RESEARCH ARTICLE

An Intelligent Approach for Machine Downtime Prediction Using Ensembled Machine Learning Models

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Abstract

In industrial settings, unplanned machine downtime is a serious risk to profitability, operational effectiveness, and production. In order to predict machine breakdowns before they occur, this research offers a machine learning-based predictive maintenance framework that enables early prediction of machine downtime. The research is carried out using recorded data sets of industrial machines that operate according to various factors or reasons for downtime. Based on these values, prediction of downtime is possible. To guarantee data quality and consistency, several preprocessing techniques, such as imputation and normalization, were used on a dataset of 2,500 records and 16 features, ranging from hydraulic pressure and temperature to spindle vibration and torque. A variety of machine learning models, such as Random Forest, Support Vector Machines (SVM), LightGBM, XGBoost, and Gradient Boosting, were created and assessed. Although models such as SVM performed at a relatively moderate level, LightGBM and Gradient Boosting performed better than others in terms of prediction performance, with test accuracies surpassing 97%. The efficiency of machine learning in shifting from reactive to proactive maintenance is demonstrated by this work. Real-time data integration, the use of deep learning techniques, and cloud or edge platform deployment for wider industrial applicability are some future approaches to the early prediction of machine downtime.

Keywords: machine downtime, machine learning, ensembled model, machine downtime predictor.

1 Introduction

In the current industrial environment, ensuring uninterrupted machinery operation is essential for sustaining productivity and profitability [1]. Unexpected machine outages can result in considerable financial setbacks and production delays. Despite technological advancements, many industries still rely on reactive maintenance methods, which address failures only after they occur.

Machine learning and data analytics offer promising alternatives to conventional maintenance techniques. Predictive maintenance enables businesses to foresee equipment faults before they happen using data-driven models [2]. By analyzing historical data—including machine performance measurements, environmental variables, and maintenance logs—this research aims to develop a machine learning-based system that reliably anticipates machine downtime.

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The main objectives of this study are:

1. To identify patterns related to machine downtime through comprehensive data analysis;
2. To develop and evaluate machine learning models (Random Forest, Support Vector Machines, Gradient Boosting, and ensemble methods) for accurate downtime prediction [3];
3. To implement a scalable and reliable system that supports proactive maintenance decision-making in industrial settings.

1.1 Problem Statement

Unplanned machine downtime is a major obstacle to profitability, efficiency, and productivity in contemporary industrial settings. Due to machinery complexity and fluctuating operational conditions, downtime events are often unanticipated, leading to production delays, increased maintenance costs, and reduced equipment lifespan.

Conventional manual monitoring is imprecise and does not provide real-time information on machine health. This necessitates an intelligent, data-driven system that can anticipate probable machine breakdowns and optimize maintenance schedules. Applying machine learning algorithms to historical downtime data offers a promising approach to predict failures, minimize unplanned outages, and improve overall equipment effectiveness.

The goal of this research is to develop a predictive model that accurately anticipates machine downtime, enabling proactive maintenance strategies and reducing production interruptions [1, 4].

1.2 Contributions

This research addresses existing gaps in the literature—including limited datasets, low-accuracy models, and the absence of machine learning approaches—by predicting machine downtime using classification algorithms trained on labeled sensor data. The key contributions are as follows:

- **Predictive Maintenance Framework:** Unlike previous research that focused on mechanical solutions, this study enables early prediction of machine downtime using machine learning techniques. A comprehensive ML-based pipeline was developed using operational data and real-world industrial sensor data to forecast downtime and facilitate early maintenance.
- **Comparative Analysis of Models and Datasets:** This study provides a comparative analysis of twelve machine learning algorithms, including LightGBM, XGBoost, CatBoost, SVM, and logistic regression, using documented machine downtime instances.
- **Ensemble Learning for Downtime Prediction:** In contrast to previous studies that relied on statistical techniques or single-model classifiers, this research employs sophisticated ensemble learning algorithms (LightGBM, XGBoost, Gradient Boosting) to achieve high-accuracy downtime prediction.
- **Addressing Data Limitations:** The absence of adequate, well-structured datasets is a common issue in existing literature. This study utilizes a publicly available dataset of 2,500 records with 16 features (including 11 sensor-related features, 1 timestamp, 2 categorical variables, and 1 binary downtime label), addressing the limitation of previous studies that did not consider all impacting factors of machine downtime.
- **Proposed Ensemble Models:** This study proposes two ensemble models combining (i) Decision Tree and Random Forest, and (ii) Naïve Bayes, SVM, and Logistic Regression. These models reduce overfitting, increase robustness and stability, and achieve more accurate predictions compared to individual classification algorithms.
- **Novel Predictive Maintenance System:** This study demonstrates how the proposed models can be deployed as an early predictive maintenance system to reduce machine downtime and boost production. Stacking techniques were used to build ensemble predictive models that effectively and accurately predict machine downtime.

