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MACHINE LEARNING-DRIVEN PREDICTIVE MAINTENANCE: OPTIMIZING NAIVE BAYES WITH SYNTHETIC DATA AND CLASS IMBALANCE TECHNIQUES

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Abstract:

Integrating machine learning into predictive maintenance has steadily gained traction across industries, revolutionizing maintenance strategies. While numerous studies have investigated this topic, and many sectors have successfully implemented machine learning models, some industries rely on inefficient and costly traditional methods. This project aims to bridge that gap by advancing machine learning-driven predictive maintenance research utilizing a synthetic dataset. Specifically, the study explores a novel approach by combining binarisation techniques with the Naive Bayes algorithm—an area largely underexplored in existing literature. Additionally, Naive Bayes is enhanced with Bagging and Boosting techniques to improve performance. At the same time, SMOTE (Synthetic Minority Over-Sampling Technique) and under-sampling are applied to address the class imbalance in predicting machine failure. Six models were developed: Naive Bayes [SMOTE], Naive Bayes with Bagging [SMOTE], Naive Bayes with Boosting [SMOTE], Naive Bayes [Under sampling], Naive Bayes with Bagging [Under sampling], and Naive Bayes with Boosting [Under sampling]. Among these, the Naive Bayes [SMOTE] model achieved outstanding results, with an accuracy of 0.999 and a precision of 1.0, outperforming previous studies and setting a new benchmark in predictive maintenance research. These findings highlight the potential of advanced machine learning techniques in significantly improving predictive maintenance accuracy and efficiency across industries.

Keywords:

Predictive Maintenance, Machine Learning, Naïve Bayes, SMOTE

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Introduction

Alongside technological advancements, daily life increasingly relies on machines, even for minor tasks. Consequently, if a machine encounters a malfunction, daily activities are likely to be disrupted due to the problems faced by the machine. To reduce the frequency of machine failures, various processes and methods have been introduced at each stage of the machine's life cycle to optimize its lifespan. Additionally, in sectors with highly critical systems that significantly impact the public, such as the rail sector, the application of system functionality assurance from the engineering to the operational and maintenance phases has become a prerequisite for project approval and operation.

Preventive Maintenance (PM) is a type of scheduled maintenance where the timing for maintenance and the interval between the current and next maintenance are determined using Failure Developing Period (FDP) calculations. FDP is when the signs of machine failure begin to appear until the machine fails. Corrective Maintenance (CM), on the other hand, is an unscheduled type of maintenance that occurs after a machine component fails. Machine failures requiring CM can occur at any time and may happen randomly. Machines maintained according to a PM schedule may still require CM if a failure occurs between the most recent PM and the next scheduled PM.

The predictive maintenance (PdM) method uses predictive tools to determine when maintenance should be performed based on data such as records, maintenance records and operating details from industrial machines (Carvalho et al., 2019; Bukhsh and Stipanovic, 2020). PdM uses real-time data collected from sensors installed on machines to monitor their status through various metrics such as temperature, vibration, and sound. Typically, PdM begins by determining and setting conditions that indicate a machine is approaching failure based on past data records stored in a system known as the Computerized Maintenance Management System (CMMS). When the data from the machine reaches or exceeds the values that indicate imminent failure, CMMS issues a warning and recommends that maintenance be performed. PdM emphasizes maintenance at the right time instead of performing maintenance when the machine still has a long lifespan before failure, as often happens with PdM or after the machine has already failed, as seen with CM (Molęda, M. et al., 2023).

Machine learning approaches are one method used in PdM maintenance due to the availability of diverse data from sensors installed on machines (Sarvaiya, 2021; Gonfalonieri, 2019). Data collected from sensors for PdM maintenance typically consists of several attributes representing machine conditions and at least one indicating machine failure status. Such data is well-suited for various machine learning algorithms, particularly classification-based algorithms. PdM maintenance typically relies on traditional methods such as CMMS, which can accurately predict regular machine failures but struggle with random failures. Using machine learning approaches, PdM can predict regular and random machine failures.

