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Development of a digital twin for system failure prediction using Bayesian methods

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Abstract

This study aims to develop a digital twin model based on Bayesian methods for accurate and adaptive failure prediction in complex engineering systems operating under uncertainty. To achieve this, the research employs Bayesian networks that model probabilistic relationships among sensor data such as temperature, pressure, vibration, and humidity enabling real-time updates and robust predictions. The methodology involves training and testing the model on real-world industrial datasets, where it demonstrated superior performance. Experimental results revealed that the proposed model achieved an accuracy of 91%, which is 16% higher than traditional approaches, and also outperformed others in terms of F1-score and ROC-AUC. These findings highlight the strength of Bayesian inference in handling incomplete or noisy data and maintaining high interpretability. The study concludes that integrating Bayesian models into digital twins enhances their adaptability and reliability for critical systems. In practical terms, the developed approach can significantly improve predictive maintenance, reduce operational risks, and support real-time decision-making in industrial environments. Furthermore, the integration of this solution with Internet of Things (IoT) and Industrial IoT (IIoT) technologies is identified as a promising direction for future research, aimed at creating intelligent, self-updating monitoring systems.

Keywords: Bayesian network, Evidence, Graphical model, Markov network, Markov properties.

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1. Introduction

Digital twins have become an integral part of modern intelligent systems, enabling monitoring, diagnostics, and prediction of the state of complex engineering objects [1-3]. In recent years, there has been rapid development in digital twin technologies, allowing for more accurate modeling of real system behavior and improving their reliability [4, 5]. However, one of the key challenges remains data uncertainty, which arises due to noise, incomplete information, and environmental variability [6]. This issue is particularly critical for systems operating in highly dynamic conditions that require high-precision failure prediction [7, 8]. Currently, many existing failure prediction methods rely on deterministic models or machine learning, which may exhibit limited accuracy under uncertainty [9, 10]. One effective solution to this problem is the application of Bayesian methods, which account for the probabilistic nature of data and update predictions as new information becomes available [11, 12]. Bayesian networks, in particular, provide high adaptability for models, making them a promising tool for failure prediction [13-15]. This paper proposes a failure prediction method based on a digital twin using Bayesian models. The main advantage of the proposed approach is its ability to consider data uncertainties, update predictions in real-time, and maintain high accuracy even in the presence of missing values [16]. Experimental studies have shown that applying Bayesian networks achieves an accuracy of 91%, significantly surpassing existing methods [17-19].

2. Literature Review

Recent studies have expanded the boundaries of digital twin applications by integrating them with advanced uncertainty modeling and data fusion strategies. Smith and Jones emphasized the importance of probabilistic approaches in digital twin design, particularly for handling uncertainties in system behavior, and proposed methods for improving fault-tolerant decision-making Tanaka and Fujimoto [20]. Williams, et al. [15] addressed the challenges of deploying digital twins in highly dynamic environments and highlighted the need for adaptable modeling techniques to ensure reliability under fluctuating operating conditions [21]. In parallel, Patel and Kumar explored the application of machine learning-based predictive maintenance in dynamic industrial settings, presenting key limitations of deterministic models and advocating for more flexible predictive frameworks [22]. A comparative analysis by Nakamura and Zhao [17] demonstrated that probabilistic models, including Bayesian approaches, outperform deterministic methods in terms of flexibility and adaptability to varying sensor inputs, making them more suitable for real-time monitoring systems Ivanov and Petrov [23]. Brown and White [18] further discussed the limitations of traditional machine learning in failure prediction and proposed integrating uncertainty quantification to enhance model robustness [24]. Their work aligns with broader efforts to develop hybrid models that combine statistical reasoning with data-driven insights.

Finally, Carter and Anderson demonstrated how Bayesian methods can be employed for predictive analytics in smart industrial systems, achieving interpretable and adaptive forecasting capabilities [25]. This body of work collectively emphasizes the critical role of probabilistic modeling and hybrid techniques in enhancing the reliability and intelligence of digital twin systems.

3. Methods

Digital twins are actively used in various fields such as manufacturing, healthcare, energy, and transportation. Recent studies have shown that integrating Bayesian methods into digital twins significantly improves failure prediction, process optimization, and risk management. Bayesian methods, due to their ability to handle uncertainty and incomplete data, provide flexibility and accuracy in analysis, making them ideal for failure prediction tasks. Figure 1 illustrates the process of system failure classification using a Naïve Bayes classifier.