2 Related Work

Table 1 presents a comprehensive literature review of machine downtime prediction studies, summarizing their contributions and identifying research gaps.

3 Methodology

3.1 Dataset Description

3.1.1 Dataset Overview

The "Machine Downtime" dataset is a valuable resource for evaluating machine performance, identifying malfunctions, and developing predictive

Table 1. Literature review of machine downtime prediction.

No.	Year	Refs.	Contribution	Gap
1	2020	[6]	Proposes joint optimization of production and maintenance strategies for a deteriorating system using a dynamic sampling strategy.	Focuses on a single machine without ML approaches; limited generalizability to multi-machine environments.
2	2019	[1]	Reviews ML methods applied to predictive maintenance, highlighting techniques, challenges, and opportunities in shifting from reactive to predictive strategies.	Broad survey of ML in PdM; no specific downtime prediction model or empirical study on industrial sensor data is proposed.
3	2021	[7]	Reviews ML adoption for failure prediction in industrial maintenance, covering preprocessing, training approaches, and evaluation practices across diverse systems.	Heterogeneity in study reporting limits knowledge accumulation; no new predictive model is proposed or validated on sensor data.
4	2022	[8]	Reviews ML techniques for mechanical fault diagnosis and prognosis across real industrial manufacturing use-cases.	Survey-based; no new predictive model is proposed or validated on structured downtime sensor data.
5	2021	[9]	Applies intelligent ML-based total productive maintenance to achieve zero downtime in industrial machinery, demonstrating significant reductions in breakdowns and downtime.	Focuses on TPM integration without considering all physical sensor-level machine factors that contribute to downtime.
6	2024	[5]	Predicts machine failures from multivariate time-series sensor data in a real industrial case study.	Limited to a specific industrial case; dataset does not cover all physical factors contributing to downtime.
7	2023	[10]	Applies ML and DL algorithms (RF, XGBoost, LSTM) for early failure detection in manufacturing, evaluating over 20 fault detection models on a synthetic dataset.	Relies on synthetic rather than real-world sensor data; real-time deployment is not addressed.
8	2023	[11]	Reviews ML-based condition monitoring techniques covering fault detection and health assessment for industrial equipment.	Survey only; no empirical predictive model proposed or validated on labeled machine downtime datasets.
9	2022	[12]	Reviews intelligent predictive maintenance models in Industry 4.0, categorizing maintenance lifecycle stages, ML methods, and deployment challenges.	No new empirical predictive model proposed or validated on industrial sensor datasets.
10	2020	[13]	Investigates ML and reasoning techniques for predictive maintenance in Industry 4.0, identifying key frameworks for failure prediction decision support.	No new classification model proposed; findings are based on literature synthesis rather than empirical experimentation.
11	2021	[14]	Systematically maps ML techniques for predictive maintenance in manufacturing, categorizing methods by algorithm type and application domain.	Bibliometric and survey-based; no new ML model proposed or validated on industrial sensor datasets.
12	2020	[15]	Reviews ML techniques for predictive maintenance in smart manufacturing under Industry 4.0, classifying algorithms by category, machinery type, and application domain.	The review is broad and domain-agnostic; no empirical evaluation on industrial machine sensor datasets is provided.
13	2022	[16]	Develops an improved ensemble learning approach for predictive maintenance in textile manufacturing to enhance fault detection accuracy.	Domain-specific to textile manufacturing; generalizability to other industrial environments requires further validation.
14	2023	[17]	Investigates ML and telemetry data to reduce vehicle downtime, focusing on air compressor mechanics.	Limited scope restricts generalizability; lack of comprehensive failure data.
15	2025	[18]	Compares deep learning models for predictive maintenance in industrial manufacturing using real sensor data.	Focuses only on deep learning; classical and ensemble ML classifiers are not evaluated; interpretability not addressed.
16	2024	[19]	Proposes an ML and IoT-based predictive maintenance approach for industrial applications to improve equipment reliability and reduce unplanned downtime.	Early failure prediction capabilities are limited; broader validation across diverse industrial equipment types is needed.
17	2023	[20]	Improves ML-based failure prediction in industrial maintenance through sliding window selection, showing that window size tuning significantly impacts accuracy on time-series data.	Focuses on a single window-selection technique; generalizability across diverse equipment types requires further validation.
18	2024	[21]	Applies ML for predictive maintenance in concrete manufacturing to enhance equipment reliability in construction management.	Restricted to concrete manufacturing; limited generalizability across industrial domains; real-time deployment not evaluated.
19	2024	[22]	Reviews ML-based PdM techniques, identifying issues such as interpretability, data requirements, and failure data scarcity.	Highlights Random Forest overfitting with small datasets and SVM limited interpretability.
20	2025	[23]	Investigates the impact of predictive maintenance on industrial enterprise performance using ML-based approaches.	Findings are context-specific; broader validation across diverse industrial sectors is needed.
21	2020	[4]	Performs a systematic literature review of predictive maintenance studies in Industry 4.0, proposing a taxonomy covering IoT, AI algorithms, and cyber-physical systems.	The survey is broad and taxonomic; no empirical ML evaluation or new prediction model is proposed.
22	2024	[2]	ML and IoT-based predictive maintenance reduces downtime by 30–40% and costs by 20–30%.	Absence of defined data integration frameworks and affordable ML-IoT solutions for SMEs.
23	2024	[24]	Uses synthetic data and deep learning (LSTMs) to reduce electrical system downtime, achieving 98% accuracy.	Limited real-world validation; need for hybrid models to improve recall and generalizability.
24	2025	[25]	Trains multiple ML models; Random Forest achieves 0.91 accuracy.	Limited fault emphasis neglects important defects such as rotor-bar problems.
25	2025	[26]	Ensemble approaches (particularly Random Forest) offer excellent accuracy for predicting machine problems.	Results could be improved with higher accuracy.
26	2025	[27]	Advanced models (ANN, MLP) outperform ARIMA for complex downtime patterns.	Limited research on data pattern comparison; interpretability and data quality challenges.
27	2025	[28]	Random Forest forecasts automobile breakdowns with 80% accuracy, reducing downtime.	Limited integrated approaches combining algorithms and decision-making tools.
28	2025	[29]	AI predictive maintenance reduces downtime and costs using IoT, ML, and digital twins.	Absence of defined data integration frameworks and affordable ML solutions for SMEs.
29	2025	[30]	Implements ML and IoT-based predictive maintenance for industrial compressors using multi-sensor data, achieving 98% accuracy in failure prediction.	Limited to a single compressor type; generalizability to other industrial equipment and broader sensor configurations requires further study.
30	2025	[31]	AI-driven predictive maintenance reduces downtime by 20–25%, costs by 15–20%, and increases lifespan by 25–30%.	Absence of XAI integration frameworks for legacy industrial systems and data quality concerns.