Many industries still rely on PM and CM methods in their maintenance processes. Although PM and CM have proven effective in ensuring machines operate well over extended periods, there is room for improvement to optimize costs, scope, and time while maintaining system quality. Traditional maintenance processes could be more efficient, as scheduled maintenance periods are determined based on predictions made during the engineering phase, often resulting in maintenance performed well before machine failure. In reality, traditional maintenance methods lead to early maintenance, wasting labour and materials and extending the

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unproductive lifespan of machines. For instance, 29.3% of aircraft maintenance costs are wasted using traditional methods (Lee & Mitici, 2023).

Maintenance processes can be optimized by utilizing data generated from sensors installed on machines to monitor their status. PdM maintenance is a solution that can address issues arising from traditional maintenance methods. Previous research shows that matching PdM models with machine learning techniques can improve system performance by 75% (Rodriguez et al., 2022), prevent 95.6% of unnecessary work (Lee & Mitici, 2023), and achieve 98% accuracy in machine failure detection (Lee et al., 2019).

Researchers have published numerous studies on machine learning approaches in PdM maintenance as valuable references (Ucar, A. et al., 2024). However, publicly accessible datasets for machine learning approaches in PdM maintenance remain limited, as many companies are reluctant to share their data. Due to this limitation, this project will utilize publicly available synthetic datasets. Techniques applied to these datasets in previous studies will be discussed, and this project will propose methods not yet used for the research dataset to develop a PdM maintenance model for predicting machine failures.

In general, PdM maintenance datasets are well-suited for classification-based models, consisting of several attributes that indicate machine condition across various metrics, with at least one attribute signalling whether the machine has failed or is still functioning. According to previous studies, commonly used machine learning techniques for PdM maintenance models include Artificial Neural Networks (ANN), Decision Trees (DT), Random Forests (RF), Support Vector Machines (SVM), k-nearest Neighbours (k-NN), Naïve Bayes (NB) and Logistic Regression (LGR).

Matzka (2020) published a synthetic dataset based on actual machine data known as the AI4I2020 dataset for research purposes. While various studies have applied machine learning approaches to this dataset, no formal papers, such as journal articles, conference papers, or research reports, have proposed using the NB approach to predict failures with this dataset. Since this dataset is publicly accessible, websites like Kaggle contain forums discussing the application of NB to this dataset. However, the NB algorithms shared on these websites do not utilize a binarisation approach, where the entire dataset is converted to binary form before data mining.

Previous studies on building PdM models for the AI4I2020 dataset often employed basic machine-learning approaches such as DT, RF, LGR, k-NN, SVM, and ANN. Ghasemkhani et al. (2023) compared these machine-learning approaches with the Balanced K-star technique proposed in their study. They concluded that the average scores obtained from these techniques were as follows: accuracy 91.74%, precision 0.8052, sensitivity 0.6666, and F1-score 0.5760, while the Balanced K-Star technique yielded the following results: accuracy 98.75%, precision 0.9877, sensitivity 0.9875, and F1-score 0.9875 (Ghasemkhani et al., 2023).

This paper aims to develop a PdM model using binarisation techniques and the NB algorithm to predict failures in the research dataset, further evaluate the developed model's performance, and compare the best model with previous studies. This paper is divided into several sections as follows: the second section reviews the literature on PdM and the relevant research on the study dataset, followed by an explanation of the research methods applied in this project; next,

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presents the research findings and analysis, and finally, the last section discusses the recommendations and conclusions of the study.