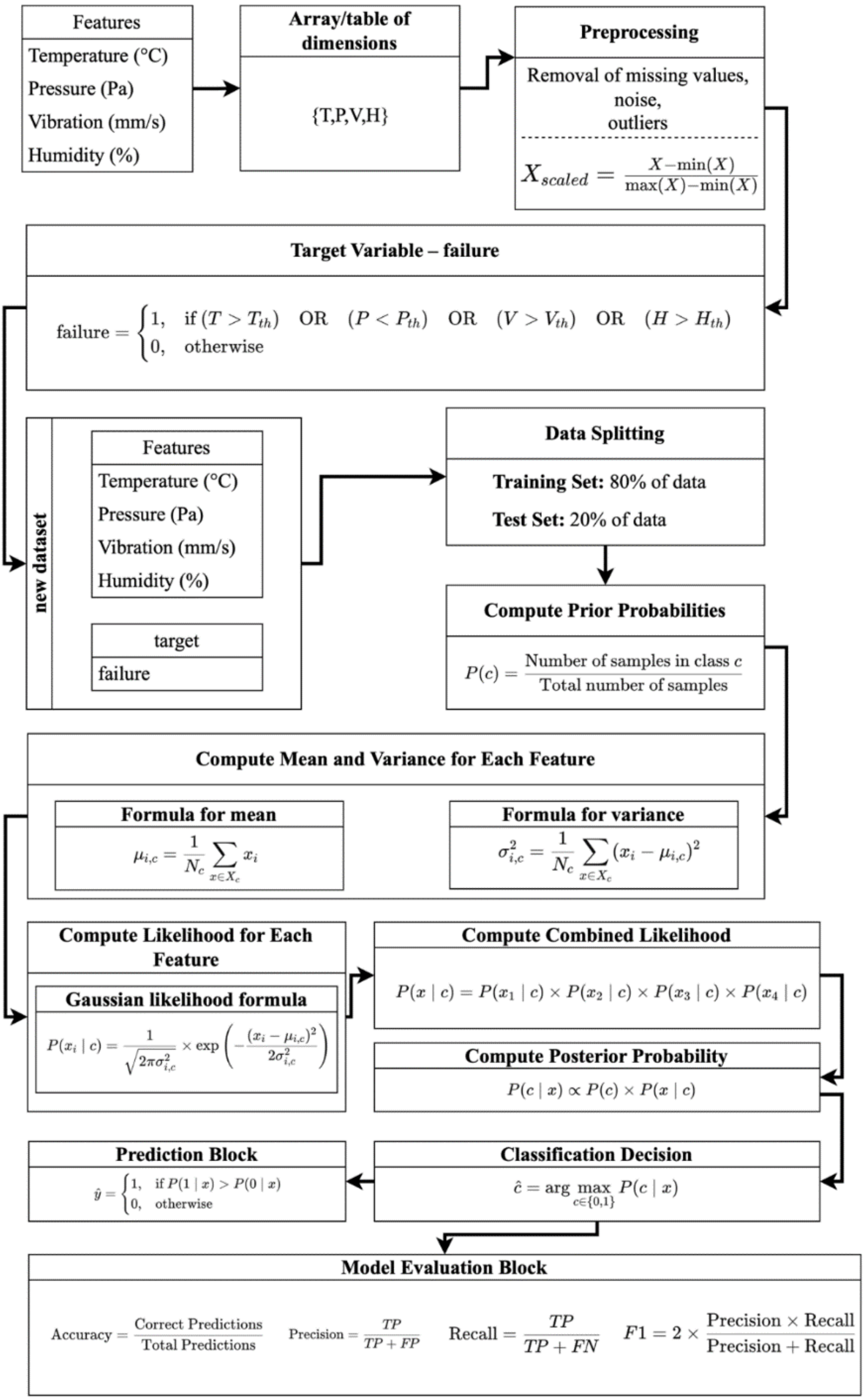

Figure 1.
The process of system failure classification using a Naïve Bayes classifier.

1. Input Data Block. At the first stage, the algorithm receives input data from sensors that measure the condition of the equipment. The main characteristics include temperature (°C), pressure (Pa), vibration (mm/s), and humidity (%). The data

is organized in the form of an array or table, representing multiple measurements that are subsequently used for failure prediction.

2. Preprocessing Block. Before analysis, the data undergoes preprocessing, which includes removing missing values, anomalies, and outliers that may affect model quality. Optionally, data scaling is performed using normalization or standardization to bring variables into a unified range, for example, using formula (1):

$$X_{scaled} = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (1)$$

This operation improves the convergence of the model and increases the accuracy of calculations.