maintenance models. It offers a multifaceted view of machine health through an extensive set of features, including pressures, temperatures, vibrations, speed, voltage, and torque. Each of the sixteen columns records distinct machine performance characteristics, such as rotational speed, voltage, torque, cutting force, temperature readings, vibration metrics, and pressure data. The dataset also includes categorical data identifying assembly lines, machines, and downtime status. Based on these features, the target variable indicates two possibilities: whether machine downtime will occur or not.

3.1.2 Feature Description

Table 2 presents a detailed description of all features in the dataset. The dataset contains 2,500 records with 16 features (including 11 sensor-related features, 1 timestamp, 2 categorical variables, and 1 binary downtime label). These features are sensor-recorded entries across different time spans. A binary label is assigned whenever downtime occurs. All features are considered impacting factors for machine operation. Figure 1 shows the correlation heatmap of the dataset features.

3.2 Data Preprocessing

Machine downtime occurs when a component or feature of equipment malfunctions, and numerous factors can contribute to such events. In this study, the sixteen features of the dataset, covering operational and sensor-level machine parameters, are analyzed. The research adopts a systematic approach that integrates multiple data processing techniques, machine learning methodologies, and ensemble models.

3.2.1 Missing Value Imputation

Missing values for several features were present in the raw dataset.

- **Numerical Features**: Missing values were imputed using mean imputation based on the data distribution.
- **Categorical Features**: Missing values in categorical variables such as `Machine_ID` and `Assembly_Line_No` were imputed using the mode (most frequent value).

3.2.2 Categorical Variable Encoding

Label encoding was used to transform categorical information into numerical form. This included factors such as Date, `Machine_ID`, and `Assembly_Line_No`.

3.2.3 Data Balancing

Data balancing was applied to address imbalanced class distributions, which helps improve model training and prediction performance.

3.2.4 Outlier Removal

The Z-score approach was used to identify and remove outliers. Data points with a Z-score exceeding ± 3 were eliminated as anomalies to ensure model robustness.

3.2.5 Feature Scaling

While tree-based models (e.g., Random Forest, XGBoost) are not sensitive to feature scaling, models such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) are. Therefore, normalization was applied to continuous numerical features (e.g., Hydraulic_Pressure, Spindle_Speed, Voltage) to ensure consistent model behavior across all algorithms.

3.2.6 Data Preprocessing Algorithm

Algorithm 1 summarizes the complete data preprocessing pipeline.

Algorithm 1: Data Preprocessing Pipeline

Data: Raw dataset $Data$
Result: Cleaned and normalized dataset $Data'$
Remove missing values from $Data$;
Encode categorical variables using label encoding;
Apply data balancing;
Remove duplicate records;
Remove outliers using the Z-score method;
Split dataset into training (70%) and testing (30%) subsets;
return $Data'$;

3.3 Classification Models

This study employed twelve distinct classification models to predict machine downtime: Naïve Bayes, LightGBM, Random Forest (RF), Extra Trees, XGBoost, Gradient Boosting (GB), Logistic Regression, CatBoost, AdaBoost, Decision Tree, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) [3].