Literature Review

Predictive Maintenance (PdM) is considered one of the most optimal maintenance strategies compared to Preventive Maintenance (PM) and Corrective Maintenance (CM). PdM not only suggests repair solutions and identifies components that need replacement but also estimates the likelihood of failures, which helps reduce costs and maximise machine availability (Sarvaiya, 2021). The increasing feasibility of PdM is primarily attributed to the widespread availability of sensors and high-performance computer processors, which are now more affordable and accessible. Access to advanced hardware allows data to be efficiently collected and analysed to support the PdM process. However, the effectiveness of PdM is not solely dependent on high-performance analytical tools; it also relies on the availability of relevant data, appropriate feature engineering, and the comparison of related predictive models (Gonfalonieri, 2019).

Traditionally, statistical methods have been widely used in PdM. In recent years, there has been a significant increase in the number of papers, proposals, and research focused on PdM, with new models being introduced periodically to enhance maintenance strategies. A study examining the implementation of machine learning in PdM within the automotive industry highlighted several key points: most studies utilise supervised machine learning, the field is likely to expand as data accessibility increases, the performance of machine learning models improves when multiple methods are employed, and there is a growing trend towards using Deep Learning (DL) for predictive maintenance (Theissler et al., 2021). Furthermore, reviewing papers on implementing machine learning in maintenance indicated that DL methods have not yet been fully integrated into PdM (Sanzana et al., 2022). While Predictive Maintenance (PdM) is widely regarded as an efficient strategy compared to Preventive Maintenance (PM) and Corrective Maintenance (CM), it is essential to acknowledge its limitations.

Even though PdM can reduce costs and maximise machine availability by predicting failures, it depends not only on hardware advancements but also on effective data management, feature engineering, and model comparison. Moreover, while machine learning (ML) has expanded PdM's capabilities, most implementations still rely on supervised learning. Although deep learning (DL) offers significant potential, its adoption in PdM is limited due to challenges such as computational demands and the need for large datasets. Therefore, achieving optimal PdM performance requires overcoming these technical barriers, particularly in data management and advanced algorithm integration.

Artificial Neural Networks (ANN) are commonly used methods in PdM. ANN has been shown to accelerate the PdM process, as demonstrated in a study on PdM for solar power plant applications, where ANN reduced processing time in achieving the highest thermal energy from solar heaters compared to the conventional Non-Linear Predictive Control (NMPC) method (Masero et al., 2023). In another study focused on PdM for aircraft maintenance, the use of ANN as a pre-failure detection algorithm was proposed as part of the Maintenance Repair and Overhaul (MRO) model (Safoklov et al., 2022). Research on ANN applications for PdM in the rail industry suggested using ANN algorithms in conjunction with dynamic time series to estimate bearing failures based on temperature data. This study demonstrated a strong

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relationship between Remaining Useful Life (RUL) and bearing temperature (Daniyan et al., 2020). Another study using ANN for PdM in the rail industry, which utilised data from wheel bearings, revealed that the RUL for these components was 500 hours over 40 days, providing insights into confidence limits and gradient detection (Daniyan et al., 2020).

In addition to ANN, other popular machine learning algorithms are widely applied in PdM. A study comparing four machine learning methods—Random Forest (RF), Support Vector Machine (SVM), k-Nearest Neighbour (k-NN), and Multi-Layer Perceptron (MLP)—for predicting the condition of water pumps (Normal, Damaged, or Recovery) using sensor data found that the k-NN model produced the highest accuracy in the shortest time (Herrero & Zorrilla, 2022). In another study, the SVM model achieved the highest accuracy (100%) for a dataset with machine damage attributes, outperforming RF and Backpropagation Neural Network (BNN) models in predicting failures based on machine vibrations (Nikfar et al., 2022). PdM for ladle maintenance at an electric steel station proved effective when Decision Trees (DT) and RF were implemented to predict ageing conditions. DT performed better than RF (Vannucci et al., 2022).

