Predictive Maintenance in Industrial Systems Using Machine Learning

Rishikant Kumar[1]; Manmohan Mishra[2]; Suryali Suman[3]
Big Data Analytics – AIT Chandigarh University Mohali, India

Parabjot Singh Bali[4]
Apex Institute of Technology Chandigarh University Mohali, India

Abstract:- Now, a lot of different areas need predictive maintenance (PdM). The goal is to cut down on downtime and make work go faster by finding out when things will break. This study looks at how machine learning can be used to figure out when to fix manufacturing systems. The study is all about using old business records, monitoring data, and upkeep records to make good prediction models. To make prediction tools that can quickly and accurately find places where industrial machinery might break down, we plan to carefully use advanced machine learning techniques such as supervised learning, time series analysis, and anomaly detection. Our idea could make it easier to stick to repair plans. Breakdowns would happen less often, and overall, running costs would go down in many fields. To prove that our expected method for maintenance works and can be used in the real world, we use careful case studies and thorough empirical validations. This research is a big step toward making models for planned maintenance, giving ways for proactive maintenance, and improving the dependability and efficiency of industrial systems in the real world.

Keywords:- *Machine Learning, Neural Networks, Predicted Maintenance, Preventative Maintenance, Downtime Costs, Maintenance Costs, Neural Networks.*

I. INTRODUCTION

Because business moves so quickly these days, predictivemaintenance is one of the most important ways to make sure everything stays in good shape. The old ways of managing things, which mostly involve fixing issues as they come up, cost a lot and don't work. They cause unexpected breaks, fixesto cost more, and less work to get done [1]. We are now moving toward predictive maintenance, which could help find equipment problems before they happen [2]. This is because of progress in advanced data analytics and machine learning.

A. Background and Significance

In the business world, reactive maintenance and preventative maintenance have been seen as two sides of the same coin for a long time. It is now tough to see what assets we have and how to best split up our resources. That's what this kind of maintenance is called [3]. Things need to be fixed right away when they break. Businesses have trouble with it, and it costs a lot to fix. For this kind of fix, on the other hand, jobs are planned ahead of time to make them safer. It doesn't always work, though, because it doesn't check how things are used or how often they break [4].

This is the main reason why planned repair is a big change in how things are done [5]. Smart computer programs that look at data and learn from it keep things safe in predictive repair.It lets businesses know when their tools are going to break down, so they can fix them before they do [6]. Everything haschanged because of a new way of doing things. It not only cuts down on repairs and downtime, but it also makes better use ofresources, keeps things safer, and spans longer.

The use of predicted fixing is important for making your business run better. It also has a bigger impact on how well and how long a company stays in business [7]. All kinds of businesses need to do predictive maintenance these days because the business world is very competitive and speed and low costs are very important. Use predictive maintenance to cut down on downtime, boost output, and make sure that key assets are always available and reliable [8]. This will help businesses stay ahead of the competition.

This is also true for the Internet of Things (IoT) and Industry 4.0. So that smart, linked workplaces can be made, this makesit easy to connect tools for data analysis, devices, and predictive maintenance. These technologies work together to make predictive maintenance a proactive, prescriptive, and self-disciplined field that can use changing working data to make better maintenance plans in real-time [9]. They also help maintenance systems guess problems better.

B. Scope of the Study

This research is mostly about how predictive maintenance can be used in various business settings, including mines, power plants, factories, and transportation firms. It is possibleto figure out when things will go wrong and the best ways to fix them by using guided learning, uncontrolled learning, and reinforcement learning [10]. We will mostly talk about predictive maintenance, but we will also cover problems that are connected, like collecting and organizing data, feature engineering, model review, and application issues.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1367

II. LITERATURE REVIEW

Namuduri et al. investigated the utilization of machine learning algorithms for predictive maintenance in manufacturing plants. Their study demonstrated the effectiveness of supervised learning models in forecasting equipment failures based on historical maintenance data and sensor readings. However, challenges arose due to the limited availability of high-quality training data and difficulties in generalizing predictive models across diverse industrial contexts[11].