3.3.1 Mathematical Formulations

Naïve Bayes

$$P(C_k \mid x) = \frac{P(x \mid C_k) \cdot P(C_k)}{P(x)} \tag{1}$$

where C_k is class k, x is the feature vector, $P(C_k)$ is the prior probability, $P(x \mid C_k)$ is the likelihood, and $P(x)$ is the evidence.

Table 2. Data description of Machine Downtime dataset.

Feature	Description
Date	The date of data collection. The most frequently recorded date appears 64 times out of 164 distinct dates in the dataset.
Machine ID	Unique machine identifier. Three machines are tracked, with 'Makino-L1-Unit1-2013' appearing 874 times as the most frequent.
Assembly Line No	Indicates which assembly line the machine belongs to. 'Shopfloor-L1' is the most commonly referenced.
Hydraulic Pressure (bar)	Hydraulic pressure in bars, ranging from -14.33 to 191. Mean pressure is 101.41 bars. Negative values may suggest sensor issues.
Coolant Pressure (bar)	Coolant pressure with a mean of 4.95 bars, ranging from 0.325 to 11.35 bars. Contains 2,481 non-null entries.
Air System Pressure (bar)	Air pressure in the system with mean 6.50 bars, ranging 5.06–7.97 bars. Minor missing data.
Coolant Temperature (°C)	Temperature of the coolant with mean 18.56°C, ranging from 4.1 to 98.2°C. 12 entries are missing.
Hydraulic Oil Temperature (°C)	Temperature of hydraulic oil, ranging from 35.2°C to 61.4°C. 2,484 non-null values.
Spindle Bearing Temperature (°C)	Mean spindle bearing temperature between 22.6°C and 49.5°C. 2,493 out of 2,500 entries are valid.
Spindle Vibration (μm)	Vibration of the spindle in micrometers. Mean is 1.01 μm, range -0.461 to 2.0 μm. Negative values may indicate sensor errors.
Tool Vibration (μm)	Tool vibration in micrometers. Mean is 25.41 μm, ranging from 2.16 to 45.73 μm.
Spindle Speed (RPM)	Spindle rotation speed in RPM. Mean is 20,275 RPM, range is 0 to 27,957 RPM.
Voltage (volts)	Denotes voltage levels of the machine. Used for operational condition monitoring.
Torque (Nm)	Torque in Newton-meters. Average is 25.23 Nm, ranging from 0 to 55.55 Nm.
Cutting (kN)	Cutting force exerted, measured in kilonewtons. Average is 2.78 kN, range is 1.8 to 3.93 kN.
Downtime	Binary indicator of machine failure. 1,265 entries show failure, 1,235 indicate no failure.

Random Forest

$$\hat{f}(x) = \frac{1}{T}\sum_{t=1}^{T} f_t(x) \tag{2}$$

where T is the total number of trees and $f_t(x)$ is the prediction of the t-th tree.

LightGBM

$$f(x) = \sum_{i=1}^{K} \gamma_i \cdot I(x \in R_i) \tag{3}$$

where K is the number of leaves, γ_i is the output for region R_i, and I is the indicator function.

3.4 Ensembled Models

To further enhance prediction accuracy, two ensembled models were developed using stacking:

- **Ensembled Model 1 (ELRC)**: Combines Decision Tree and Random Forest as base classifiers, with Logistic Regression as the final estimator (Figure 2).
- **Ensembled Model 2 (EXGC)**: Combines GaussianNB, SVM, and Logistic Regression as base classifiers, with XGBoost as the final estimator (Figure 3).