Hybrid techniques combine two or more machine learning algorithms and are employed in PdM. These approaches involve integrating various methods within a single model, which may include combinations of machine learning algorithms with non-machine learning methods or multiple machine learning algorithms. For example, research focused on multivariate time series forecasting in PdM combined a Naïve model with statistical methods such as VARMA, Theta, LSTM, GRU, and ERNN to analyse data from various sources, including the Federal Reserve Economic Data (FRED), air quality measurements, appliance forecasts, Beijing PM2.5 levels, and gas turbine CO and NOx emissions. The study found that the VARMA combined model performed the best, while the Naïve and Theta hybrid was the weakest (Tessoni & Amoretti, 2022). Various machine learning models have been applied in PdM to enhance industry efficiency and accuracy. Combining multiple models and hybrid techniques is also gaining attention for improving forecasting accuracy.

This study employs a maintenance dataset from the research "Explainable Artificial Intelligence for Predictive Maintenance Applications" (Matzka, 2020), made publicly available in Kaggle to facilitate further academic inquiry. Although the specific machine from which the data originated is not disclosed, the paper provides a detailed description of the dataset's structure, indicating that it was derived from actual machine operations. The AI4I2020 dataset comprises 14 attributes with diverse characteristics. These attributes are categorised into four types: two ordinal attributes, one categorical attribute, two interval attributes, three numerical attributes, and six binary attributes. This dataset's primary variable of interest is the "Machine failure" attribute, the critical target for predictive modelling. Table 1 summarises the performance of models from previous studies on predictive maintenance using the AI4I2020 dataset. This table also includes the performance of the Naïve Bayes (NB) model using the same dataset, publicly available on the Kaggle website. The results from 12 research papers proposing PdM models based on the AI4I2020 dataset are compared in Table 1. The XGBoost model proposed by Nazara (2022) achieved the highest accuracy score of 0.991. The Balanced K-Star model used by Ghasemkhani et al. (2023) demonstrated the highest values for precision (0.988), sensitivity (0.988), and F1-score (0.988). Gujarati (2021), who employed the NB model, achieved the highest AUC-ROC score of 0.901.

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Table 1: Summary of Models Performance of Naïve Bayes (NB) Model Using the Same Dataset

Research	Model	Accuracy	Precision	Sensitivity	F1-Score	AUC – ROC	AUC-Precision-Sensitivity
(Gaur 2021)	NB	0.785	0.96	0.83	0.88	N/A	N/A
(Ghasemkhani, Aktas & Birant 2023)	*Balanced K-Star*	0.988	0.988	0.988	0.988	N/A	N/A
(Gujarathi 2021)	NB	0.829	0.836	0.823	0.830	0.901	N/A
(Harichandran, Raphael & Mukherjee 2023)	HUS-ML	0.985	~0.850	~0.750	0.791	N/A	N/A
(Iantovics & Enachescu 2022)	*Binary* LGR	0.971	N/A	N/A	N/A	N/A	N/A
(Kodihalli 2021)	NB	0.985	0.682	0.968	0.8	N/A	N/A
(Lallahom 2022)	NB	0.843	0.758	0.144	0.242	0.879	N/A
(Nazara 2022)	XGBoost	0.991	N/A	N/A	N/A	0.972	N/A
(Papathanasiou, Demertzis & Tziritas 2023)	*Random Survival Forest*	0.972	N/A	N/A	N/A	N/A	N/A
(S. K. 2021)	NB	0.789	0.113	0.766	0.196	N/A	N/A
(Sharma et al. 2022)	*Random Forest*	0.984	N/A	N/A	N/A	0.837	N/A
(Shrimant 2021)	NB	0.762	0.103	0.768	0.182	N/A	N/A

This comparative analysis reveals that more sophisticated models, such as Balanced K-Star and XGBoost, outperform simpler models like Naive Bayes. While Naive Bayes provides a good balance between simplicity and computational efficiency, its performance can be significantly lower, as seen in models like Shrimant (2021) and Lallahom (2022). On the other hand, hybrid and more advanced models, particularly XGBoost and Balanced K-Star, demonstrate superior accuracy and F1 scores across multiple studies. These models excel in predictive accuracy and provide better generalization across datasets, making them more suitable for complex real-world predictive maintenance tasks.