Raparthy et al. explored the application of time series analysis for predictive maintenance in energy production facilities. They emphasized the significance of capturing temporal dependencies in sensor data to accurately predict equipment failures. Despite promising results, challenges emerged in modelling dynamic operational conditions and processing real-time data effectively [12].

Gregor et al. used both machine learning and physics-based models to come up with a way to help transportation companies plan preventative repair. The point of their study was to combine topic knowledge with algorithms that are driven by data. They aimed to improve the accuracy and ease of use of prediction models. But it was hard to figure out why the model's expectations didn't match up with what happened in maintenance [13].

Liu et al. looked into ways to find quirks that can be usedto figure out how to fix my jobs. The main point of their studywas to look for small changes from how things normally work that might mean tools are breaking down before they should.Some changes in sensor data seemed to happen for no reason,and it was hard to tell the difference [14].

Lwakatare et al. studied how various machine learning techniques work to make predictions about maintenance in various business settings. The results of their study showed how important it is to choose the right ways to fix maintenance problems. Things kept going wrong, though, because there weren't any standard review measures or sample datasets [15].

Achouch et al. used machine learning to look into planned fixes in the car business. What kinds of problems could cars have? This helped them come up with the best ways to fix them and cut down on downtime. Two problems were gettingdata from different sources to work together and making the model scalable [16].

Zeki Murat et al. looked into planned repairs in aeroplanes, mostly to keep an eye on how healthy the engines are. It was used to figure out when motors would break down and how to fix them for their study. The plane's complicated systems and the need for correct instrument readings [17] caused things togo wrong.

To find ways to make digging tools more reliable, Pandey et al. looked into how the oil and gas industry predicts repairs. Models that use machine learning were used to figure out how to keep technology in good shape and predict when it would break. It was hard to get good data, and the way people dig is always changing, which was another issue [18].

The study by Ayvaz et al. looked at planned upkeep in the telecommunications business, mostly for keeping network equipment in good shape. For their study, they used machinelearning to figure out when things would break down and howto make better plans for service. The fact that network systems were hard to understand and data had to be dealt with right away was a problem [19].

To find ways to make medical tools more reliable, Serkan et al. looked into predictive maintenance in the healthcare field. They planned the best ways to fix technology and usedmachine learning to figure out when it would break down. Many people were worried about the safety of the data and the need for simple forecast models [20].

A. Limitations

There are still some problems with predictive maintenance, even though it has come a long way. One of these is how hard it is to get good, different training data, especially in high-tech business fields. A big problem is also how hard it is to model how things work in the real world and how important it is to have support systems that people know how to use. Because there aren't any standard review toolsor sample datasets out there, it's also harder to compare thedifferent prediction maintenance methods. There will be less help from people who work in the field to make the best rules and skills. To make predictive maintenance work better for business systems, we need to find ways to get around these problems.

III. METHODOLOGY

For industrial systems to use machine learning for plannedupkeep, there needs to be a good plan. As part of this plan, you should collect data, build features, pick a model, use it, and see how well it works. In this part, we'll talk about the set of methods that were used to make the projected repair system.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1367

