Predictive Maintenance for Industrial Machines – A Review

P.D.Khandait[1], Rutuja Malwe[2], Khushabu Gorle[3], Abhishek Sahare[4], Pranay Zilpe[5]

[1]*Head of the Department, Department of Electronics and Telecommunication Engineering, KDK College of Engineering, Nagpur, Maharashtra, India*

[2,3,4,5]*Student, Department of Electronics and Telecommunication Engineering, KDK College of Engineering, Nagpur, Maharashtra, India*

***Abstract*—Industrial machines play a major role in modern manufacturing because they allow industries to produce goods faster and in large quantities. As factories expand and more equipment becomes automated or computer-controlled, keeping these machines healthy and reliable becomes extremely important. When any machine unexpectedly stops working, it can slow down the entire production line, harm other equipment, and even create safety risks for workers. This makes traditional maintenance methods less effective today, as they usually detect problems only after a breakdown or during routine inspections. Small faults often go unnoticed and gradually grow into serious issues, leading to costly downtime and operational difficulties. Predictive maintenance offers a better solution by identifying potential failures before they occur. It uses continuous monitoring and intelligent technologies to observe machine conditions in real time. Modern tools such as IoT sensors, cyber-physical systems, and industrial data analytics allow tracking of factors like vibration, temperature, pressure, and electrical current. The collected data is then processed using machine learning algorithms, which help detect unusual patterns that may signal early faults. Techniques like Random Forest, Support Vector Machines, and deep learning models are highly effective in identifying abnormal behavior in industrial systems.Studies show that combining IoT-based sensing with data-driven models creates reliable and scalable solutions for machine health monitoring. These advanced methods help extend machine life, reduce maintenance expenses, and improve overall production efficiency. With Industry 4.0, smart factories rely on connected devices, automated inspections, and intelligent monitoring to minimize downtime and ensure smooth, uninterrupted operations. Predictive maintenance has become essential for safer, smarter, and more efficient industrial environments.**

***Index Terms*—Failure Prediction, Fault Prediction, Machine Learning, Predictive maintenance, Systematic Review**

I. INTRODUCTION

Industrial machines are important in today's factories. They help companies make products fast and in big numbers. As industries get bigger and more machines use computers, it is even more important to keep them running well. A machine that stops can slow down work or even break other equipment. It can also put people's safety at risk. This is why old ways of keeping machines working are not enough now. Often, these older ways only find problems after something breaks or during regular checks. Many times, small problems get missed, and they get worse with time. Then, production gets stopped and there are more troubles for workers and companies. To solve these problems, predictive maintenance helps find machine trouble before it happens. It uses real-time checking and smart tools to spot issues early. New technologies like IoT sensors, cyber-physical systems, and industrial analytics let you watch machine parts such as vibration, temperature, pressure, and how much electrical current is used. The data from these sensors can be looked at with machine learning to see patterns or anything strange that could mean there is a fault coming soon. Models like Random Forest, Support Vector Machines, and deep learning work well to find strange things in the real-time data from industry. These can let you know about problems before they happen and help you take early steps. New studies show that mixing IoT-based checking with data-focused models helps to make systems that you can grow and trust for taking care of machine health before trouble starts. These smart technologies help machines last longer. They keep costs low. They also make production run better and smoother. With Industry 4.0, smart factories use connected devices. They use automated inspections and smart monitoring systems. This cuts down on the time machines are not working. It helps production keep going without stopping. Predictive care for machines is now very important in modern factories. It makes things safer. It moves industries toward systems that use digital tools for everything.

II. LITRATURE REVIEW

A) Hector and Panjanathan (2024) looked at over two hundred studies up to 2023. They put predictive-maintenance planning into three types: descriptive, predictive, and prescriptive. They say that vibration monitoring with supervised classification or regression is still the most used option in industry. But, real world systems keep having trouble because data quality is not always the same, it is hard for sensors to work together, and there are bad links to plant software.

B) Martínez-Heredia et al. (2025) focused on weak-supervision techniques. These methods are important when there are very few labelled failures. They grouped the methods based on the type of supervision that is not perfect. They tested these methods on common datasets. The team found that using self-supervised pre-training, with goals that handle noise well, now gives the best mix of good results and real-world use in production.

C) Kumar et al. (2024) did a direct test of nine deep-learning models with real factory vibration and current data. They found that small 1D-convolutional designs and temporal convolutional networks got better results and worked faster with much less time than big LSTM or Transformer models. This shows that when you use models in real places, limits like speed and size are very important.

D) Ben Cheikh and others (2025) used the PRISMA steps to look at 127 studies about making things from 2018 to 2024. They found that the biggest things stopping to move past test runs are trouble linking new systems to old maintenance software, not having enough trained workers, and poor ways that companies handle change in both small and large firms.

