

MACHINE AI

AI-BASED MALFUNCTIONING INDUSTRIAL MACHINERY FAULT DETECTION AND MAINTENANCE REPORT SYSTEM

Kunchapu Hima Bindu — Department of Computer Science & Engineering (AIML), PIET, Parul University, Vadodara, Gujarat, India — 2303031460098

Tinga Prashanth — Department of Computer Science & Engineering (AIML), PIET, Parul University, Vadodara, Gujarat, India — 2303031460242

Under the Guidance of Prof. Arpan Sadhukhan — Department of Computer Science & Engineering (AIML), PIET, Parul University, Vadodara, Gujarat, India

Abstract?

Industrial machines are used continuously in many manufacturing environments, so a small fault can quickly affect production, increase maintenance cost, or cause unexpected downtime. Bearing failure is a common example. Before a bearing becomes seriously damaged, the machine may start producing an unusual sound. Finding these changes by manual listening requires experience and regular monitoring. Machine AI was developed to support this task by analyzing machine sounds with artificial intelligence. The system accepts recorded machine audio or a WAV file and uses a Convolutional Neural Network (CNN) to decide whether the sound represents normal operation or a bearing fault. Industrial audio data, including the MIMII dataset, is used during model development. Librosa and SoundFile are used to prepare the audio, while PyTorch supports the machine-learning model. After the CNN gives a prediction, the result is sent through the Gemini API to a generative-AI module. Gemini prepares a maintenance report with the detected condition, possible causes, severity, and suggested actions. This gives the user more useful information than a fault label alone. The complete application is delivered through HTML, CSS, JavaScript, and Flask, with a database for user details, audio-analysis results, predictions, and reports. Overall, Machine AI combines audio analysis, deep learning, and generative AI to support predictive maintenance in a practical web-based system.

Machine Fault Detection, Predictive Maintenance, CNN, Audio Analysis, Deep Learning, Generative AI, Bearing Fault, MIMII

I. INTRODUCTION

Industrial machines are an important part of manufacturing and many other industrial operations. Since production often depends on machines being available for long periods, an unexpected stoppage can lead to delays, financial loss, additional repair work, and sometimes safety concerns.

Traditional maintenance generally follows two approaches: scheduled maintenance and manual inspection. Scheduled checks are carried out at fixed intervals, even when equipment is still operating normally. Manual inspection depends strongly on the technician's experience. Although both methods are useful, they may not reveal a fault while it is still developing.

Machine sound can provide another useful indication of equipment condition. When a component such as a bearing starts to develop a problem, the sound produced by the machine may change. A person may not notice these changes consistently, especially during continuous operation, while an AI model can learn repeated patterns in the audio signal.

Machine AI was developed around this idea. The system listens to machine audio and uses a deep-learning model to identify the machine condition, with the current implementation focusing on normal operation and bearing faults. A CNN is used because it can learn useful patterns from structured audio representations without requiring every feature to be selected manually.

The project also includes automated maintenance reporting. A prediction such as "Bearing Fault?" may not be enough for someone who is not familiar with machine-learning output. Therefore, the prediction is sent to Gemini, which prepares an understandable explanation covering the possible cause, severity, and recommended action. The application is provided through a web interface, so the user can upload or record machine audio and view the prediction and generated report without running the ML code directly.

audio file or record audio through the interface and then view the prediction and generated report.

II. PROBLEM STATEMENT

Machine failures can create serious problems in industrial environments. If a developing fault is not noticed in time, the result may be unexpected downtime, higher repair expenses, or disruption to production. Conventional maintenance commonly depends on scheduled checks and manual inspection, which can miss faults that appear between inspections.

Some of the main problems are:

1. Manual inspection depends on technical knowledge and experience.
2. Continuous monitoring of machines is difficult.
3. Some faults are not easily visible during a normal inspection.
4. Fixed maintenance schedules can lead to unnecessary maintenance work.
5. A developing fault may remain unnoticed until it becomes serious.
6. Machine-learning predictions may be difficult for ordinary users to understand.
7. Preparing maintenance reports manually requires extra time.

Machine AI addresses these issues by taking machine audio as input, applying CNN-based classification, and producing an automatic maintenance report.