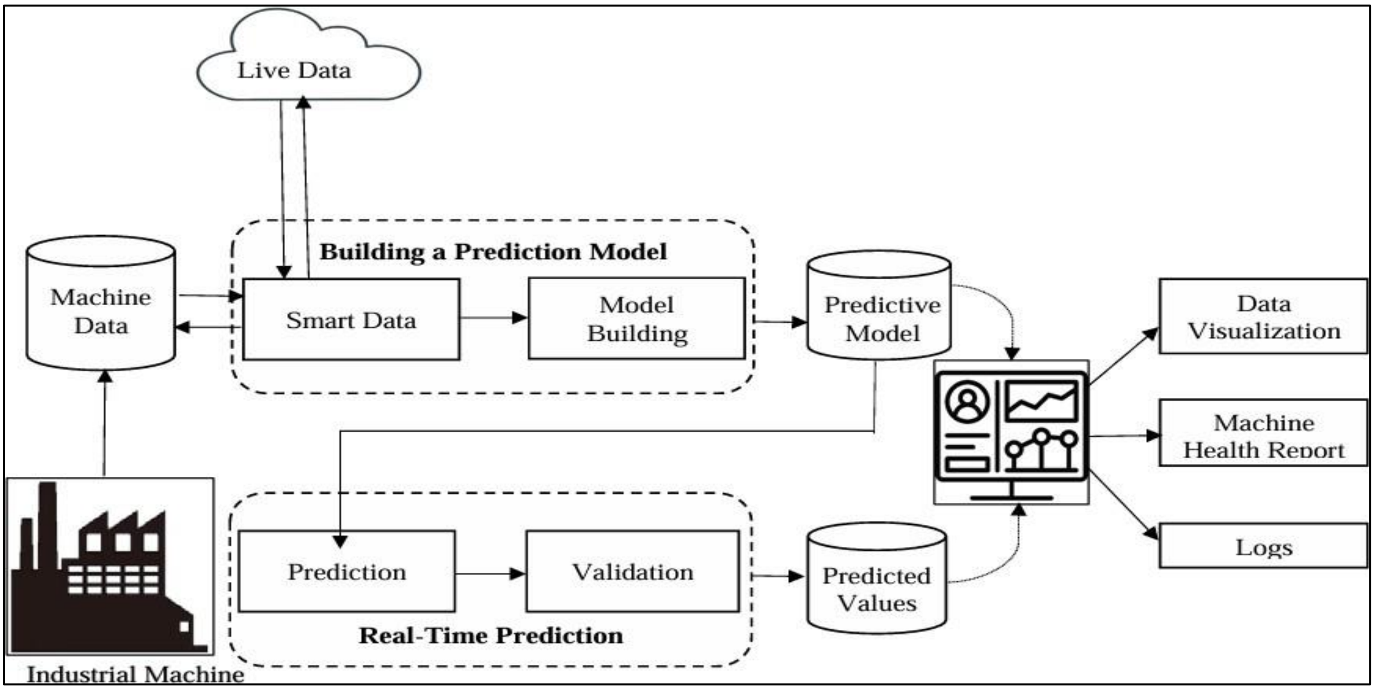

Fig. 1: System Architecture

System design is the big-picture plan for how software is put together and how it talks to other software. Things go faster, are more stable, can be changed, are scalable, and people have more freedom when the system is broken up into smaller parts that can be used again and again. You can be sure that the system will reach its goals quickly and correctly if you plan it well.

A. Architecting the Data Pipeline: Collection and Preparation

The best way to use predictive maintenance is to have a well-thought-out data flow. Getting this done means planninghow to collect data and getting it ready to use [21]. After collecting good data, it is very important to make sure that the next steps, like creating features, making models, and reviewing performance, are built on top of that.

The first step in getting data is to get raw data from places like monitors, machine logs, service records, and systems that are already working. This raw data includes varied types of information, such as working conditions, weather, machine health indicators, and fixed jobs that have already been carried

Greater magnitude features are less likely to be prominent during model training when numerical data are normalized toa consistent scale due to the use of scaling and normalizing procedures. Some methods, like min-max scaling and z-scorenormalization, make sure that there is just the right amount ofdata for the model to work well.

Business records keep track of different kinds of group traits. So that machine learning programs can use them, these traits need to be turned into numbers. A great many people like the ways of label encoding and one-hot encoding. Label encoding gives each group its own number, and one-hot encoding turns each group into a binary vector.

Forecasts are often kept up to date with time information.We need to be careful with this information if we want to findpatterns and links over time. You can get more useful data from temporal data streams if your box the data, move the dataaround, or match time series. [22].

Mathematically, the preprocessing of raw data can be encapsulated as:

out. It's tough to work with lots of different data sources that give you various kinds, rates, and amounts of data.

$$X_{preprocessed} = f_{prep}(X_{raw}) \quad (1)$$

After collecting the raw data, it goes through a lot of stepsto make it clean, fill in any holes, and find any outliers. Fill in the blanks for missing data points with mean imputation, median imputation, or estimates in this very important step. They can be found and dealt with in a way that doesn't mess up future studies. Some examples are using statistics or having information about a certain subject.

