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IDENTIFICATION OF THE CAUSES OF PRODUCTION EQUIPMENT FAILURE USING MACHINE LEARNING METHODS – A CASE STUDY

Izabela ROJEK[1], Małgorzata JASIULEWICZ-KACZMAREK[2*], Mariusz PIECHOWSKI[3], Dariusz MIKOŁAJEWSKI[4]

[1] Faculty of Computer Science, Kazimierz Wielki University, Bydgoszcz; izabela.rojek@ukw.edu.pl, ORCID: 0000-0002-9958-6579
[2] Faculty of Engineering Management, Poznan University of Technology in Poznan; malgorzata.jasiulewicz-kaczmarek@put.poznan.pl, ORCID: 0000-0002-8332-3192
[3] Faculty of Engineering Management, WSB Merito Univeristy of Poznań; mariusz.piechowski@wsb.poznan.pl, ORCID: 0000-0002-8518-5336
[4] Faculty of Computer Science, Kazimierz Wielki University, Bydgoszcz; dariusz.mikolajewski@ukw.edu.pl, ORCID: 0000-0003-4157-2796
* Correspondence author

Purpose: This paper aims to present the possibility of using decision tree (DT) to increase the efficiency and effectiveness of maintenance activities by identifying the probable cause of failure based on historical data.
Design/methodology/approach: This study used classifiers based on General Chi-square Automatic Interaction Detector (CHAID) and random forests. Using this group of classifiers brings with it faster u performance, the possibility to process symbolic data directly, and the possibility to add a tree as part of interactive tree building. A separate tree was built for each input parameter to aggregate the results from both trees by considering them together. The proposed solution also analyzes the importance of features (input data).
Findings: Based on the research conducted, we have shown that using ML techniques can improve the accuracy of decisions regarding the type of maintenance work that should be carried out to efficiently and effectively remove failures and reduce losses caused by machine downtime.
Research limitations/implications: The research is worth extending to use other novel artificial intelligence methods to compare the developed models. A limitation was the amount of data. As new data becomes available, the developed models should be trained to respond to the new data and better adapt to it.
Practical implications: Relatively simple AI-based solutions such as CHAID and random forests have yielded fairly high accuracy with very short execution times. Within edge processing, this fulfills the complex trade-off between accuracy and speed in predictive maintenance applications. The presented families of simple algorithms should be developed as a transparent source of opinion for industrial decision-making processes.
Originality/value: What is new is the automation of maintenance activities by identifying the probable cause of failure using AI methods. The solution is aimed at company employees who diagnose the causes of failure, ultimately improving the accuracy and speed of diagnostics and service response.

Keywords: data-driven maintenance, decision-making, machine learning, CHAID decision tree, random forests.
Category of the paper: Case study.

1. Introduction

Maintenance management involves organizing resources to deal with the problems of maintaining production equipment and obtaining maximum benefits from the decisions made. Maintenance decision-making includes but is not limited to selecting maintenance strategies, setting maintenance priorities, scheduling work orders, etc. Computerized maintenance management systems (CMMS) are commonly used to support maintenance management processes. These systems enable integrating related data on equipment, work performed and costs, spare parts suppliers, and inventory to manage maintenance workflows, including proactive maintenance planning, reactive maintenance ordering, order fulfillment tracking, and maintenance performance benchmarking.

However, few CMMS systems on the market provide decision-making capabilities, so maintenance personnel must make decisions based on their experience, the information in the operator's system event report and/or maintenance manual, or a combination thereof. This empirical approach to decision-making usually does not produce the expected results. Poor decisions can result in unnecessary or inappropriate maintenance, inefficient use of human resources and time, and unnecessary spare parts purchases.

The operational data collected in CMMS systems is significant and large enough to be used to make decisions regarding the scope and frequency of preventive maintenance. However, if a decision is made about reactive actions (i.e., actions taken after a failure), appropriate analysis of historical data in connection with the information contained in the failure report in the CMMS system will enable better resource allocation and shorten the service implementation time. Historical data contains information about emergency events that occurred on the production line, their causes, and actions taken. With this data, it is possible to automate decision-making processes based on a data-driven approach.

Data-driven approaches, particularly machine learning (ML), are attracting attention (Bousdekis et al., 2021; Justus et al., 2024). The concept of ML is not new, but it still enjoys great interest. Thanks to advances in algorithms, computing power, inexpensive memory, and large amounts of data, recent years have seen a significant increase in the applicability of ML in various areas of engineering practice, such as maintenance processes (Çınar et al., 2020; Cline et al., 2017; Arena et al., 2022; Nguyen et al., 2022; Antosz et al., 2023; Vanderschueren et al., 2023). According to Quatrini et al. (2020), “by using ML tools it is possible to discover the relationship between different factors and analyze the degree of influence of related variables”. ML-based approaches can be applied to high-dimensional and unstructured data and extract hidden relationships within data in the manufacturing environment.

Decision tree (DT) and random forest (RF) models are important ML tools for decision analysis due to their visualization and interpretability features (Kaparthi, Bumblauskas, 2020; Amruthnath Gupta, 2019; Misaii et al., 2022). The article aims to present the possibility of using DT and RF to increase the efficiency and effectiveness of maintenance activities by identifying the probable cause of a failure based on historical data stored in the enterprise's CMMS system.