TABLE I. PROJECT OVERVIEW

Project Component	Details
Project Name	Machine AI
Primary Input	Industrial machine audio / WAV file
Main Detection Task	Normal operation and bearing-fault detection
Deep-Learning Model	FanFaultCNN / CNN-based classifier
AI Reporting	Gemini API for maintenance report generation
Backend	Flask
Audio Processing	Librosa and SoundFile
ML Framework	PyTorch

III. AIM AND OBJECTIVES

A. Aim

The aim of Machine AI is to build a practical and user-friendly system that can identify possible machine malfunctions from sound using artificial intelligence. It is intended to help technicians and other users monitor machine condition and notice possible faults before they become more serious.

B. Objectives

The main objectives of the project are:

- Analyze audio produced by industrial machines.
- Detect abnormal machine conditions from sound.
- Classify machine audio using a CNN-based deep-learning model.
- Distinguish normal operation from bearing-fault conditions.
- Use industrial machine-audio datasets for model development.
- Provide an easy way to upload or record machine audio.
- Turn the prediction into useful maintenance information.
- Generate maintenance reports automatically using Gemini AI.
- Store analysis results and reports for later reference.
- Provide a simple web interface for users.
- Keep the design open for additional machine types and fault categories.

IV. LITERATURE SURVEY

Several studies have explored artificial intelligence and machine learning for industrial fault detection. These studies provide the background for using sound and data-driven methods in Machine AI.

A. Audio-Based Machine Fault Detection Using Deep Learning

Research in audio-based machine monitoring shows that machine sounds can reveal abnormal operating conditions. Traditional systems often rely on vibration sensors or manual checks. Audio provides another possible way to observe machine health. CNNs are useful because they can learn patterns from audio representations automatically.

B. Machine Fault Detection Using CNN Models

CNN-based fault detection often converts sound or vibration data into a structured representation and then classifies it with a neural network. This approach is suitable for Machine AI because the project also learns patterns from processed machine sound rather than depending completely on manually selected features.

C. Predictive Maintenance Using Machine Learning

Predictive maintenance tries to identify possible machine problems before a breakdown. Machine-learning methods can study machine data and learn patterns related to abnormal operation. The main advantage is that maintenance can be planned according to the machine condition instead of relying only on fixed schedules.

D. Audio Classification Using Deep Learning

Deep-learning methods for audio classification commonly use representations such as spectrograms and MFCCs. These representations expose useful time and frequency information to the neural network. Machine AI follows the same general idea when preparing industrial machine sounds for classification.

E. Automated Report Generation Using Generative AI

Generative AI can convert technical model output into text that is easier for people to understand. In this project it is used after classification. Instead of displaying only "Bearing Fault," Gemini prepares an explanation of the condition, possible reason, and recommended action.

F. Bearing Fault Detection

Bearings are widely used in rotating machinery, which makes bearing faults an important maintenance concern. Deep-learning methods have been studied for identifying bearing-related abnormalities from machine data. Machine AI focuses on this type of fault because changes in operating condition may also appear in the machine sound.

G. Machine Learning for Industrial Fault Diagnosis

Industrial fault-diagnosis research uses different data sources, including sound, vibration, and temperature. Methods such as Decision Trees, Random Forests, and neural networks have been investigated for this purpose. This work supports the broader idea of using data-driven methods to monitor machine condition.

H. Real-Time Machine Monitoring

Real-time monitoring systems continuously observe machine information and look for abnormal behavior while equipment is running. Such systems can support quicker action and reduce unexpected downtime. Continuous monitoring is an important future direction for Machine AI.

I. Audio Signal Processing for Fault Detection

Audio contains useful information in both time and frequency domains. Techniques such as Fast Fourier Transform (FFT) can help examine these characteristics and identify patterns in sound. This supports the use of audio as an additional source for machine-condition monitoring.

J. AI-Based Predictive Maintenance Systems

AI-based predictive-maintenance systems use machine data with machine-learning or deep-learning methods to support maintenance decisions. Machine AI follows this general approach and adds automatic report generation so that the prediction is easier for users to understand.

V. PROPOSED SYSTEM

Machine AI combines audio analysis and maintenance reporting in one workflow. The user can record machine audio through the web application or upload a WAV file. The submitted audio is checked and prepared using Librosa and SoundFile. Useful characteristics are extracted and passed to the CNN model.

The current model mainly considers two conditions: normal operation and bearing fault. After classification, the prediction is stored and sent to Gemini. The generated report can include the machine condition, detected fault, confidence information, possible causes, severity, and recommended corrective actions. The final result is shown through the web interface, so the user receives an explanation instead of only a classification.

Machine AI is designed as an integrated platform where machine audio analysis and maintenance reporting are handled in one workflow.