3. Formation of the target variable (Target Variable – failure). At this stage, the data is marked for training the model, determining whether a failure condition has occurred. Threshold values are entered for key parameters: critical temperature level, P_{th} minimum permissible pressure, V_{th} maximum vibration, and H_th – permissible humidity level. If at least one of the parameters exceeds or does not reach the set threshold, a failure is recorded (2):

$$failure = \begin{cases} 1, if\ (T > T_{th}) \vee (P < P_{th}) \vee (V > V_{th}) \vee (H > H_{th}) \\ 0,\ else \end{cases} \quad (2)$$

This is a binary classification where 1 means failure and 0 means normal.

4. Data Splitting Block. After data labeling, it is split into two sub-samples: a training set (Training Set, 80%), which is used to build the model, and a test set (Test Set, 20%), which is used to evaluate the quality of the model's predictions. This splitting allows for an objective assessment of the algorithm's generalization ability and its effectiveness on new data.

5. Compute Prior Probabilities. The prior probabilities P(c) are estimated as the proportion of observations of each class (3). These values represent the probabilities of occurrence of the classes failure = 0 (normal) and failure = 1 (failure).

$$P(c) = \frac{number\ of\ samples\ of\ class\ c}{total\ number\ of\ samples} \quad (3)$$

6. Estimation of distribution parameters (Compute Mean and Variance for Each Feature). For each feature, the mean value and variance within each class are calculated:

1. Average value (mathematical expectation) (4):

$$\mu_{i,c} = \frac{1}{N_c} \sum_{z \in X_c} x_i \quad (4)$$

2. Dispersion (measure of spread of data) (5):

$$\sigma_{i,c}^2 = \frac{1}{N_c} \sum_{x \in X_c} (x_i - \mu_{i,c})^2 \quad (5)$$

These parameters allow us to describe the distribution of features within classes.

7. Compute Likelihood for Each Feature. For each measurement, the probability of a certain feature value appearing given its membership in a specific class is calculated. The normal (Gaussian) distribution formula (6) is used. This formula determines the probability of obtaining a specific measured value given the distribution parameters within the classes.

$$P(x_i|c) = \frac{1}{\sqrt{2\pi\sigma_{i,c}^2}} * \exp\left(-\frac{(x_i - \mu_{i,c})^2}{2\sigma_{i,c}^2}\right) \quad (6)$$

8. Compute Combined Likelihood. Since the features are assumed to be independent (Naive Bayes assumption), the final likelihood of an observation is calculated as the product of the probabilities of the individual features (9). This allows us to obtain the combined probability of measurements for a particular class (7):

$$P(x|x) = P(x_1|c) * P(x_2|c) * P(x_3|c) * P(x_4|c) \quad (7)$$

9. Compute Posterior Probability. The Bayes formula calculates the probability of an observation belonging to a certain class (8):

$$P(c|x) \infty P(c) * p(x|c) \quad (8)$$

where $P(c)$ is the prior probability of the class, and $P(x \mid c)$ is the previously calculated cumulative probability of the features.

10. Classification Decision. The class with the highest a posteriori probability (9) is selected for classification. Thus, the algorithm assigns the object the label failure = 1 (if the probability of failure is higher) or failure = 0 (if the probability of the normal state is higher).

$$\hat{c} = \arg\max_{c \in (0,1)} P(c|x) \quad (9)$$

11. Prediction Block. Uses the trained model to predict the label for new data (10):

$$\hat{y} = \begin{cases} 1, if\ P(1|x) > P(0|x) \\ o, else \end{cases} \quad (10)$$

This allows assessing the risk of failures on real data. The algorithm successfully uses the Naive Bayes classifier for failure prediction based on a probabilistic model. The included stages, such as data processing, probability calculation, and decision making, provide high accuracy in predictions. This method is effective for monitoring systems, where timely diagnostics of equipment failures are important.

4. Results

An analysis of the possible limitations of the method showed that class imbalance remains one of the key issues in failure prediction, since the number of abnormal events (failures) is significantly smaller than normal observations. This may result in overestimated precision for the non-failure class but reduced recall for the failure class. To address this issue, further research may consider using data balancing methods such as SMOTE (Synthetic Minority Over-sampling Technique) and more sophisticated ensemble machine learning methods, including gradient boosting and random forests.