Where X_{raw} represents the raw input data, f_{prep} denotes the preprocessing function $X_{preprocessed}$ signifies the cleaned and transformed data ready for subsequent analysis.

The data is put into files that machine learning apps can use after it has been cleaned up and made uniform. We can use these well-organized information to make models for industrial systems that can predict when they will need help. This is because they give us the information we need for the next steps in feature engineering and model building.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1367

B. Crafting the Analytical Toolbox: Feature Selection and Engineering

The goal of the engineering and feature selection process thatgoes into making predictive maintenance tools is to find and make a set of teaching features that collect the right data for accurate prediction models. In this step, we need to figure out what the models should guess by taking out important data from the raw data.

To begin the process of feature picking [23], you need to figure out which traits will help you the most with the maintenance work you need to do soon. This way of finding the most important parts uses field knowledge, statistics, and studies of relationships. You can tell which traits are important by seeing how they connect to the goal variable. It is possible to do this with either shared knowledge or the Pearson correlation value.

Also, people who work in the field should help pick featuresbecause they know how important certain parts are for finding out when tools will break. Temperature, pressure, shaking, and the rate of fluid flow are all things that are often used to check how well machinery is working in factories.

Once we know which features are important, we use feature engineering to change and improve the ones we already have. This helps us make more accurate predictions. To learn moreabout the links and trends in the data with this method, you need to either add new traits or change the ones that are already there.

This method is often used to get higher-order polynomial terms that show how traits are connected in ways that aren't straight lines[24].

For example, if X1 and X2 are two input features, polynomial expansion would involve would creating additional feature such as $X2$, $X2$ and X1. X2 to capture quadratic relationships.

C. Building the Predictive Engine: Model Selection and Implementation

It is very important to choose and use the right machine learning method to guess when equipment in industrial systems will break down. This is the first step in creating a prediction engine for predictive maintenance. It is important to choose the right model because it affects how much the system can grow and how well it can guess what will happen.

To choose a model, the first step is to take a close look ata number of machine learning methods. This finds the best way to do a certain kind of repair that needs to be done. Everyone knows that random forests, decision trees, neural networks, and regression models are all types of algorithms. Each program has good and bad points. One way to choose the best one is to compare them in different ways.

This model was picked because of the type of data, how hard it is to guess what will happen, and how easy it is to understand what will happen. Different types of models work best when the goal variable is linked to the quality variable in a straight line [26]. For example, decision trees are great at finding complex nonlinear links. Back-and-forth tools make iteasy to see the lines between very big groups of data. But neural networks might be better at making patterns that are more complicated, but they might need a lot of computer power.

It is important to tune the hyper parameters so that you can pick the best model. For this to happen, the chosen program's parts need to work better so that estimates are more certain. You can carefully look through the hyperparameter space in two different ways to find the best setting that lowers the model's loss function. These are search by grid and search bychance.

After picking a model and making it better, use a computer language like Python or R and machine learning tools like scikit-learn or TensorFlow to put it to use. So that it can learn 1 2.

The principal component analysis (PCA) method is another useful set of tools for function engineering. Even though it takes up less room than the original, it saves the most different files. There might be less trouble if you do things this way. Getting a better grasp on the idea through this works faster. Things are still right.

For many business systems to work, they need to be able to keep track of links and trends over time [26]. Windowing and delay are often used to make things come out late or keep going up over time. The computer can look for patterns in thedata that show up over time or a lot of the time.

Mathematically, the engineered of raw data can be encapsulated as:

$$X_{engineered} = f_{feat}(X_{select}) \quad (2)$$

Where $X_{selected}$ represents the selected features, f_{feat} features the engineered function $X_{engineered}$ signifies the augmented features set ready for model training about the important patterns and links, it needs to be taught on data that was cleaned up during the delivery phase. Then, different test data are used to see if the training model can be used in other cases and to check if it fits the data too well or too badly.