E) Depuru et al. (2024) looked at many ways deep learning can help with keeping things working. They showed how the work moved from simple early models like multilayer perceptrons and recurrent networks to using a mix of CNN-LSTM and attention-based methods. Still, they said that not using thoughtful feature work often makes the models look good during tests, but they stop working well when used in real-life settings.

F) Seifeddine et al. (2024) looked at more than performance. They talked about trustworthiness too. The team came up with a model that checks explainability, strength, and fairness. They said that most real-world tools do not do well with how clear they are. These tools also do not handle changes at work very well. Both things can stop technicians from using them.

G) Ran et al. (2024) updated their well-known 2019 survey with five more years of research. The new report shows the rise in the use of models that use physical rules, edge-based work, and shared learning. These steps help keep plant data safe.

H) Li et al. (2022) gave a clear way to group data-driven methods that try to predict outcomes. Their work still helps many, and people read it often. They looked at several methods like statistical types, classic machine-learning, and deep-learning. They kept track of how well each one did, how much computer power was used, and how much data was needed. This study is still used in a lot of new research.

I) Zanke et al. (2024) made and tested a full system that can predict problems for a pumping station. Their hands-on results showed that the simple XGBoost model, which used features made by people, did better than several deep learning methods when there were just a few failure cases to work with.

J) Zaki et al. (2020) showed how predictive maintenance is useful for big sustainability goals. By stopping repairs that are not needed and needing fewer emergency shipments of spare parts, smart factories can use less energy and put out less carbon .

K) Dalzochio et al. (2020) looked at a big group of papers (142 in total) about predictive maintenance in Industry 4.0. That was one of the first times anyone checked this much research all at once. They found problems with adoption, like low data quality, people in a company saying no to change, and trouble mixing systems together. These same issues are still seen in studies done in 2025.

L) De Souza et al. (2024) looked at how different industries use predictive upkeep. They saw that the parts of the market where work goes on without stopping are far ahead of others that make goods in steps. The team also made a useful tool to help companies pick the right technology. That tool uses the worth of their gear and the kind of data they have.

M) Depuru et al. (2023) added to their survey with a talk at a conference. This talk shows that using a group of different methods together and picking the best features with the help of machines can be strong choices. They say these ways are more steady than just using deep learning from start to finish in work environments.

N) Wang (2023) talked about some trends we might see soon. The report says we will likely see more edge AI, digital twins, and big pre-trained time-series models. The author also said that we need to agree on what a health-score means and do more to connect these systems to company upkeep systems. These things have not happened yet.

O) Rakhman and the team (2025) looked at what happens with real-world use. They found three things help most with good results. First, people count a lot on features that come from physics. Next, many people like to spot odd things instead of trying to say exactly how long something will last. Also, they link tools straight to old CMMS platforms.

III. DISCUSSION AND RESEARCH GAP

From 2023 to 2025, the progress in research has been great, but there is still a big gap between what works in labs and what works in real factories. The most advanced networks show good results when you look at test data. But when they are used in real work spaces, they give too many false warnings, lose good results when things change, and do not move easily to other machines that are alike. Because of this, many work teams still choose easier models with basic rules and signals.

These bring more steady results and are easy for people to know and trust over time. A big challenge here is also how hard it is to turn a high risk score into a real fix. A lot of company systems do not take these scores well. This means workers need to do extra steps by hand, and these extra steps lower trust and slow down how fast the work brings good outcomes. The ongoing lack of real failure cases is still a big challenge.

Most new studies say that major problems in plants do not happen often by design. Still, most ways to solve this expect that there will be lots of labeled breakdown examples. The problem is, most plants do not have these examples. There are some good new ideas out there. Things like one-class learning, weak supervision, and using knowledge learned on one system in a new place come up often. But you do not see many cases where people use these ideas for more than a few months without going back to fix or change them often.

Over time, changes in process, the wearing out of important parts, or shifts in the environment show there just are not enough smart, automated tools that can keep up with the steady flow of data from plant sensors. So, there are many good chances for research here.

These include coming up with easy ways to spot problems early for things that do not have much failure history. Another is making systems that check and fix themselves so people do not have to watch them all the time. It is also good to put together safe teamwork plans that let people from different plants share what they know without having to send the main data around. Making basic health checks and clear alert rules that everyone understands is needed. Having honest big tests that show the money side of things is important too.

There is a need to build simple models that can be trusted to run on devices with less power and space. It helps to add clear ways to explain things so technicians will feel good about using them. Aiming for less energy use and lower carbon emissions is smart. Solving these everyday problems is what will really make people feel good about using industrial machine failure systems everywhere, more than just working on public tests and small changes.