The overall process begins when the user provides machine audio. The audio can either be recorded through the web application or uploaded as a WAV file.

The submitted audio is first checked and processed. Audio-processing libraries such as Librosa and SoundFile are used during this stage. Important characteristics of the sound are extracted so that the machine-learning model can process them.

The processed audio is then passed to the CNN model. The model has been developed to recognize patterns associated with machine operating conditions. The current system mainly considers two conditions:

TABLE II. CURRENT FAULT CLASSIFICATION

Condition	System Interpretation
Normal	Machine audio associated with normal operating conditions.
Bearing Fault	Machine audio showing patterns associated with a bearing fault.

After the prediction is generated, the result is stored and then passed to the generative AI module.

Gemini is used to generate the maintenance report. The report can contain:

- Machine condition
- Detected fault
- Confidence information
- Possible causes
- Severity
- Recommended corrective actions

The user can then view the result through the web interface.

This makes the system more practical because the user does not need to understand the internal CNN implementation to use the result.

VI. SYSTEM ARCHITECTURE

The Machine AI system is made up of several connected components. The frontend, backend, audio-processing module, machine-learning model, generative-AI service, and database work together as one workflow from audio input to the final maintenance report.

Machine AI system workflow

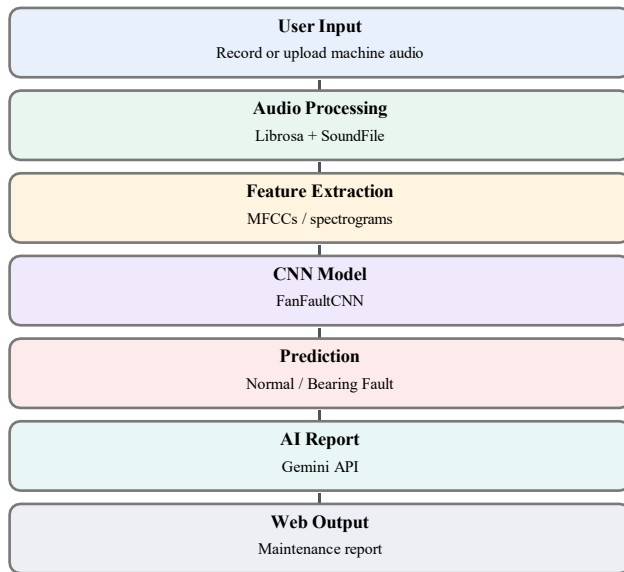


Fig. 1. Machine AI system workflow.

A. Frontend

The frontend is the part of the application through which the user interacts with the system. HTML, CSS, and JavaScript are used to create the interface. The user can log in, upload machine audio, record audio, start the analysis, view the prediction, and read the generated maintenance report.

B. Backend

Flask is used as the backend framework. It connects the frontend with the database, audio-processing functions, machine-learning model, and AI reporting module. It receives the audio request, processes it, calls the required model, and returns the result.

C. Audio Processing Module

This module prepares uploaded or recorded sound before it is analyzed. Librosa and SoundFile are used to read and process the audio files. The current workflow supports WAV-format machine audio.

D. Machine Learning Module

The machine-learning component performs fault classification. PyTorch is used to implement and run the CNN model. The model learns patterns from processed machine audio and predicts the operating condition.

The basic workflow is:

Machine Audio ? Audio Processing ? Feature Extraction ? CNN Model ? Prediction

E. Generative AI Module

After the CNN prediction is obtained, the result is passed to Gemini. The purpose of this module is not to replace the CNN classifier, but to explain its result in a form that is more useful to the user.

The generated report gives a technician additional context about what the predicted fault may mean and what action could be considered.

F. Database

The database stores system information and analysis results. It can keep user information, uploaded-audio details, prediction results, maintenance reports, and other system records. Keeping these records allows previous analyses to be reviewed later instead of losing the information after each prediction.

VII. METHODOLOGY

The development of Machine AI was completed through a sequence of stages.

7.1 Requirement Analysis

The first stage was to identify the problems with conventional maintenance and define what the proposed application should provide. The main requirements were machine-audio input, fault prediction, report generation, user authentication, database storage, and a web interface.

7.2 Dataset and Audio Collection

Industrial machine-audio datasets such as MIMII were considered for training and development. The data contains normal and abnormal machine sounds and provides examples from which the model can learn different operating conditions.

7.3 Audio Preprocessing

Raw audio cannot always be supplied directly to a machine-learning model. It is therefore read and prepared using Librosa and SoundFile before useful patterns are extracted.