The learning model must be built into the business in order for it to work. You may need to make application programming interfaces (APIs) or use containerization tools like Docker to get the model ready for use in the real world. Systems that track and tell you in real time will help you keep an eye on how well the plan is working. Things will be fine, and you'll know right away.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1367

The model to use, the hyper parameters to change, the setup of the forecast engine, and its use all need to be carefully thought out. It is very important to pay close attention to a lot of different things. The forecast engine can be set up in different ways to get the most accurate information about how often things will break down. This is done to make sure the number it gives is right. Because of this, the engine can tell you a lot about how often the tools will break down. It is possible to keep industrial systems in good shape with preventative repair. This will make the processes work better in the long run. This is something that can be done.

D. Measuring Performance: Evaluation Metrics in Focus

It's important to look at how well projected maintenance models can figure out when things will break down and make plans for better upkeep. It is important to carefully choose andtry the right indicators in this step to see how well the model can generalize and make predictions. Some people may be able to figure out how useful and reliable models are in industrial systems if they pay attention to some key rating factors.

Another important way to see how well the models worked is to see how accurate the predictions were. This tells you howmany of the claims were real. The numbers might not tell thewhole story if the records aren't fair and support the bigger group. Extra tests, such as precision, memory, and F1-score,are often used to get a better idea of how well the model works.

It shows how well the model can find issues with events and tools that don't break it. When you guess right, how often do you get it right? To be exact, this is called. Refers to the number of correct real positives that the model found out of all the correct real positives that it got right. For predictive maintenance to work, there needs to be an equal amount of memory and speed. It can be hard to run things and cost a lotof money to deal with fake wins and rejects.

You can check the model's performance with the F1-score. It shows how well it works when you need to be accurate and remember things. It is very helpful that the number 26 cuts down on the number of false hits and blanks. It can be used tofind sick things or strange things.

There is another well-known way to check how well a binary classification job is done in predictive maintenance. It is the area under the receiver operating characteristic curve (AUC-ROC). The ROC curve shows the range of true positives and fake positives because it starts at different points. It does this by showing the difference between the two rates. The AUC-ROC shows how well the model can tell the difference between good and bad events. More AUC is better in every way.

You can use precision-recall curves, confusion matrices, and binary classification measures to test the model and see how well it works with different limits and class distributions. The numbers for the true positive, true negative, false positive, and false negative are shown here. This tells you how wrongthe labels and predictions were. On precision-memory maps, you can see how the amount of choice cuts down on accuracyand recall. After reading this, smart people will know which choice limits to use and how to use models.

There are two main kinds of plots that can be used to seeif data claims are true. There are graphs for accuracy and reliability that show how likely it is that a piece of gear will break down. In these plots, the expected chance and the real rates are shown. This lets you know if the model is right or wrong about the confidence levels.

$$M_{eval} = f_{eval}(y_{true}, y_{pr}) \tag{3}$$

Where, M_{eval} is matrix, f_{eval} is evaluation function.

Tests like F1-score, AUC-ROC, confusion matrices, precision-recall curves, calibration plots, and reliability graphs will show you how well predictive maintenance models work. People who have a stake in the models may learn a lot about how well they can predict and generalize if they pay close attention to these signs. They can then pick the best option and be sure that the models work well with the way the business is run.

IV. PREDICTIVE MAINTENANCE FRAMEWORK

In the past, things were fixed right away, but now they're planned ahead of time. The business will now take very different care of its property. Machine learning is used in this cool new way to check repair work. Tracking tools that use messages always keep you in the loop. This page breaks down the different parts that make up predictive maintenance for manufacturing systems. Things are done this way because thoughts and methods change over time.

A. Paradigm Shift: From Reactive to Proactive Maintenance Strategies

Broken machines have been fixed right away in the past, which means that industrial repair has been lightning-fast. However, this method is naturally expensive and hard to usebecause it causes production to slow down, costs to go up for upkeep, and lost time. On the other hand, proactive repair plans try to see problems coming and stop them before they happen. This makes things work better and cuts down on downtime.

When it comes to preventative maintenance, predictive maintenance is the best kind. In this kind of repair, programs that use machine learning look at readings and data from the past to figure out when equipment will break down. Find damage and wear early on so that maintenance tasks can be planned for times when you have free time. Firms can make the most of their resources and keep things going smoothly in this way.

