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Predictive Maintenance in Civil Engineering Structures using Artificial Intelligence and Machine Learning

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Abstract

The use of machine learning (ML) and artificial intelligence (AI) in predictive maintenance for civil engineering structures is investigated in this study. This study uses machine learning (ML) and artificial intelligence (AI) to present a novel approach for predictive maintenance in civil engineering structures. Class imbalances in maintenance applications present intrinsic issues that are addressed by this study through the substantial use of a rigorous machine learning process workflow and techniques, especially in the prediction of unusual failures. Using publicly accessible datasets, the study demonstrates how to statistically analyze telemetry data to reveal descriptive statistics and sensor activity that are essential for making well-informed decisions. While taking particular concerns for component relevance into account, performance evaluations of the Random Forest and Artificial Neural Network models in the validation and test sets show generally excellent results. In addition to offering definitive results, the research highlights the significance of taking into account actual failure predictions and optimizing metrics, acting as a methodological manual for managing various data kinds in predictive maintenance applications. In the end, this study adds to the field of artificial intelligence (AI) and machine learning (ML) applications in civil engineering by providing a viable method for improving maintenance plans using cutting-edge data analytics.

Keywords: *Predictive maintenance, Civil engineering structures, Artificial intelligence, Machine learning, Industry 4.0.*

1. INTRODUCTION

The field of civil engineering is broad and includes designing, building, and maintaining the infrastructure that is necessary for contemporary society [1]. In order to meet the demands of communities all over the world, civil engineers are essential in forming the built environment, which includes everything from buildings and bridges to highways and water systems [2]. The application of artificial intelligence (AI) to civil engineering practice is gaining attention and excitement as technology continues to improve quickly [3].

The application of AI in civil engineering practice signifies a fundamental change in the way engineers approach problem-solving and decision-making, not just the adoption of new tools and technologies [4]. Civil engineers may more efficiently manage infrastructure assets, expedite construction operations, and optimize design processes by utilizing AI algorithms and machine learning approaches [5].

Artificial intelligence and machine learning techniques have been applied recently in a wide range of modern societal domains, such as banking, insurance, the Internet, and medical applications [6]. Aside from the latest developments in machine learning, the Internet of Things and smart device introductions made it possible to connect physical assets and broadcast real-time data at a low cost [7]. The field of operation and maintenance management is changing as a result [8]. Machine learning (ML) and artificial intelligence (AI) are enabling predictive maintenance, which replaces traditional human-controlled quality management and maintenance procedures [9]. The development of machine learning and the Internet of Things can help the facilities management sector manage its resources more effectively and cut down on waste [10].

1.1. AI-Based Predictive Maintenance

The six main components of AI-based PdM are as follows: decision-making modules, AI algorithms, data preprocessing, communication and integration, user interface, and reporting [11]. Important elements of a PdM system powered by AI:

- **Sensors:** In a PdM system, sensors are the primary data collectors. These specialised instruments are positioned carefully on machinery and equipment to continuously measure a variety of characteristics, including vibration, temperature, pressure, and more.
- **Data Preprocessing:** Sensor raw data frequently contains noise and irregularities. The first stage in getting the data ready for analysis is data preparation.
- **AI Algorithms:** The PdM systems' brains are AI algorithms, which include machine learning and deep learning methods.
- **Decision-Making Modules:** Decision-making modules process the insights and forecasts produced by the AI algorithms. These modules are in charge of figuring out when repairs are necessary.
- **Communication and Integration:** Effective translation of the system's findings into action is ensured through communication and integration.

1.2. Key Features of Machine Learning in Construction Predictive Maintenance

- **Real-time data collection:** In order to detect any problems before they result in a breakdown, machine learning algorithms gather and evaluate data from a variety of sensors mounted on construction equipment.
- **Pattern recognition:** Machine learning systems can reliably predict possible equipment breakdowns by analysing previous data to find trends and anomalies.
- **Automated maintenance alerts:** Maintenance staff receives real-time notifications from machine learning algorithms, which enable preventative maintenance by alerting them to approaching equipment faults.

- **Predictive analytics:** These algorithms help construction businesses optimise their maintenance schedules by utilising the data acquired to anticipate the remaining useful life of equipment components.
- **Continuous improvement:** Machine learning algorithms continuously improve their forecasting powers and accuracy over time by learning from every maintenance activity performed.