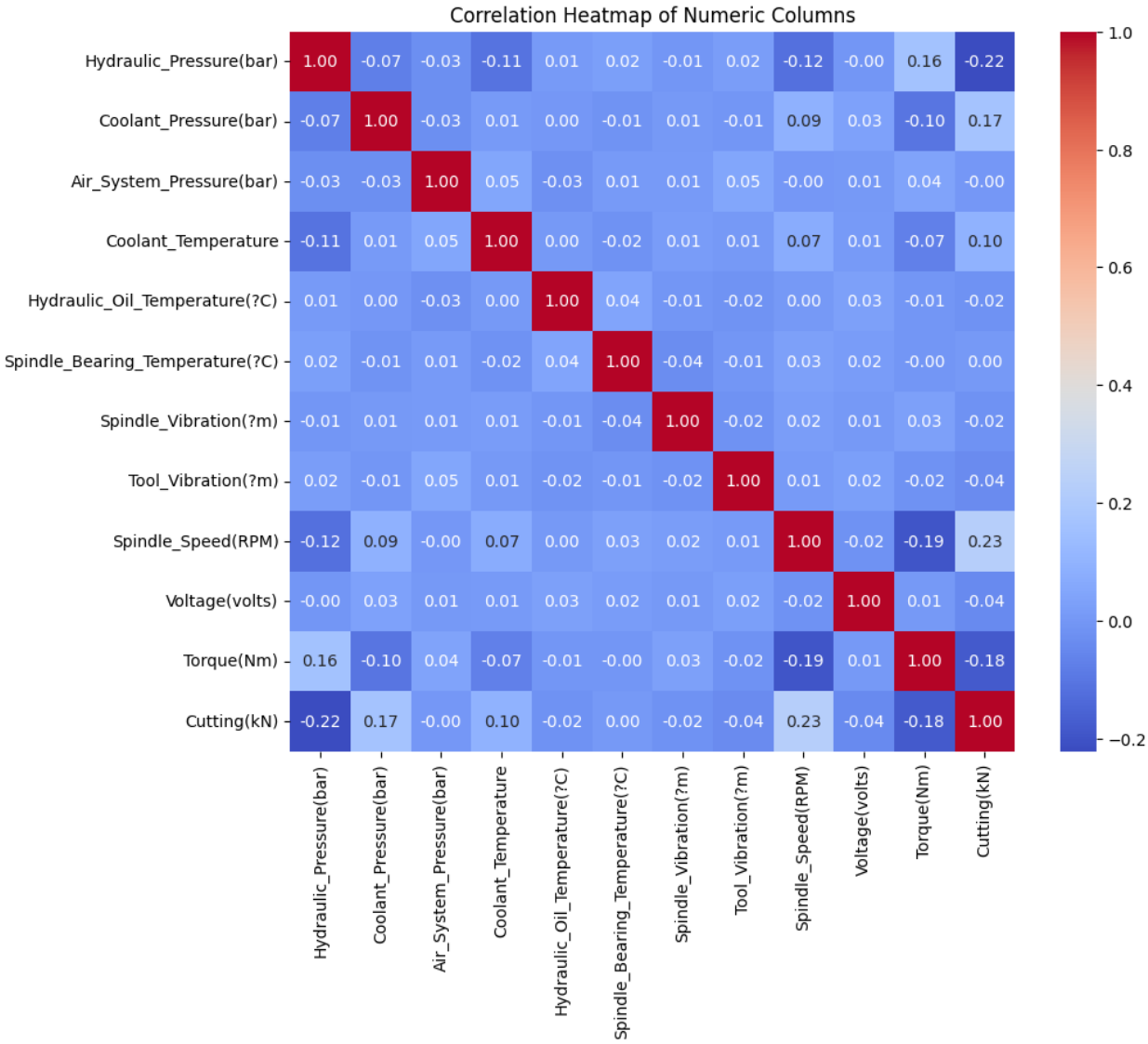

Figure 1. Correlation heatmap of the dataset features.

Figure 4 illustrates the complete workflow of the proposed machine downtime prediction system. The workflow consists of the following steps:

1. Historical data is collected from industrial settings.
2. Data is processed using the preprocessing pipeline described in Algorithm 1.
3. The processed data is split into training (70%) and testing (30%) datasets.
4. Twelve individual classifiers and two ensemble models are trained and evaluated.
5. The best-performing model is used for machine downtime prediction.

4 Experiments and Results

4.1 Experimental Setup

The machine learning models described in Section 3 were implemented using Python in a Jupyter Notebook environment. The preprocessed dataset was split into training (70%) and testing (30%) subsets. Model performance was evaluated using four metrics: accuracy, precision, recall, and F1-score.

4.2 Performance Comparison

Table 3 presents the performance metrics of all twelve classification models evaluated in this study.

4.3 Key Observations

Based on the results presented in Table 3, the following key observations can be made. LightGBM achieved the highest accuracy (99.37%), precision (99.38%), recall