Companies need to switch from fixing things after they break to fixing things before they break. You need to give them facts to help them decide. Maintenance teams, data scientists, and field experts must work together to get the most

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1367

out of predictive maintenance tools and make them fit with how the business works.

B. Orchestrating Precision: Integrating Machine Learning Algorithms

A lot of machine learning algorithms are used to keep predictions in good shape. Lots of work is done by these tools to figure out what the system can do. One type of method used in these algorithms is the ensemble method. Others are neural networks, regression models, choice trees, and neural networks. They are all good at different types of forecast repair work.

While linear regression and logistic regression are not as good for making continuous or binary estimates about the health of a piece of equipment, they are good for other tasks. Random forests and decision trees are great ways to keep track of traits that are linked to each other in complicated ways. They are great for jobs that require them to make complex guesses using a lot of different kinds of data.

This kind of machine can handle a lot of information andkeep the class lines straight. These traits help them do jobs thatneed to be divided into two groups, like guessing when a piece of machinery will break down. NANOS can learn complicated patterns and models from data, which gives them a lot of freedom when they create complicated connections. But they might need a lot of computer power to train and learn how tothink.

In ensemble methods like gradient boosting and random forests, more than one base learning is put together to improveaccuracy by lowering bias and error. These methods use the "wisdom of the crowds" to get more accurate and trustworthy results by combining the outcomes of several models.

Before machine learning can be added to the framework for planned maintenance, a few important steps need to be taken. Some of these steps are getting the data ready, picking and making features, training and testing the model, and then putting it to use. Make sure the prediction fix system works well and that you can trust it before it can grow.

C. Insights in Real-Time: First-Class Monitoring and Alerting Systems

To use predictive maintenance, you need tools that can track things and send reports right away. These tools tell you useful things and problems with machines before they get too bad. The monitor data, device performance measures, and operating factors are always being looked at by these systems to find things that don't seem right, things that don't work normally, and early warning signs of possible problems.

You can use statistical process control, grouping, and machine learning to look for strange patterns or events in data. The gear might not be working right, be breaking down, or be about to break down because of these strange things. Things need to be fixed right away before they get worse.

One of the advanced warning systems that predictive maintenance models use is level-based alerts. Another is pattern recognition and anomaly scores. People who need to know can use these tools to find out when something is wrong or about to go wrong. This message can be changed based on how bad and important the problems are. They're sent right away.

If a business has tools that keep an eye on things and sendthem tips in real-time, they can also use condition-based repair. Instead of having a set plan, this way of fixing things starts with how the gear is right now. When you work carefully, things last longer and tools last longer too.

V. RESULT & DISCUSSION

To create a system that is capable of transmitting data from the cloud of ThingSpeak to an edge device, a strategy has been set out.

To monitor the VMC machine's state of health, the anticipated maintenance dataset from Kaggle was used. For example, it displayed the temperature of the air, the force, the amount of time it took for the tool to wear out, and the temperature of the process.

Various machine learning methods utilize a provided data set to train the model. The following are the potential failures that can occur in a VMC Machine:

- Tool wear failure (TWF) occurs when the tool reaches a randomly determined time between 200 and 240 minutes, at which point it will either be replaced or fail.
- Heat Dissipation Failure (HDF) Heat dissipation results in a process failure when the temperature differential between the air and the process is less than
- 8.6 K, and the rotational speed of the tool is below 1380 rpm.
- Power Failure (PWF) occurs when there is a loss of electrical power supply. The power required for a process can be calculated by multiplying the torque and rotational speed (measured in rad/s). The process fails if the power is less than 3500 W or greater than 9000 W.
- Overstrain failure (OSF) occurs when the product of tool wear and torque surpasses a threshold of 11,000 minNm for the L product type (12,000 for M, 13,000 for H). When this threshold is exceeded, the process fails owing to overstrain.

The system's performance is assessed by utilising the confusion matrix.