7.4 Feature Extraction

Machine audio contains information in the time and frequency domains. MFCCs and spectrograms can represent important characteristics of the sound in a structured form, making them suitable inputs for the CNN.

7.5 CNN Model

A Convolutional Neural Network is used for classification. The CNN learns patterns from processed audio and uses them to distinguish normal and faulty conditions. The model used in the project is called FanFaultCNN.

7.6 Prediction

After processing the audio, the model produces a prediction indicating whether it is associated with normal operation or a bearing fault. The prediction can then be stored in the database

Module	Technology / Role
Frontend	HTML, CSS, JavaScript — user interaction and audio submission.
Backend	Flask — application logic and component communication.
Audio Processing	Librosa and SoundFile — reading and preparing audio.
Machine Learning	PyTorch + CNN — machine-condition classification.
Generative AI	Gemini API — maintenance report generation.
Database	Stores users, audio-related records, predictions, and reports.

TABLE III. SYSTEM TECHNOLOGY STACK

7.7 Maintenance Report Generation

A major feature of Machine AI is the automatic maintenance report. The CNN result is passed to Gemini AI, which converts the prediction into a clearer report. Instead of displaying only a fault label, the report can describe the possible reason and suggest suitable maintenance actions.

7.8 Web Application

The complete workflow is provided through a web application. The frontend handles user interaction while Flask manages the backend processing. This makes the system easier to use because the user does not need to run machine-learning scripts manually.

VIII. IMPLEMENTATION

The implementation of Machine AI combines several technologies.

Python

Python is used as the main programming language because it supports machine learning, audio processing, web development, and AI integration.

PyTorch

PyTorch is used to implement and run the CNN-based fault-detection model.

Librosa

Librosa is used for audio processing and analysis.

SoundFile

SoundFile supports reading and handling the audio files used by the application.

Flask

Flask provides the backend web application and connects the different components.

HTML, CSS and JavaScript

These technologies are used to create the user-facing web interface.

Database

The database stores users, analysis information, predictions, and generated reports.

Gemini API

Gemini is integrated to generate maintenance reports from the fault-detection result. The complete implementation combines audio analysis, CNN prediction, web interaction, database storage, and generative-AI reporting.

This approach is useful because the output is not limited to a simple classification label. A technician or user can obtain additional information about the possible cause and recommended action.

The system also provides a database for storing relevant information. This can help maintain a history of machine analyses and generated reports.

From a practical point of view, the system demonstrates how several AI technologies can be combined into a single maintenance workflow.

It is important to note that the available final report does not provide a verified numerical test accuracy, precision, recall, or F1-score.

Therefore, this research paper does not claim a specific model accuracy that is not supported by the project documentation.

X. ADVANTAGES OF THE PROPOSED SYSTEM

The proposed system has several practical advantages.

1. Early Fault Identification

Changes in machine sound may appear when a fault is developing. Analyzing these sounds can provide an early indication of abnormal operation.

2. Reduced Manual Inspection

The system automatically analyzes submitted machine audio, reducing the need for continuous manual checking.

3. Easy to Use

Users interact with the system through a web interface rather than working directly with machine-learning code.

4. Automated Maintenance Reports

The Gemini integration creates maintenance information automatically after the CNN prediction.

5. Better Decision Support

The report gives possible causes and recommended actions, making the prediction easier to interpret.

6. Historical Information

The database keeps prediction and report information for later reference.

7. Expandable Architecture

The design can be extended to additional machines and different types of faults.

XI. LIMITATIONS

Machine AI is useful as a fault-detection approach, but the current version has some limitations. It mainly covers normal operation and bearing faults and does not represent every mechanical or electrical failure. Prediction quality can also depend on the quality of the recorded audio; background noise and different recording conditions may affect the result. The current project is not a complete real-time industrial monitoring solution and would require suitable hardware and continuous monitoring for such deployment. A wider range of machine types and fault categories would also be needed for a more general system. These limitations provide clear opportunities for future work.

IX. RESULTS AND DISCUSSION

TABLE IV. RESULTS AND EVIDENCE SUMMARY

Aspect	Observation from Project
Detection	CNN-based classification of machine audio.
Output	Normal or bearing-fault prediction.
Report	Gemini-generated maintenance explanation and recommendations.
Storage	Database records analysis and report information.
Verified Metrics	No numerical accuracy, precision, recall, or F1-score is provided in the project documentation.