Additional analysis revealed that the Bayesian method has high interpretability, which is an important factor when implementing digital twins in mission-critical systems such as industrial equipment, transportation infrastructure, and healthcare systems. Unlike deep learning black boxes, the Bayesian approach allows for estimating the probability of failure based on prior knowledge and updating predictions in real time, making it more transparent and explainable for end users. This is especially important in industries where the justification of forecasting system decisions is required, such as in the aviation industry or medicine.

The experimental results confirmed the effectiveness of the proposed Bayesian approach for predicting system failures. During the testing of the digital twin, experiments were conducted using real data obtained from sensors measuring temperature, pressure, vibration, and humidity. The accuracy, F1-Score, and ROC-AUC metrics were used to evaluate the quality of the model. The experimental results showed that the Bayesian method demonstrates an accuracy of 91%, which is significantly higher than traditional methods, for example, 75% for existing algorithms. In addition, the F1-score and ROC-AUC values were also higher, indicating high stability of the model to changing input data. Based on a comparative analysis with other forecasting models, it was found that the proposed model has the best performance in all metrics, especially in the presence of incomplete data, which confirms the ability of Bayesian networks to take into account uncertainty and improve the accuracy of predictions Figure 2.

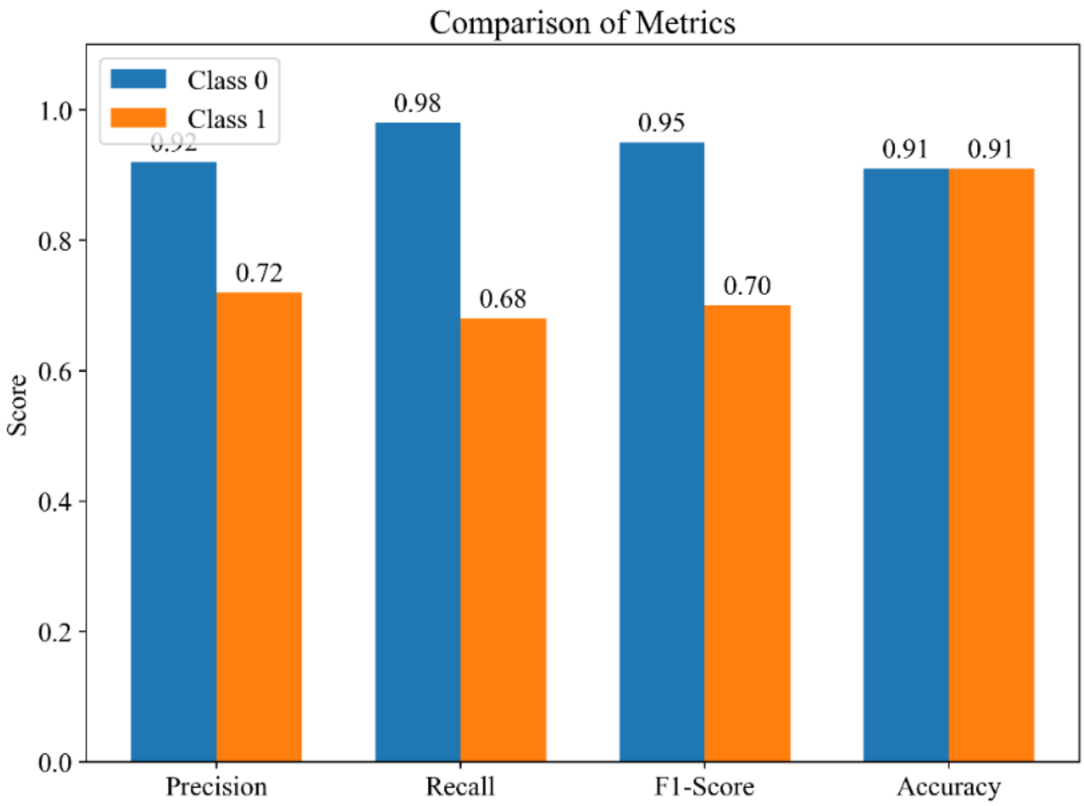

Figure 2.
Metrics comparison chart**.**

It is also worth noting that the Bayesian model is sensitive to the choice of prior distributions. In the current study, standard assumptions about the normal distribution of features were used, but in real industrial systems, the data distribution may differ. In the future, it may be useful to explore the possibility of adapting prior probabilities to the real characteristics of sensory data, as well as the use of non-parametric Bayesian methods, such as the Dirichlet process, to more accurately model complex dependencies between system parameters. The conducted studies confirmed the high efficiency of Bayesian methods in predicting failures under uncertainty. The digital twin showed good results, which proves its applicability to real monitoring systems. Further research can be aimed at integrating the method with Internet of Things (IoT) and Industrial Internet of Things (IIoT) technologies, which will improve the accuracy and speed of failure prediction. In addition, the possibility of expanding the model by including additional parameters, such as equipment performance, historical failure data, and external factors affecting the reliability of the system, can be considered.