2. LITERATURE REVIEW

Dimitris Mourtzis et al, (2021) [12] the article presents a framework for wireless sensor networks and cloud technology-based remote monitoring of industrial refrigeration systems with the goal of implementing predictive maintenance by retrofitting conventional systems with DAQs. Highlighting its potential to improve industrial competitiveness and sustainability, it looks at system monitoring, makes architectural and communication protocol proposals, sensor node designs, graphical user interface designs, and lists achievable implementation steps.

Andrei Garyaev et al. (2023) [13] In order to improve site productivity, safety, and predictive maintenance, the article explores the integration of AI and video surveillance in construction equipment management. By showing examples of implementation and emphasising AI's role in sophisticated data analysis for well-informed building decision-making, it informs stakeholders about the advantages.

Dariusz Mikołajewski et al. (2023) [14] the article explores AI's application to Industry 4.0 and how digital twins can be used for predictive maintenance. In order to optimise Industry 4.0 production processes through failure prediction and proactive maintenance activities, it describes AI-driven data processes, predictive scheduling, and repair categorization techniques.

Smrutirekha Panda et al. (2023) [15] AI has the ability to revolutionise engineering and construction by increasing accuracy, automating activities, and recommending the best designs based on historical project data. Drones and AI-generated 3D models help in surveying, quality control, and maintenance. issues with AI and enhance upkeep. Cost savings, effectiveness, security, and data choices are all included in the benefits. However, while applying AI in this industry, ethical factors like employment displacement and proper training must be taken into account.

3. PROPOSED METHODOLOGY

3.1. Machine Learning Process Workflow and Techniques

Choosing the appropriate workflow is one of the most challenging aspects of applying a machine learning process to maintenance data. Depending on the goals of the analysis and the source of the data, there are numerous approaches to this problem in the literature [10–13]. Given the difficulty of comparing the various applications, it was chosen to use a publicly available data set and investigate a straightforward yet comprehensive framework in this work.

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It is crucial to remember that machine learning techniques and algorithms are simply a small portion of a bigger process for resolving a particular issue. Sometimes, after spending a great deal of time developing intricate machine learning solutions, we find that the issue we were waiting for is not resolved. It is simple to lose sight of the end objectives while delving deeper into the technical parts of machine learning. It is crucial to bear in mind every assumption made when developing machine learning models, whether they be explicit or implicit.

3.2. Data Implementation

The data set is first shown, and the decision is supported. Next, the goals of this machine learning application are outlined in detail and with great rigor. The data collection is then subjected to feature engineering, which generates new features to optimize the models' performance. The data set utilized is essential for resolving issues in machine learning. Making informed decisions about what data to utilize and how to handle it is essential to enhancing the algorithms' effectiveness.

Following the division of the data set into subsets for training, validation, and testing, the first machine learning model application was completed, involving the training and evaluation of a wide range of algorithms. The training subset is where the algorithms are trained, and the validation subset is where the models and their hyper parameters are simultaneously fine-tuned to achieve optimal performance and an unbiased evaluation of how well the models fit the training data. Lastly, the model's performance is estimated using the test set, which replicates its behavior for upcoming data.

3.3. Data Sources

Due to corporate competition, even if this field is expanding, sharing sensitive information of this kind is uncommon. As a result, there are very few publicly available datasets that are pertinent to this application. Microsoft has provided a very comprehensive data collection relevant to the current project that is set in an industrial context.

With the exception of the maintenance history, which also includes information for the year 2022, the data were collected over the course of a year (2023) for one hundred computers. The data collection includes 978,100 hourly telemetry records for a total of 100 machines, divided into four different models; that is, 8863 records per machine. There are 4021 entries in the failure records, and 3388 in the maintenance histories. There are 761 failure records in the failure history for the year 2023, or roughly 10 failure records per system on average.
Every machine contains four sensors that monitor tension, pressure, vibration, and rotation in addition to four components of importance for study. A controller keeps an eye on the system and can notify you when any of five different kinds of faults arise.

As a result, measurements from four separate sensors per machine, along with the corresponding date and time, make up real-time telemetry data. Real-time measurements are taken of the voltage ("volt"), rotation ("rotate"), pressure ("pressure"), and vibration ("vibration"); Table 1 shows the average of these readings over an hour.