The paper is structured as follows: Section 2 provides literature reviews. Section 3 explains the methods and materials used in the study. Section 4 presents the study's results. Finally, Section 5 presents the conclusions of this research.

2. Background

Maintenance is defined as “a set of all technical, organizational, and managerial activities during the life cycle of an object, the purpose of which is to maintain or renew the state in which it can be used to fulfill the required function” (EN 13306: 2017). Maintenance plays an important role in every manufacturing company, and its costs, depending on the industry, may constitute a significant percentage of the company's production costs (Rebaiaia, Ait-Kadi, 2023).

Effective and efficient implementation of maintenance processes allows you to achieve numerous benefits, including reduced operating costs, stable level of product quality, reduced environmental impact (e.g., energy consumption, consumables), and more efficient use of resources (Hallioui et al., 2023). Maintenance management professionals implement various maintenance strategies to avoid unexpected production downtime and increase the efficiency of production assets (Mahmud et al., 2024; Gatta et al., 2024). Broadly speaking, maintenance strategies can be divided into three main categories: corrective, preventive, and predictive maintenance. In reactive strategy, maintenance actions are taken when anomalies or failures occur. This approach leads to high costs of unexpected production downtime. Additionally, emergency repairs often require expedited parts shipping, overtime costs, and higher service fees from third-party vendors, further increasing overall expenses. Preventive maintenance (PM) is “carried out intended to assess and/or to mitigate degradation and reduce the probability of failure of an item” (EN 13306:2017). PM can be considered the most common maintenance policy in which a system is maintained preventively at set intervals regardless of the system's failure history. Despite the various benefits that PM can bring, there are many shortcomings, which result mainly from the fact that maintenance activities are generally carried out prematurely, resulting in reduced availability and increased costs (Polenghi et al., 2023).

As modern production systems become increasingly complex and involve highly interconnected machines, traditional maintenance strategies (reactive and preventive) are insufficient. The answer to these challenges is a predictive maintenance strategy supported by the development of digital technologies (Pinciroli et al., 2023; Sanchez-Londono et al., 2023; Wanget al., 2023). Maintenance is an area that can benefit the most from digitalization (Shaheen, Németh, 2022; Saihi et al., 2023) because acquiring and processing data from both machines and the environment in which the production process is carried out can significantly improve maintenance decision-making processes. Regardless of the maintenance strategies adopted in the company, historical data on emergency events, maintenance activities undertaken and their effectiveness are very important. In the case of reactive maintenance, the response time is important, i.e. the time from reporting the incident by the operator to taking corrective actions. The length of this time depends on the quality of the information contained in the notification, as it allows for the identification of the job, the estimation of the required labor force, the identification of spare parts, and the determination of whether and what tools are needed. Analysis of the data contained in the CMMS system allows you to make the right decision and shorten both the response time and the service implementation time.

Concerning the preventive strategy, it is important to define the plan and schedule of maintenance interventions (e.g., time intervals and scopes of individual services) so that they are not performed in excessive amounts and scope. Availability of resources must also be ensured. According to Campbell et al. (2015), planning determines what needs to be done, in what order, and with what skills. The degree to which companies can derive value from data processing and draw actionable conclusions can be an important factor in improving production processes, reducing costs and resource consumption, and thus meeting customer demands.

According to (Carvalho et al., 2019; Emmanouilidis, 2023), one of the promising tools in the proactive maintenance approaches is machine learning (ML) methods. Machine learning is defined as "a set of methodologies and algorithms capable of extracting knowledge from data, and continuously improving their capabilities, by learning from experience (i.e., from data accumulating over time)" (Bertolini et al., 2021). According to Ruiz-Sarmiento et al. (2020), ML techniques "are data-driven approaches that find complex and non-linear patterns in data and build models from them that can be used for prediction, detection, classification or regression". The literature analysis indicates that the use of ML models in maintenance is becoming more and more popular (Dalzochio et al., 2020; Campos et al., 2019; Abidi et al., 2022; Surucu et al., 2023; Arena et al., 2022; Alsina et al., 2018; Alvarez Quiñones et al., 2023; Chakroun et al., 2024). Decision trees and random forest models are important tools in machine learning.

3. Material and methods

3.1. Problem statement

The present study covered a medical device company. To formulate the research problem, it was assumed that the response time (i.e. the time that elapses from the notification of a failure to the start of the repair process of a localized damaged technical object) is a key indicator of the effectiveness of maintenance activities and translates into the economic efficiency of the enterprise (downtime is a loss). For the aforementioned reasons, particular emphasis should be placed on effectively reducing the aforementioned response time. This is important not only for reducing machine downtime itself but consequently also for optimizing the production process as a whole. To minimize the response time, several preventive measures are taken, starting with maintaining an adequate number and level of training of maintenance services, ensuring monitoring and rapid alarming of equipment anomalies and failures that have occurred, to the rapid and accurate identification and classification of the causes of failures, determining the human resources, tools, materials, and spare parts required for their removal. Mistakes or delays in the latter activities (e.g., the location and identification of failure causes) can significantly affect the efficiency of maintenance operations. The consequences can be costly, leading not only to increased machine downtime but also to increased repair and downtime costs. For the aforementioned reasons, solutions that explore, support, and automate this area are scientifically and economically important. Effective methods and tools, including AI-based ones, are constantly being sought to support human service decision-makers with easier, faster, more efficient maintenance activities using prediction and/or classification. For the aforementioned reasons, ML is increasingly used to speed up failure identification and diagnosis processes.