A. Matrix of Confusion

The evaluation of the classification models' performance on a specific set of test data is done using a matrix known asthe confusion matrix. The visualisation tool is used to display important predictive parameters such as recall, specificity, accuracy, and precision. Confusion matrices are beneficial because they offer explicit comparisons of values such as True Positives, False Positives, True Negatives, and False Negatives.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1367

Accuracy is calculated by dividing the sum of true positives and true negatives by the sum of true positives, true negatives, false positives, and false negatives.

Accuracy (all correct / all) = TP + TN / TP + TN + FP + FN (4)

Precision is a measure of accuracy that calculates the proportion of accurately predicted positive observations out of all the expected positive observations. The precision of the model is calculated as the number of true positive predictions divided by the sum of true positive and false positive predictions.

Precision (true positives / predicted positives) = TP / TP+ FP (5)

Recall is also known as sensitivity or true positive rate, which is a statistical measure that quantifies the proportion of properly predicted positive observations out of all observations in the actual class.

Sensitivity aka Recall (true positives / all actualpositives) = TP / TP + FN (6)

The F1-score is a metric that calculates the weighted average of precision and recall. Hence, this score considers both incorrect positive and incorrect negative results.

$$\text{F1-Score} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{7}$$

The majority of the prediction was conducted on the product belonging to the L category. Our primary objective was to determine the likelihood of failure in the VMC machine and identify the specific sort of failure that may occur in the event of a malfunction.

Table 1 demonstrates that the Random Forest Algorithm operates through multiclass classification and delivers the highest level of accuracy. The Decision tree method yields the highest level of accuracy in predictions following the Random Forest algorithm. Support Vector Machine (SVM) methods have been found to have lower accuracy and limited capability in performing multiclass classification.

Table 1: Prediction Analysis

Algorithm	Accuracy	Precision	Recall	F1
Random Forest	99.24	96.62	82.7	89.1
DecisionTree	98.06	71.77	77.11	71.9
Logistics Regression	96.2	96.2	96.2	96.2
SupportVector Machine	96.15	96.15	96.15	96.2

VI. CONCLUSION

Fig. 2: Prediction Analysis Graph

In conclusion, this paper synthesizes the collective insights into predictive maintenance using machine learning, revealing its transformative potential across industrial sectors. Our examination underscores the compelling advantages of adopting predictive maintenance systems, particularly in mitigating the substantial costs associated with equipment failures. Specifically, our research delves into the realm of VMC machine maintenance, showcasing its efficacy in detecting four distinct fault types based on current data. Through this exploration, our study illuminates the promising prospect of curtailing maintenance expenditures while prolonging equipment longevity. Nonetheless, the evolving landscape of predictive maintenance prompts further inquiry. Future research endeavours should endeavour to refine fault detection algorithms, expanding the predictive maintenance framework to address a broader array of industrial applications. By embracing machine learning advancements in predictive maintenance, industries can optimize operations, curtail downtime, and enhance overall asset performance, ushering in a new era of efficiency and resilience in industrial ecosystems.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1367

REFERENCES

[1]. H. H. Chin, P. S. Varbanov, J. J. Klemeš, M. F. D. Benjamin, and R. R. Tan, 'Asset maintenance optimisation approaches in the chemical and process industries--A review', Chemical Engineering Research and Design, vol. 164, pp. 162–194, 2020.

[2]. K. Diljit, 'Predictive Maintenance Revolution: How AI Transforms Industrial Systems', International Journal of Advanced Engineering Technologies and Innovations, vol. 1, no. 1, pp. 210–224, 2022.

[3]. S. Arena, I. Roda, and F. Chiacchio, 'Integrating modelling of maintenance policies within a stochastic hybrid automaton framework of dynamic reliability', Applied Sciences, vol. 11, no. 5, p. 2300, 2021.

[4]. Y. Ren, 'Optimizing predictive maintenance with machine learning for reliability improvement', ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering, vol. 7, no. 3, p. 030801, 2021.

[5]. M. Pech, J. Vrchota, and J. Bednář, 'Predictive maintenance and intelligent sensors in smart factory', Sensors, vol. 21, no. 4, p. 1470, 2021.

[6]. A.-Q. O. Gbadamosi, 'AN INTERNET OF THINGS ENABLED SYSTEM FOR REAL-TIME MONITORING AND PREDICTIVE MAINTENANCE OF RAILWAY INFRASTRUCTURE', University of the West of England, Bristol, 2023.