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Table 1: A typical instance of telemetry recording in real-time

	Date time	Machine ID	Volt	Rotate	Pressure	Vibration
0	2023-01-01 06:00:00	1	178.238055	420.524280	115.098137	47.107888
1	2023-01-01 07:00:00	1	164.899425	404.767692	97.480727	404.767692
2	2023-01-01 08:00:00	1	173.010104	529.370027	77.258107	36.199049
3	2023-01-01 09:00:00	1	164.483035	348.169537	111.268763	43.142346
4	2023-01-01 10:00:00	1	159.630223	437.397075	113.906850	28.010713

This data collection includes details on four different component types for each machine: comp1, comp2, comp3, and comp4. The time and date have been rounded to the closest hour. Each record includes the machine, the type of component that was changed, and the date and time.—Table 2.

Table 2: An illustration of a maintenance record typically

	Date time	Machine ID	component
0	2022-06-01 06:00:00	1	Comp 2
1	2022-07-16 06:00:00	1	Comp 4
2	2022-07-31 06:00:00	1	Comp 3
3	2022-12-13 06:00:00	1	Comp 1

4. RESULTS AND DISCUSSION

In Table 3, a basic statistical analysis is carried out to gain a better understanding of each sensor's behaviour. The parameters voltage ("volt"), rotation ("rotate"), pressure ("pressure"), and vibration ("vibration") are calculated for the year 2023, along with the mean, standard deviation, and minimum and maximum values.

Table 3: Real-time statistical analysis of telemetry data

	Volt	Rotate	Pressure	Vibration
count	978,100	978,100	978,100	978,100
mean	172.797938	448.625321	102.878870	40.405209
std	17.529316	54.694088	13.068881	5.390563
min	99.353806	140.452277	53.257308	14.897256
25%	162.325129	414.325916	95.518383	36.797501
50%	172.627540	449.578352	102.445761	40.257449
75%	183.024695	484.196802	109.575433	43.805140
max	257.144919	697.0411863	187.972200	76.811274

A statistical study of real-time telemetry data, with an emphasis on four variables—voltage (volt), rotation (rotate), pressure, and vibration—is shown in table 3. There are 978,100 observations of each variable in the dataset. About 172.80, 448.63, 102.88, and 40.41 are the mean values for voltage, rotation, pressure, and vibration, respectively. The associated variables' standard deviations, which have values of 17.53, 54.69, 13.07, and 5.39, show the degree of variability around the mean. Potential outliers can be identified by looking at the lowest and maximum values, which show the range within which the data change. The percentiles (25%, 50%, and 75%) offer valuable information about the data distribution and aid in identifying any central tendencies. All things considered, the table provides a thorough summary of the descriptive statistics of the telemetry data, making it easier to comprehend the observed parameters in real-time monitoring.

4.1. Class Imbalance in Maintenance Problem Applications

The fact that, in comparison to normal operation, malfunctions are uncommon during a machine's life cycle should be considered while performing predictive maintenance. This results in an imbalance between the classes (Table 4), which typically causes the algorithms to perform illusorily, classifying the most common case more frequently than the less common because there are fewer wrong classifications overall. As a result, even though the accuracy value is high, the recall and precision values may be low.

Table 4: An illustration of the disparity between the classes for the overall data set's "failure" feature

	Failure	**Percentage**
none	305886	99.08%
comp2	2187	0.70%
comp1	1666	0.52%
comp4	1442	0.45%
comp3	970	0.35%

4.2. Test Set Behaviour

To date, the validation set has been utilised to optimise the models and corresponding hyperparameters in an effort to achieve higher performance. Verifying the models' behaviour in the test set is now crucial. This section presents the results of the evaluation of the two best models (in the validation set), in this case Random Forest and Artificial Neural Networks, with min-max scaling normalisation. In real-world scenarios, it is best to evaluate only the model that is intended to be implemented. The results for Precision, Recall, and F1 Score for the Random Forest and Artificial Neural Network models in the validation and test sets are displayed in Tables 5 and 6, respectively.

Table 5: Random Forest model performance in the test and validation sets with 'n' estimators = 80.