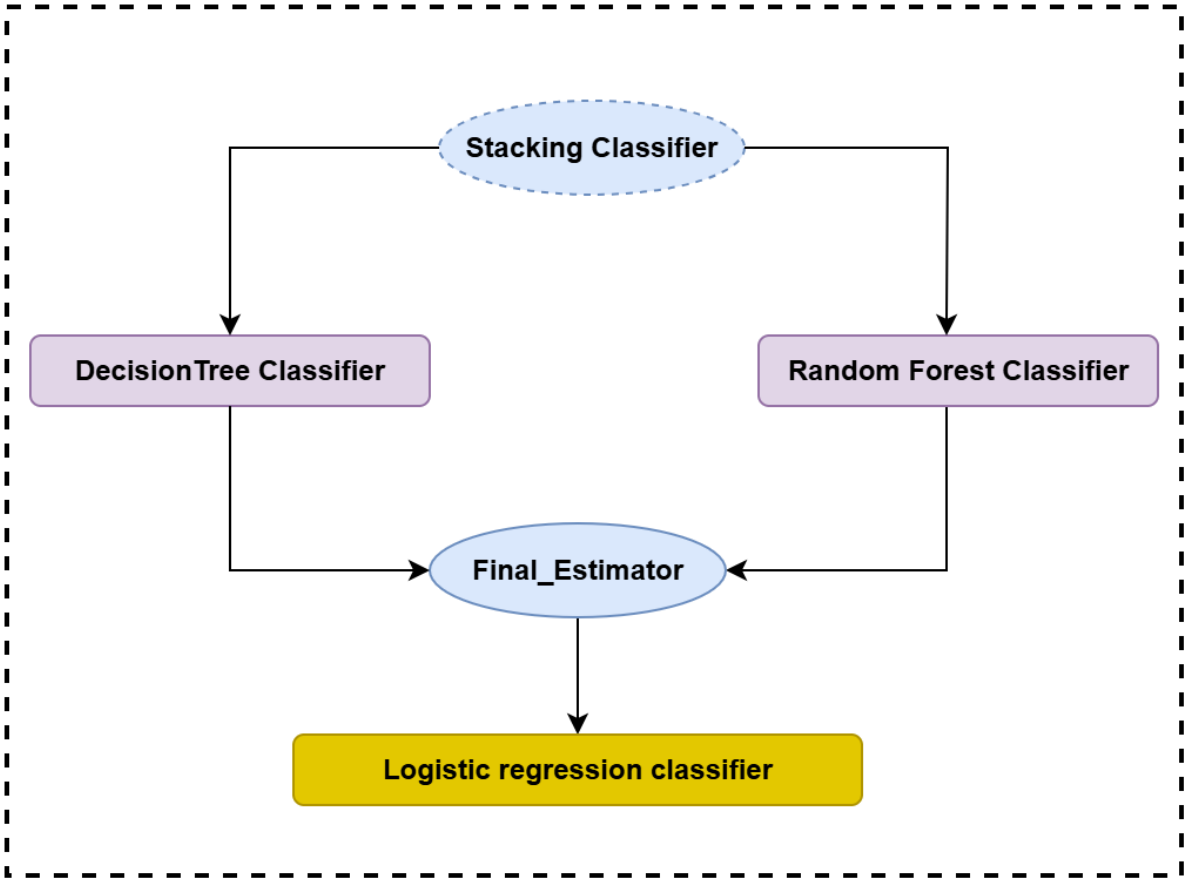

Figure 2. Architecture of Ensemble Model 1 (ELRC): Logistic Regression as final estimator with Decision Tree and Random Forest as base classifiers.