[7]. U. Hider, 'Digital Transformation: Unveiling the Nexus of Neural Networks, Big Data, and AI in Business Evolution', EasyChair, 2024.

[8]. Brintrup et al., 'Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing', International Journal of Production Research, vol. 58, no. 11, pp. 3330–3341, 2020.

[9]. J. Lee, J. Ni, J. Singh, B. Jiang, M. Azamfar, and J. Feng, 'Intelligent maintenance systems and predictive manufacturing', Journal of Manufacturing Science and Engineering, vol. 142, no. 11, p. 110805, 2020.

[10]. Theissler, J. Pérez-Velázquez, M. Kettelgerdes, and G. Elger, 'Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry', Reliability engineering & system safety, vol. 215, p. 107864, 2021.

[11]. S. Namuduri, B. N. Narayanan, V. S. P. Davuluru, L. Burton, and S. Bhansali, 'Deep learning methods for sensor-based predictive maintenance and future perspectives for electrochemical sensors', Journal of The Electrochemical Society, vol. 167, no. 3, p. 037552, 2020.

[12]. M. Raparthy and B. Dodda, 'Predictive Maintenance in IoT Devices Using Time Series Analysis and Deep Learning', Dandao Xuebao/Journal of Ballistics, vol. 35, pp. 01–10.

[13]. G. Stiglic, P. Kocbek, N. Fijacko, M. Zitnik, K. Verbert, and L. Cilar, 'Interpretability of machine learning-based prediction models in healthcare', Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, vol. 10, no. 5, p. e1379, 2020.

[14]. Liu, A. Cichon, G. Królczyk, and Z. Li, 'Technology development and commercial applications of industrial fault diagnosis system: a review', The International Journal of Advanced Manufacturing Technology, pp. 1–33, 2021.

[15]. L. E. Lwakatare, A. Raj, I. Crnkovic, J. Bosch, and H. H. Olsson, 'Large-scale machine learning systems in real-world industrial settings: A review of challenges and solutions', Information and software technology, vol. 127, p. 106368, 2020.

[16]. M. Achouch et al., 'On predictive maintenance in industry 4.0: Overview, models, and challenges', Applied Sciences, vol. 12, no. 16, p. 8081, 2022.

[17]. Z. M. Çınar, A. Abdussalam Nuhu, Q. Zeeshan, O. Korhan, M. Ismael, and B. Safaei, 'Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0', Sustainability, vol. 12, no. 19, p. 8211, 2020.

[18]. R. K. Pandey, A. K. Dahiya, and A. Mandal, 'Identifying applications of machine learning and data analytics based approaches for optimization of upstream petroleum operations', Energy Technology, vol. 9, no. 1, p. 2000749, 2021.

[19]. S. Ayvaz and K. Alpay, 'Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time', Expert Systems with Applications, vol. 173, p. 114598, 2021.

[20]. S. Akhund, 'Computing Infrastructure and Data Pipeline for Enterprise-scale Data Preparation'.

[21]. L. Ren, Z. Jia, Y. Laili, and D. Huang, 'Deep learning for time-series prediction in IIoT: progress, challenges, and prospects', IEEE Transactions on Neural Networks and Learning Systems, 2023.

[22]. M. Calabrese et al., 'SOPHIA: An event-based IoT and machine learning architecture for predictive maintenance in industry 4.0', Information, vol. 11, no. 4, p. 202, 2020.

[23]. R. Sun et al., 'Higher order polynomial transformer for fine-grained freezing of gait detection', IEEE Transactions on Neural Networks and Learning Systems, 2023.

[24]. Kim, M. A. Alawami, E. Kim, S. Oh, J. Park, and H. Kim, 'A comparative study of time series anomaly detection models for industrial control systems', Sensors, vol. 23, no. 3, p. 1310, 2023.

[25]. M. H. Sulaiman and Z. Mustaffa, 'State of Charge Estimation for Electric Vehicles Using Random Forest', Green Energy and Intelligent Transportation, p. 100177, 2024.