Moreover, the Random Forest models from Papathanasiou et al. (2023) and Sharma et al. (2022) offer a competitive alternative with high accuracy and strong AUC values, further emphasizing the importance of selecting the appropriate algorithm based on the dataset and task complexity. The balanced performance of Random Forest models suggests that they remain a reliable choice, particularly when interpretability and computational efficiency are desired alongside predictive power. In summary, the analysis of these models underlines the

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growing relevance of advanced algorithms like XGBoost and Balanced K-Star in predictive maintenance, showcasing their superior performance over traditional models like Naive Bayes. Nonetheless, the application context remains critical in determining the best model choice, as even simpler models may outperform complex ones in specific scenarios, such as when interpretability or computational resources are limited.

Even though, the previous studies indicate that Naive Bayes (NB) is not frequently recommended in Predictive Maintenance (PdM) research utilizing machine learning approaches for officially published datasets. However, broader investigations into machine learning methods in PdM consistently highlight NB as an essential and widely adopted algorithm for various applications. This underscores the necessity for further exploration of NB's potential in PdM, mainly using the AI4I2020 dataset, to enhance understanding and application of the technique in predictive models.

Moreover, several publicly available codes have implemented NB algorithms for PdM model development to predict machine failures using the AI4I2020 dataset Nevertheless, these NB-based implementations often need to fully convert the dataset structure into binary form, which leaves a gap in the literature. This observation points to the need for further research on the binarisation process and its effectiveness when combined with NB techniques in building more robust PdM models using the AI4I2020 dataset for machine failure predictions.

Methodology

The research is divided into two phases as shown in Figure 1. The first phase is aimed at conducting experiments. The second phase involves the analysis of study results along with conclusions.

First Phase: Experimentation Setup

In the first phase, the objective is to apply the steps related to developing a Predictive Maintenance (PdM) model using selected techniques and algorithms.

Data Exploration.

Data exploration will begin by analysing the attributes, their types, data quality, and visualisations for the AI4I2020 synthetic dataset, which contains 10,000 entries with 14 attributes. The dataset's features will be analysed in detail to identify the appropriate steps for processing the dataset in the next step. It also involves selecting suitable processing packages in Python that contain the necessary functions to build the proposed PdM models for this project.

Data Preparation and Feature Engineering

Next, data preparation, such as addressing general data issues like missing values, noise, outliers, imbalanced data, and irrelevant data, will be conducted in this step, followed by binarisation of the study dataset through feature engineering using techniques such as scaling one-hot encoding, binning, and normalisation. Model selection, including using the Naïve Bayes (NB) algorithm with ensemble techniques combining boosting and bagging methods, is one of the activities in this phase. The data will be cleansed and transformed through feature engineering to ensure it is suitable for the experiment. Among the steps are:

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Dimensionality Reduction: To reduce the complexity of the model and improve processing time and accuracy, dimensionality reduction will be applied. A new attribute, Power [W], will be derived by combining Torque and Rotational speed, and these original attributes will be removed.