The prediction is then used by the report-generation module. Gemini produces a maintenance report that presents the result in a more understandable format.

than focusing mainly on bearings.

XII. FUTURE WORK

D. Real-Time Monitoring

There are several ways in which Machine AI can be improved in the future.

A. Better AI Models

More advanced deep-learning models can be explored to improve fault detection and maintenance recommendations.

B. More Machine Types

The system can be expanded to support additional industrial machines such as pumps, valves, gearboxes, motors, and compressors.

C. More Fault Categories

Instead of focusing mainly on bearing faults, future versions can identify multiple mechanical and electrical fault conditions.

D. Real-Time Monitoring

The system can be connected to microphones or industrial sensors so that machine conditions can be observed continuously.

E. Industrial IoT Integration

IoT devices could send machine information directly to the application, allowing it to become part of a larger industrial monitoring environment.

F. Mobile Application

A mobile version could let engineers and technicians upload machine audio and view maintenance reports using smartphones or tablets.

G. Chatbot Support

A chatbot could be added so that users can ask questions about a detected fault and the generated report.

H. Stronger Security

Additional security measures, such as two-step verification, could improve protection for user accounts and machine information.

I. User Feedback

Feedback from technicians and engineers could be collected to improve the interface and make the system more useful in real industrial settings.

XIII. CONCLUSION

Machine AI presents a practical approach to detecting industrial machine faults from audio. The main idea is that changes in the sound of equipment can provide useful information about its operating condition.

The system uses a CNN-based deep-learning model to classify machine audio as normal or associated with a bearing fault. Librosa and SoundFile are used to prepare the audio, while PyTorch supports the machine-learning component.

An important part of the project is the use of generative AI after classification. Once the CNN produces a prediction, Gemini generates a maintenance report describing the detected condition, possible causes, severity, and recommended actions.

The application is implemented as a web system using HTML, CSS, JavaScript, and Flask. A database stores user information, audio-related records, predictions, and generated reports. The overall workflow shows how audio processing, deep learning, web technology, database storage, and generative AI can work together for predictive maintenance.

The current project also provides a base for future development. Better models, more machine types, additional fault categories, real-time monitoring, mobile access, stronger security, and IoT integration could make the system more complete.

Overall, Machine AI demonstrates a useful application of artificial intelligence in machine maintenance. By combining audio-based fault detection with automated reporting, the system can reduce some manual effort, support earlier fault identification, and make maintenance information easier to understand.

REFERENCES

- [1] J. Smith, A. Kumar, R. Lee, "Audio-Based Machine Fault Detection Using Deep Learning," *IEEE Transactions on Industrial Informatics*, Vol. 15, Issue 4, pp. 210–218, 2019.
- [2] S. Patel, M. Verma, "Machine Fault Detection Using Convolutional Neural Networks," *International Journal of Engineering Research*, Vol. 10, Issue 2, pp. 95–102, 2020.
- [3] R. Sharma, P. Singh, "Predictive Maintenance Using Machine Learning Techniques," *Elsevier Journal of Manufacturing Systems*, Vol. 12, Issue 3, pp. 150–160, 2021.
- [4] K. Tan, Y. Chen, "Audio Classification Using Deep Neural Networks," *ACM Multimedia Conference*, 2023 Proceedings, pp. 320–328.
- [5] L. Brown, D. Wilson, "Automated Report Generation Using Generative AI," *Springer AI Journal*, Vol. 8, Issue 1, pp. 45–55, 2022.
- [6] H. Zhao, X. Li, "Bearing Fault Detection Using Deep Learning Techniques," *IEEE Access*, Vol. 9, pp. 50000–50010, 2021.
- [7] P. Mehta, S. Iyer, "Machine Learning Approaches for Industrial Fault Diagnosis," *International Journal of Advanced Engineering*, Vol. 11, Issue 5, pp. 200–210, 2020.
- [8] R. Gupta, N. Shah, "Real-Time Machine Monitoring Using Artificial Intelligence," *IEEE Conference on Smart Systems*, 2022 Proceedings, pp. 120–128.
- [9] D. Roy, K. Das, "Audio Signal Processing Techniques for Fault Detection," *Journal of Signal Processing Systems*, Vol. 14, Issue 3, pp. 310–320, 2021.
- [10] M. Khan, A. Ali, "AI-Based Predictive Maintenance Systems for Industry," *Springer Journal of Industrial AI*, Vol. 6, Issue 2, pp. 75–85, 2022.