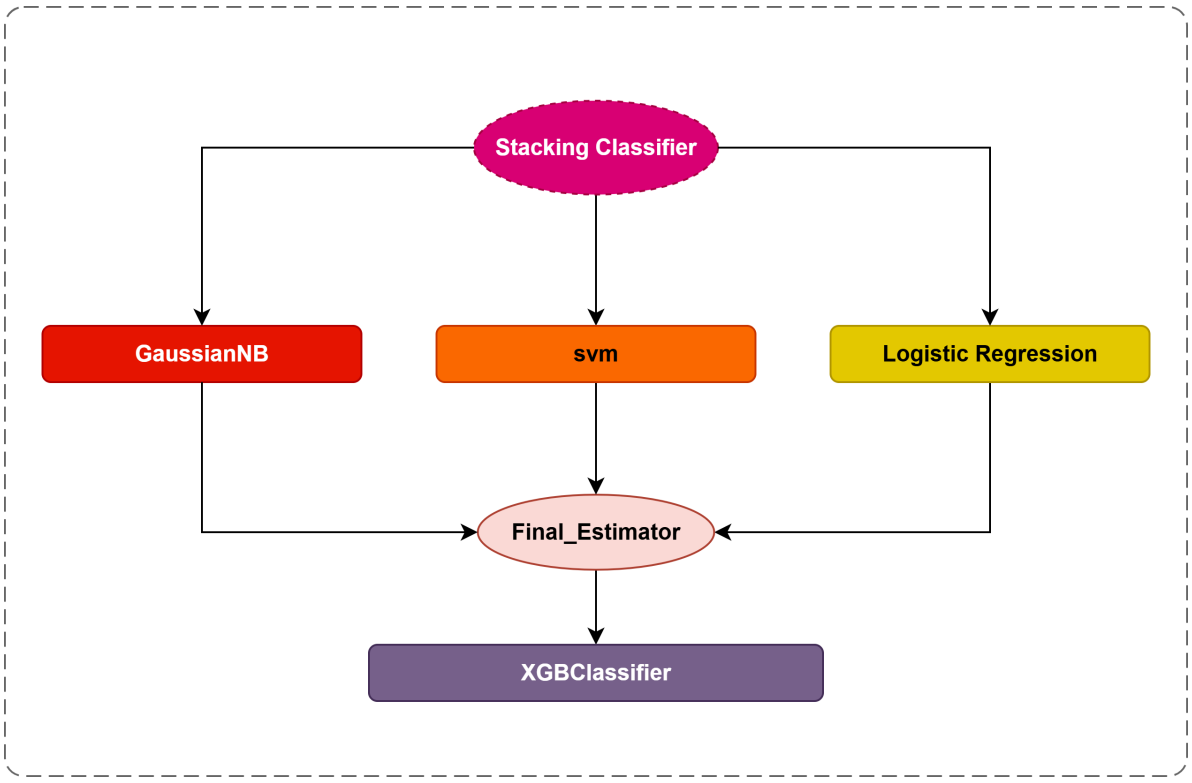

Figure 3. Architecture of Ensemble Model 2 (EXGC): XGBoost as final estimator with GaussianNB, SVM, and Logistic Regression as base classifiers.

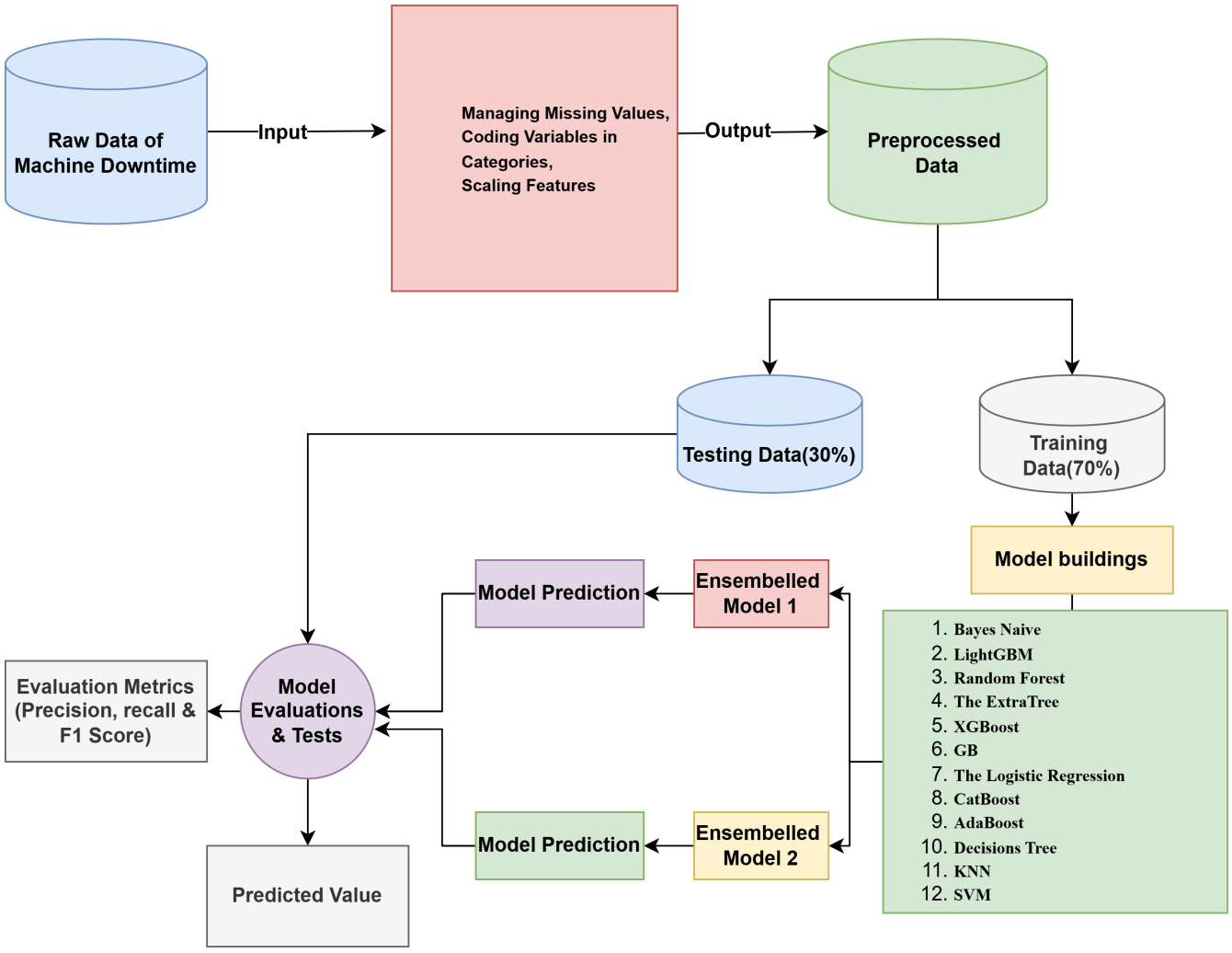

Figure 4. Complete workflow of the machine downtime prediction system.