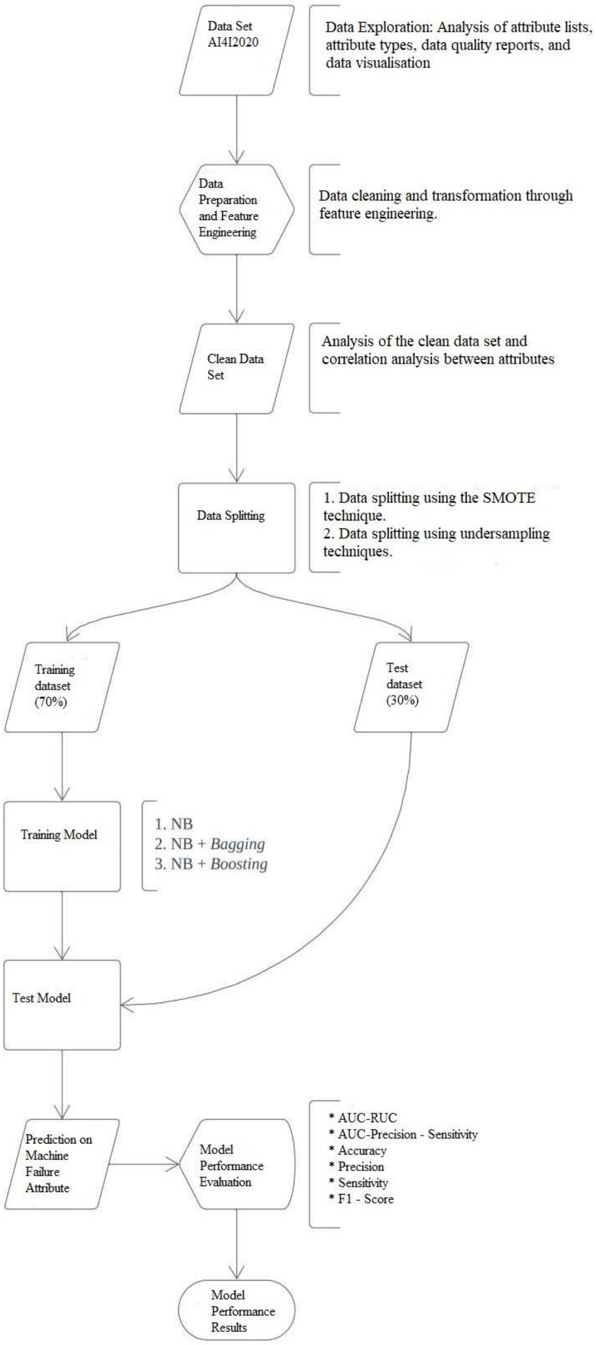

Figure 1: Research Methodology

One-Hot Encoding: To convert Categorical data into binary form. The 'Type' attribute, which has three categories (Low, Medium, High), will be replaced by binary attributes, each representing one of these categories.

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Binning: Continuous data attributes will be binned to simplify the data structure and address issues like outliers and uneven distribution. This technique will be applied to Power [W], Tool wear [min], Process temperature [K], and Air temperature [K].

Binarisation: One-hot encoding will binarise the entire dataset, including continuous attributes after binning, ensuring consistency in data format.
Standardisation: After splitting it into training and testing sets, the dataset will be standardised using the StandardScaler () function from Python.

Clean Dataset Review

The cleaned dataset will be reviewed, and a correlation analysis between attributes will be performed.

Data Splitting

The dataset will be split into training (70%) and testing (30%) sets with SMOTE and under-sampling methods applied before model evaluation to create balanced training models.

Training Models

Three machine learning techniques were selected for use in the training model: Naïve Bayes (NB), NB with Bagging, and NB with Boosting. Six different models, which are the NB model [SMOTE], the NB model with Bagging [SMOTE], the NB model with Boosting [SMOTE], the NB model [Under sampling], the NB model with Bagging [Under sampling], and the NB model with Boosting [Under sampling], will be produced from the use of two data partitioning techniques and the selection of three machine learning methods.

Model Evaluation

The training models will be tested using the test dataset to predict the machine failure attribute. The experimental results from the model performance, consisting of AUC of the ROC curve, AUC of the Precision-Recall curve, F1 Score, Accuracy, Precision, and Recall, will be analysed for the next study phase.

Second Phase: Result Analysis

The final phase of the study involves the analysis of study results and conclusions. This phase aims to analyse the performance of the proposed PdM models at the beginning of this project. Activities in this phase include the analysis of results from the previous phase, including the configuration of the clean dataset that underwent the binarisation process and performance evaluation based on experimental outcomes using the developed models. Another activity in this phase is selecting the best model from the six developed models, which will be used for comparison with previous models. The expected output from this phase includes explanations of the dataset after the data pre-processing steps, a summary based on various performance metrics for the six models built for this project, and a comparison of the best model with previous models from past studies.