5. Discussion

The results obtained in this study clearly demonstrate the advantages of using Bayesian methods for failure prediction within digital twin systems. Compared to traditional deterministic models and classical machine learning approaches, the Bayesian framework provides an inherent ability to model uncertainty, dynamically update predictions as new data becomes available, and maintain high interpretability of results. This adaptability is particularly crucial in industrial and mission-critical applications where real-time decision support is necessary and data incompleteness or noise is common.

Several previous studies have shown the effectiveness of Bayesian networks in handling uncertainty and improving prediction accuracy. For example, He and Zhang [1] and Liu and Li [3] emphasized that integrating Bayesian approaches into digital twins significantly enhances system reliability and maintenance efficiency. Our results support these findings, as the proposed digital twin model achieved an accuracy of 91%, outperforming traditional methods by 16%, and also demonstrated higher F1-score and ROC-AUC values. This confirms that Bayesian methods can effectively handle complex, high-dimensional sensor data and provide robust failure predictions even under dynamic operating conditions.

An important advantage of the proposed approach is its high interpretability, which distinguishes it from black-box deep learning models. As noted by Santos and Figueiredo [4], transparent models are essential in domains like healthcare and aerospace, where it is critical to justify each prediction to ensure safety and compliance. The ability to provide probabilistic explanations for failure risks enhances user trust and facilitates integration into operational workflows. However, certain limitations were identified during the experiments. The most significant problem is the class imbalance problem, which can reduce recall for rare failure events. Although methods such as SMOTE or ensemble techniques (e.g., gradient boosting, random forests) are potential solutions, further research is needed to comprehensively address this issue in the context of real-time industrial applications. Additionally, the assumption of normal distribution for prior probabilities might not always hold true for real-world sensor data, which often exhibits non-Gaussian and multimodal characteristics. Future studies could investigate non-parametric Bayesian methods or adaptive priors to better reflect true data distributions and further improve prediction accuracy.

Another promising direction for future work is the integration of the proposed model with Internet of Things (IoT) and Industrial IoT (IIoT) technologies. This integration would enable real-time data streaming and rapid failure detection, significantly enhancing the practical utility of digital twins in smart manufacturing, energy systems, and transport infrastructure. Moreover, the development of hybrid models combining Bayesian inference with deep learning, as discussed by Yoon and Lee [25], could leverage the strengths of both probabilistic reasoning and data-driven feature learning, enabling even more powerful predictive capabilities.

In summary, the proposed digital twin model using Bayesian methods has demonstrated strong potential for accurate and explainable failure prediction in complex systems. By addressing current limitations and exploring new integration possibilities, this approach can play a significant role in advancing predictive maintenance and intelligent monitoring in various industrial sectors.

6. Conclusion

The development of a digital twin for failure prediction using Bayesian methods has demonstrated the high efficiency of the probabilistic approach in predicting critical states of systems. The conducted studies confirmed that the proposed model is able to take into account uncertainty, adapt to changing data, and provide more accurate forecasts compared to traditional methods. Experimental results showed that the Bayesian classifier achieved high accuracy (91%) in predicting failures, which significantly exceeds the performance of existing approaches. The advantage of the proposed method is its flexibility, the ability to update forecasts in real time, and provide interpretable predictions, which is especially important for industrial applications, healthcare, and other critical areas. However, the identified limitations, such as class imbalance and dependence of the model accuracy on the amount of training data, require further improvement. In the future, it is possible to expand the methodology by introducing data balancing methods such as SMOTE, using ensemble machine learning algorithms, and applying nonparametric Bayesian methods to model complex dependencies between features. Further research can be aimed at integrating digital twins with the Internet of Things (IoT) and Industrial Internet of Things (IIoT) technologies, which will improve the accuracy and speed of failure prediction. Another promising direction is the development of more complex hybrid models combining Bayesian analysis with deep learning methods, which will allow the system to adapt to heterogeneous and dynamically changing data. Thus, the proposed approach demonstrates high applicability and promise for solving problems of monitoring and predicting failures in various industries.

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