IV. PROPOSED METHODOLOGY

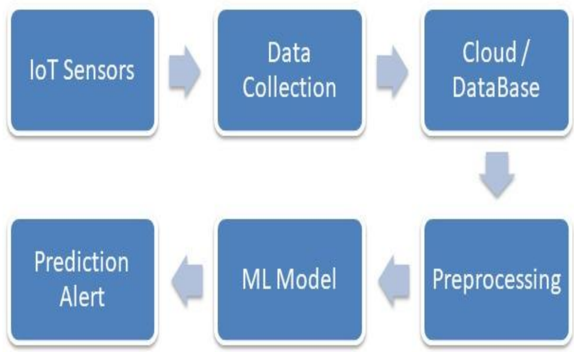

Fig-1: Workflow of Industrial Machines Failure Prediction System

To close the ongoing gaps between testing ideas and using solutions in the real world, this review gives a usable six-stage plan . The plan is made for real-life work settings like factories. It bring together things that people learned from 2023 to 2025 research. It also deals with the problem of starting from nothing, model changes over time, limits on devices, trust from people at the controls, and making sure big company systems work well together.

Stage 1 – Multi-sensor instrumentation Each asset that is checked has vibration, temperature, sound, current, pressure, and oil-condition sensors. The types of sensors depend on how important the asset is and how it might break. All these devices send out data by common industry rules such as OPC-UA or MQTT. They are linked to strong edge units that can keep data close and still work on their own even when the main line is down.

Stage 2 – Resilient data acquisition Edge nodes keep picking up data from sensors all the time. They mark the time and hold the data for a short bit. Simple checks are done close to the sensors before safe, low-bandwidth sending to the main storage. The way this works means you do not lose any data when the connection drops. It works for live streaming and also for storing data and sending it later.

Stage 3 – Unified data repository Incoming streams get stored in a cloud and on-site time-series data lake. This keeps the raw waveforms and also saves every version of the schema right away. A real-time message bus works at the same time to support tasks that must get done fast.

Stage 4 – Two-step prep work and making features Lightweight computations like filtering, basic statistics, and simple flags for any problems happen at the edge. These let you get an immediate answer. Central systems do more advanced tasks. They do things like wavelet analysis, find features about how often something happens, normalise for different running conditions, and use learned models. A shared store keeps indicators from real-world rules and also data from models that learn by themselves. This way, different algorithms use them as needed.

Stage 5 – Layered and adaptive modelling Three modelling layers work together: Edge layer: small detector for odd patterns (can be a simplified autoencoder or isolation forest) that works without the internet and gives early warnings. Edge and cloud layer: A group of tree-based models work together using features that have been set up before. There is also a small self-supervised transformer. They are mainly trained on healthy data. These models get updated a little bit at a time. Cloud-only prognostic layer: deeper networks that follow physics rules will turn on when there are enough examples of bad performance collected. Drift detectors always watch how a model is working. They start retraining or change the model when it is needed.

Stage 6 – Easy-to-understand alerting and closing the loop for action Every alert includes a look at key signals, a clear explanation of what pattern was noticed, and a standard 0–100 health score that matches with health issue scales used for maintenance. Predictions go straight into plant CMMS/EAM platforms using APIs. They make work orders on their own and give possible failure types and needed spare parts. When the technician gives feedback or shares how repairs went, that information goes back into the system. This helps to keep the system getting better all the time through active learning. This framework gets rid of the biggest problems that stop factories from using new tools. It lets you use it right away on machines that have never broken down before. It keeps working well, even when things change. It still works when the connection is down. It also gives explanations that people can understand and believe. You can fit it right in with how you already take care of your equipment. Because of this, you get a plan you can use right now to spot problems early and keep things running well in today's factories.

V. CONCLUSION

Industrial machine breakdown warnings used to be tested as an experiment. Now, they help companies make things work better and cost less money. From 2023 to 2025, new sensors, better setup for data, and smarter computer programs made it possible to spot problems early. Now, companies can see which machines might soon stop working. They also find out how much time is left before equipment may break down.

When you use these systems the right way, they often cut down the number of unscheduled stoppages. The cost to fix things stays lower, and the equipment lasts longer. Companies in energy, transportation, and other manufacturing businesses now see these good results.

Even with these achievements, using these methods all the time in industry is still not common.Most reports still expect things like the right setup, enough data, and fast connection. These things are rare outside of special tests. In a plant, people still trust strong signal checking from experts, simple models that work well, setups that are good for edge, and most of all, an easy link to the usual way of working and the people who do the job.

New answers need to start up well without many old problem records. They must adapt on their own to changes in how things are made. They need to keep private data safe, even while learning from many machines. They must also explain themselves so clearly and honestly that operators can follow what to do. Until then, predictive maintenance will stay in a few costly jobs, and it will not be the normal way everywhere.

The future influence of this technology will not be about making new algorithms. It will be about fixing real world engineering problems. There will need to be fast work with new tools and clear info that is easy for people to read. It will be important to keep the system working well without needing to restart it all the time. Safe ways to share what is learned between different places will be key as well. People have to think about energy and ways to help the earth, not just about always being ready to work. When these problems are solved, breakdown warning systems will run quietly in the background. They will stop most problems before they happen. These systems help to meet work and earth-friendly goals. Beating these last big problems is the step to make sure the field grows more in the next years.

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