Results and Discussion

After undergoing data preparation and feature engineering, the cleaned dataset's structure differs from the original dataset. The cleaned dataset contains 35 attributes, whereas the original dataset had 14 attributes. Additionally, the cleaned dataset only has one type of feature, binary, while the original dataset contains various features. The performance of the models

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developed in this study has been evaluated across several metrics, and the results are summarized in Table 2.

Table 2: Performance of the Developed Models

Model	Accuracy	Precision	Sensitivity	F1-Score	True Label for *Machine Failure* = 0	False Label for *Machine Failure* = 0	True Label for *Machine Failure* = 1	False Label for *Machine Failure* = 1	AUC – ROC	AUC – Precision - Sensitivity
NB [SMOTE]	0.999	1.0	0.968	0.984	2907	0	90	3	0.9794	0.9699
NB + *Bagging* [SMOTE]	0.999	1.0	0.968	0.984	2907	0	90	3	0.9794	0.9699
NB + *Boosting* [SMOTE]	0.929	0.3	0.968	0.458	2697	210	90	3	0.9776	0.9693
NB [Persampelan Terkurang]	0.997	0.927	0.968	0.947	2900	7	90	3	0.9810	0.9361
NB + *Bagging* [Persampelan Terkurang]	0.987	0.714	0.968	0.822	2871	36	90	3	0.9813	0.9707
NB + *Boosting* [Persampelan Terkurang]	0.997	0.927	0.968	0.947	2900	7	90	3	0.9827	0.9343

The NB [SMOTE] model and the NB + Bagging [SMOTE] model demonstrated superior performance, achieving the highest scores in Accuracy (0.999), Precision (1.0), F1-Score (0.984), and the number of actual instances for label 0 (2907). All models achieved identical Sensitivity scores of 0.968. Furthermore, each model could predict machine failure, correctly identifying 90 out of 93 machine failure instances. In terms of the area under the curve (AUC) for the Receiver Operating Characteristic (ROC) curve, the NB + Boosting [Under sampling] model achieved the highest value of 0.9827, followed by the NB + Bagging [Under sampling] model with an AUC of 0.9813. The NB + Bagging [Under sampling] model also obtained the highest AUC for the Precision-Recall curve at 0.9707, with the NB [SMOTE] and NB + Bagging [SMOTE] models close behind, both scoring 0.9699.

Overall, all models exhibited strong performance in predicting machine failure. However, the NB [SMOTE] and NB + Bagging [SMOTE] models were particularly effective, excelling in predicting machine failure and accurately classifying non-failure instances. To compare the best-performing model from this project and prior studies, the NB [SMOTE] model was selected as the optimal model. This selection was based on its balance of strong performance and lower computational complexity, as adding Bagging did not provide a significant performance enhancement over the base model. Table 3 presents a comparative analysis of the NB [SMOTE] proposed model from this study against models from previous research (highlighted in yellow box).

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Table 3: Comparison of the Proposed Model's Performance with Previous Studies