Table 3. Performance metrics of the classification models.

Model	Accuracy	Precision	Recall	F1-score
Naïve Bayes	0.8449	0.8461	0.8449	0.8448
Random Forest	0.9811	0.9812	0.9811	0.9811
LightGBM	0.9937	0.9938	0.9937	0.9937
Gradient Boosting	0.9916	0.9916	0.9916	0.9916
Extra Trees	0.9790	0.9791	0.9790	0.9790
XGBoost	0.9874	0.9875	0.9874	0.9874
Logistic Regression	0.8532	0.8539	0.8532	0.8532
AdaBoost	0.9874	0.9874	0.9874	0.9874
CatBoost	0.9895	0.9895	0.9895	0.9895
Decision Tree	0.9476	0.9482	0.9476	0.9476
KNN	0.9560	0.9562	0.9560	0.9560
SVM	0.9378	0.9065	0.9478	0.9197

(99.37%), and F1-score (99.37%) among all evaluated

models, followed closely by Gradient Boosting with an accuracy of 99.16%. Tree-based ensemble methods (Random Forest, Extra Trees, XGBoost, CatBoost, AdaBoost) consistently outperformed single classifiers, with accuracies ranging from 97.90% to 99.37%. In contrast, Logistic Regression (85.32%) and Naïve Bayes (84.49%) showed moderate performance, while SVM (93.78%) performed better but still lagged behind ensemble methods. Additionally, XGBoost demonstrated a good balance between precision (98.75%) and recall (98.74%).

5 Discussion

The experimental results demonstrate that machine learning-based approaches can effectively predict machine downtime, enabling a shift from reactive to proactive maintenance strategies.

5.1 Comparison with Traditional Methods

Traditional maintenance approaches rely on reactive strategies or scheduled inspections, which cannot anticipate unexpected failures. In contrast, the proposed ML-based framework achieves prediction accuracy exceeding 97%, making it feasible for real-world industrial deployment.

5.2 Performance Analysis of Ensemble Models

Ensemble learning methods consistently outperformed individual classifiers due to their ability to reduce overfitting and improve generalization. Among these, LightGBM achieved the highest accuracy (99.37%), followed by Gradient Boosting (99.16%) and CatBoost (98.95%). The superior performance of LightGBM can be attributed to its efficient handling of large-scale data and categorical features, as well as its leaf-wise tree growth strategy.

5.3 Limitations and Future Directions

While the proposed approach demonstrates high accuracy, several limitations should be acknowledged:

- The dataset contains 2,500 records, which may not fully capture all possible machine failure modes.
- Real-time data integration was not implemented in the current framework.
- Model interpretability remains a challenge for complex ensemble methods.

Future work will focus on:

- Integrating real-time sensor data streams
- Exploring deep learning approaches (e.g., LSTM, transformers) for temporal failure prediction
- Deploying the model on edge or cloud platforms for industrial scalability
- Enhancing model interpretability using SHAP or LIME

5.4 Summary of Findings

In summary, this study provides empirical evidence that ensemble machine learning models, particularly LightGBM and Gradient Boosting, can achieve high accuracy (above 97%) in predicting machine downtime. These findings support the development of intelligent predictive maintenance systems that can reduce unplanned downtime and improve operational efficiency in industrial settings.

6 Conclusion

Machine downtime is a major concern in industrial settings, as it can significantly impact production rate and equipment efficiency. In this study, machine downtime can be predicted using machine learning classification algorithms; the prediction is entirely based on factors such as Hydraulic Pressure (bar), Coolant Pressure (bar), Air System Pressure (bar), Coolant Temperature, among others. The dataset includes records of the downtime and operational metrics of several machines. In real-world scenarios, machine downtime can be effectively predicted based on these operational factors. The paper presents a predictive and ensemble machine learning-based approach capable of forecasting machine downtime based on operational sensor features. The proposed approach can significantly reduce production delays caused by machine downtime. Early prediction enhances machine efficiency and helps prevent unplanned downtime. The proposed ensemble model is applicable to downtime prediction across various industries, including manufacturing and healthcare. Incorporating more detailed machine data or larger datasets could further improve prediction accuracy and contribute to increased production efficiency. Future research should incorporate downtime variables from a wider range of machine types to further improve prediction performance.

7 Recommendation of the study

The industries should use an advanced machine learning or deep learning integrated machine downtime predictor. Industrial settings should be

integrated with advanced IoT devices to capture environmental and operational variables, which may be helpful in machine downtime prediction. The ensemble models can be more accurate with different combinations of machine learning models. The industries should adopt advanced AI techniques to predict machine downtime.

Data Availability Statement

The data that support the findings of this study are openly available in the Kaggle repository at: https://www.kaggle.com/datasets/srinivasanusuri/optimization-of-machine-downtime.

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Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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