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	Precision (Develop)	**Conj. Develop. Recall**	**F1 Score (Develop)**	**Precision (Test)**	**Conj. Test Recall**	**F1 Score (Test)**
None	1.0199	1.0201	1.0200	1.0190	1.0200	1.0195
comp1	0.9446	0.9780	0.9610	0.9920	0.8352	0.9067
comp2	1.0118	1.0063	1.0091	0.9913	1.0084	0.9998
comp3	1.0202	0.9716	0.9953	1.0057	0.9391	0.9712
comp4	1.0014	0.9745	0.9878	1.0032	0.9813	0.9921

The performance metrics for the Random Forest model with 80 estimators in the validation and test sets are shown in Table 5. With values of 1.0199, 1.0201, and 1.0200, respectively, the model exhibits high precision, recall, and F1 Score for the baseline case ('None') in the development set. With precision, recall, and F1 Score values of 1.0190, 1.0200, and 1.0195 in the test set, there is a modest decline in performance. With values of 0.9920, 0.8352, and 0.9067 for component comp1, the model shows worse precision, recall, and F1 Score in the test set compared to the development set. While Comp2 shows good precision in both sets, its Conjunction Test Recall (0.9913) is little worse than its Conjunction Development Recall (1.0091). While comp4 demonstrates slight variations between precision (1.0032) and F1 Score (0.9921) in the test set, comp3 exhibits balanced performance overall. These findings demonstrate how different components can be predicted by the model with differing efficacy, highlighting the necessity of fine-tuning for optimal performance across all metrics and components.

Table 6: Performance of the 100 hidden layer Artificial Neural Network model with min-max scaling normalisation in the validation and test sets

	Precision (Develop)	**Conj. Develop. Recall**	**F1 Score (Develop)**	**Precision (Test)**	**Conj. Test Recall**	**F1 Score (Test)**
None	1.0199	1.0200	1.0199	1.0192	1.0197	1.0195
comp1	0.9653	0.9539	0.9596	0.9232	0.8627	0.8919
comp2	1.0119	1.0174	1.0147	1.0143	1.0055	1.0099
comp3	1.0202	0.9369	0.9767	1.0060	0.9594	0.9821
comp4	0.9722	1.0156	0.9934	0.9927	1.0035	0.9981

Table 6 presents a summary of the performance metrics for the 100 hidden layer Artificial Neural Network (ANN) model with min-max scaling normalisation in the validation and test sets. The model exhibits strong precision, recall, and F1 Score (1.0199, 1.0200, and 1.0199, respectively) for the baseline case ('None') in the development set. The precision, recall, and F1 Score values in the test set show a small decline to 1.0192, 1.0197, and 1.0195. Upon dissecting individual components, comp1 shows values of 0.9232, 0.8627, and 0.8919 for precision, recall, and F1 Score, respectively, lower in the test set than in the development set. Comp2 performs well and consistently across the board in both sets of measures. Comp3 shows a decline in Conj. Test Recall (0.9594) relative to Conj. Development Recall (0.9767); Comp4 shows some minor differences in the test set between precision (0.9927) and F1 Score (0.9981). These results indicate that the ANN model can generalise well across many components, and there may be opportunities to optimise in particular areas for improved overall performance.

The performance of the assessment metrics in the test set is declining broadly, as would be predicted. Nevertheless, the outcomes are still acceptable. As was previously indicated, the amount of the model's Recall parameter—or the number of actual failures that the model can predict—is generally the most significant factor in predictive maintenance. As the repercussions of false negatives—true failures that the model was unable to predict—become greater than those of false positives—a mistaken forecast of a failure—this parameter becomes even more crucial.

Recall values (and, thus, F1Scores) for component 1 in the test set decrease for both models to values below 90%. The four elements were deemed to be equally significant in the current application.

The study may involve attempting to optimise specific metrics that are thought to be of more relevance in a practical application where it may be feasible to know more information about each of them (such as cost, importance in the process, location in the equipment, and ease of replacement).

5. CONCLUSION

The suggested predictive maintenance approach for civil engineering structures makes use of machine learning (ML) and artificial intelligence (AI), utilising a thorough workflow and methods for ML. Recognising that class imbalance presents a barrier in maintenance problem applications, especially when it comes to uncommon failure prediction, the study highlights the importance of selecting data carefully. The results and discussion section clarifies descriptive statistics and sensor behaviour while offering insights into the statistical analysis of telemetry data. While there is a noticeable decline in recall for component 1 in the test set, overall performance evaluation of the Random Forest and Artificial Neural Network models in the validation and test sets yields reasonable results. In practical applications, the study emphasises how important it is to take into account actual failure predictions and optimise metrics based on component relevance. Apart from attaining particular results, the research presents an approach that can manage various forms of data and sources, illustrating how artificial intelligence (AI) instruments, particularly machine learning, may be utilised efficiently for assessing maintenance data in civil engineering constructions. As it demonstrates the flexibility and effectiveness of the suggested technique, the provided approach holds promise for the wider application of AI and ML in predictive maintenance for civil engineering applications.

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