Research	Model	Accuracy	Precision	Sensitivity	F1-Score	AUC – ROC	AUC – Precision - Sensitivity
Proposed Model	**NB + SMOTE**	**0.999**	**1.0**	**0.968**	**0.984**	**0.9794**	**0.9699**
(Gaur 2021)	NB	0.785	0.96	0.83	0.88	N/A	N/A
(Ghasemkhani, Aktas & Birant 2023)	*Balanced K-Star*	0.988	0.988	0.988	0.988	N/A	N/A
(Gujarathi 2021)	NB	0.829	0.836	0.823	0.830	0.901	N/A
(Harichandran, Raphael & Mukherjee 2023)	HUS-ML	0.985	~0.850	~0.750	0.791	N/A	N/A
(Iantovics & Enachescu 2022)	*Binary* LGR	0.971	N/A	N/A	N/A	N/A	N/A
(Kodihalli 2021)	NB	0.985	0.682	0.968	0.8	N/A	N/A
(Lallahom 2022)	NB	0.843	0.758	0.144	0.242	0.879	N/A
(Nazara 2022)	XGBoost	0.991	N/A	N/A	N/A	0.972	N/A
(Papathanasiou, Demertzis & Tziritas 2023)	*Random Survival Forest*	0.972	N/A	N/A	N/A	N/A	N/A
(S. K. 2021)	NB	0.789	0.113	0.766	0.196	N/A	N/A
(Sharma et al. 2022)	*Random Forest*	0.984	N/A	N/A	N/A	0.776	N/A
(Shrimant 2021)	NB	0.762	0.103	0.768	0.182	N/A	N/A

In terms of Accuracy, the proposed NB [SMOTE] model achieved the highest score of 0.999, followed by the XGBoost model by Nazara (2022) with a score of 0.991, and the Balanced K-Star model by Ghasemkhani et al., (2023) with a score of 0. 988.. For Precision, the proposed model also outperformed others with a score of 1.0, followed by the Balanced K-Star model (0.988) and the NB model by Gaur (2021) (0.96). The Balanced K-Star model (Ghasemkhani et al., 2023) achieved the highest Sensitivity at 0.988, while the proposed model and the NB model by Kodihalli (2021) scored 0.968. In terms of F1-Score, the Balanced K-Star model had the highest value (0.988), followed by the proposed model (0.984) and the NB model by Gaur (2021) (0.88). For the AUC of the ROC curve, the proposed model from this study scored the highest at 0.9794, surpassing the XGBoost model by Nazara (2022) with a score of 0.972 and the NB model by Gujarathi (2021) with a score of 0.901. The proposed model also achieved a Precision-Recall AUC of 0.9699, a metric not reported in previous studies. Based on these

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results, it is clear that the NB model developed in this project outperforms models from previous research in terms of Accuracy, Precision, and AUC for both the ROC and Precision-Recall curves. Furthermore, the NB model built in this study exceeds the performance of models shared on Kaggle, particularly regarding Accuracy, Precision, and F1-Score. These findings highlight the efficacy of the proposed model in predicting machine failure.

Conclusion

In conclusion, this research successfully addressed the primary objective of developing a PdM model using binarisation techniques and the NB algorithm to effectively forecasting machine failures using a synthetic dataset. The proposed model demonstrated robust performance, accurately predicting nearly all instances of machine failure. Although the focus was on a machine learning approach utilising binarisation techniques and the Naïve Bayes (NB) algorithm within PdM, the developed model shows potential for broader applications beyond PdM. Several possibilities for future research have been identified. First, applying the proposed models to real-world datasets obtained directly from machines would offer validation of the model's performance in practical settings. Second, expanding the prediction scope to include other failure attributes such as TWF, HDF, PWF, OSF, and RNF could provide further insights into the model's ability to predict more minor system failures. Third, while this study utilised binarisation with the NB algorithm, future work could explore other machine learning algorithms alongside binarisation to assess whether the binarisation technique enhances or hinders performance across different methods. Additionally, future studies should incorporate more advanced data partitioning techniques, such as cross-validation, to allow more comprehensive comparisons with the SMOTE and Under-sampling methods used in this research. Moreover, integrating stacking techniques alongside bagging and boosting, employed in this study, could offer valuable comparisons and improve model performance. Finally, while the binarisation method proved effective for the dataset used in this study, it is essential to acknowledge the potential for information loss inherent in binarisation. To mitigate this, future research should test the method on datasets from machines operating in varying environments and compare their failure predictions with those of the models developed in this study. This will provide a more holistic understanding of the method's effectiveness across different contexts.

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