecasts of each decision tree for new data points and allocate the new data points to the category with the most votes.

V. CONCLUSION

The complete topic may be stated as follows: the deployment of a predictive maintenance system can minimize breakdown costs in companies.

Using current data, the investigation was carried out successfully on a pump system. The predictive analytic system mentioned in the study can identify system problems or breakdowns and alerting the user in order to avert them. As a result, it is possible to conclude that the system is capable of lowering maintenance costs while increasing equipment life and efficiency. Additionally, it decreases machinery downtime and boosts the efficiency of the manufacturing system, consequently improving the company's profit.

VI. FUTURE SCOPE

Higher efficiency: To attain higher performance and improve outcomes, more sophisticated and deep learning models and algorithms may be implemented in the system.

Integrated systems: In an integrated system, predictive systems may be used by several machineries. The suggested system may be applied on a wide range of machines with varying qualities and characteristics.

Health care systems: A predictive analytic system in emergency rooms can be used in the health care system. The technique may be applied in real-time clocks to create medical alarms. The technology will provide an alert to health experts based on the patient's health variations. It will ensure that patients receive prompt care and attention.

VII. REFERENCES

- [1] Paolanti, M., Romeo, L., Felicetti, A., Mancini, A., Frontoni, E. and Loncarski, J., 2018, July. Machine learning approach for predictive maintenance in industry 4.0. In 2018 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA) (pp. 1-6). IEEE.
- [2] Amihai, I., Gitzel, R., Kotriwala, A.M., Pareschi, D., Subbiah, S. and Sosale, G., 2018, July. An industrial case study using vibration data and machine learning to predict asset health. In 2018 IEEE 20th Conference on Business Informatics (CBI) (Vol. 1, pp. 178-185). IEEE.
- [3] I. Jaksch, "Fault diagnosis of three- phase induction motors using envelope analysis," in SDEMPED, Atlanta, USA, 2003, pp. 289-293.
- [4] Zijun Zhang; Verma, A.; Kusiak, A., "Fault Analysis and Condition Monitoring of the Wind Turbine Gearbox," in Energy Conversion, IEEE Transactions on , vol.27, no.2, pp.526-535, June 2012, doi: 10.1109/TEC.2012.2189887
- [5] Andrew Kusiak, Zijun Zhang, Anoop Verma, "Prediction, operations, and condition monitoring in wind energy."
- [6] Butte, S., Prashanth, A.R. and Patil, S., 2018, April. Machine learning based predictive maintenance strategy: a super learning approach with deep neural networks. In 2018 IEEE Workshop on Microelectronics and Electron Devices (WMED) (pp. 1-5). IEEE.
- [7] Dos Santos, T., Ferreira, F.J., Pires, J.M. and Damásio, C., 2017, May. Stator winding short circuit fault diagnosis in induction motors using random forest. In 2017 IEEE International Electric Machines and Drives Conference (IEMDC) (pp. 1-8). IEEE.
- [8] Onur, K.O.C.A., Kaymakci, O.T. and Mercimek, M., 2020, May. Advanced Predictive Maintenance with Machine Learning Failure Estimation in Industrial Packaging Robots. In 2020 International Conference on Development and Application Systems (DAS) (pp. 1-6). IEEE.