3.2. Data set

The company under study uses a CMMS system and operators enter emergency reports into it. The emergency event thus entered is described in a uniform procedure using line segment, unit, component, and type of failure. In this way, it is possible to identify where the failure occurred. As part of the same procedure, information on the cause of the failure, the extent of the maintenance work carried out (this may be only adjustment, for example), and the resources involved are entered into the CMMS after the failure has been rectified. These are entered post-hoc by the maintenance technicians.

In the study, the computational analyses were based on actual data over 18 months from the company studied. The data comprised 5000 occurring failure reports and the maintenance staff's associated responses (service actions). The following input parameters were assumed:

- line segment,
- unit,
- component,
- type of failure.

It was also assumed that the following output parameters would be used in the system:

- task type,
- type of repair.

This treatment of the data set enabled the design and testing of the computational tools presented next.

3.3. Statistical and Computational Methods

In this study, Statistica 13 software (StatSoft Power Solutions Inc., Tulsa, USA) was used to perform statistical analyses of the data and develop computational models. This software is relatively often used in scientific research, including the analysis and modelling of industrial issues (Ciężak, Kutyłowska, 2023; Musiał et al., 2023).

Various statistical and computational methods and tools have been used to achieve such a goal (Rojek et. al., 2023; Scaife, 2024). This study used classifiers based on General Chi-square Automatic Interaction Detector (CHAID) and random forests. Using this group of classifiers brings with it faster u performance, the possibility to process symbolic data directly, and the possibility to add a tree as part of interactive tree building. A separate tree was built for each input parameter to aggregate the results from both trees by considering them together. The choice of this solution is based on the need to compromise between the large amount of data to be processed, accuracy, and speed. For the aforementioned reasons, preprocessing or edge processing, i.e., the reduction of the entire input data set to a vector of the most relevant features, is increasingly used, saving computational complexity at the expense of classification accuracy. In our solution, we also applied feature (input data) importance analysis (example for task type: Figure 1).

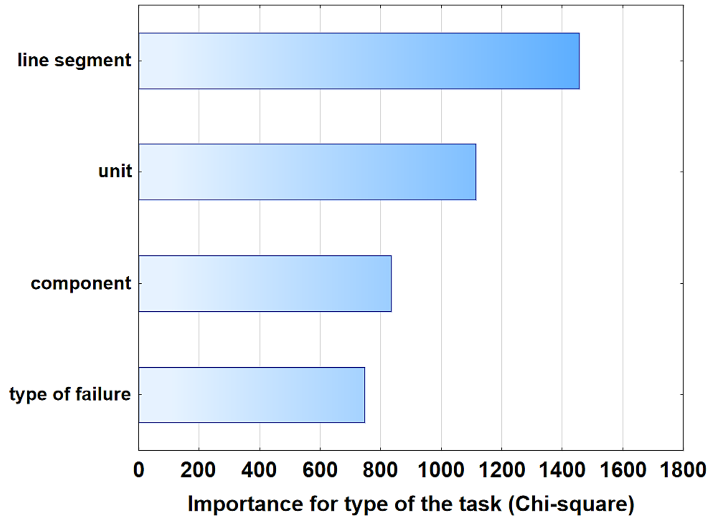

Figure 1. Feature importance for "type of task".

The tree-building algorithm analysis presented below aims to find a set of logical IF partitioning conditions that ensure an unambiguous classification of objects. In this study, we compared the results of two computational methods: CHAID and the random forest algorithm obtained on the studied data set.

CHAID enables the construction of an optimal tree using cross-validation (optional) for classification problems with quantitative and qualitative predictors. The program can determine various statistics of results (predicted classes). For classification, the basis for splitting the node is the chi-square test (p-value with Bonferroni correction). The advantages of this solution include the automatic selection of n-way splits in the node, but the disadvantage is that this approach requires quite large data sets.

The random forest algorithm involves creating and combining many different classification trees. Each tree is created on a random sample of n observations taken with replacement from the training set (bootstrap sample). For classification, random forest is an ensemble ML method that involves constructing many decision trees during training and generating a class - the dominant of the classes of individual trees. In this way, random decision forests improve overfitting to the training set. Random forests provide smoother results with large data sets than traditional decision trees. However, the disadvantage is a certain opacity of decisions: the final decision of the random forest is the average of many independent partial decisions, and it is difficult to simply explain the reasons for making it.

4. Results

4.1. Results for “type of tasks”

In the CHAID tree for “type of task” the number was obtained:

- 5 shared nodes,
- terminal nodes 9 (Figure 2).

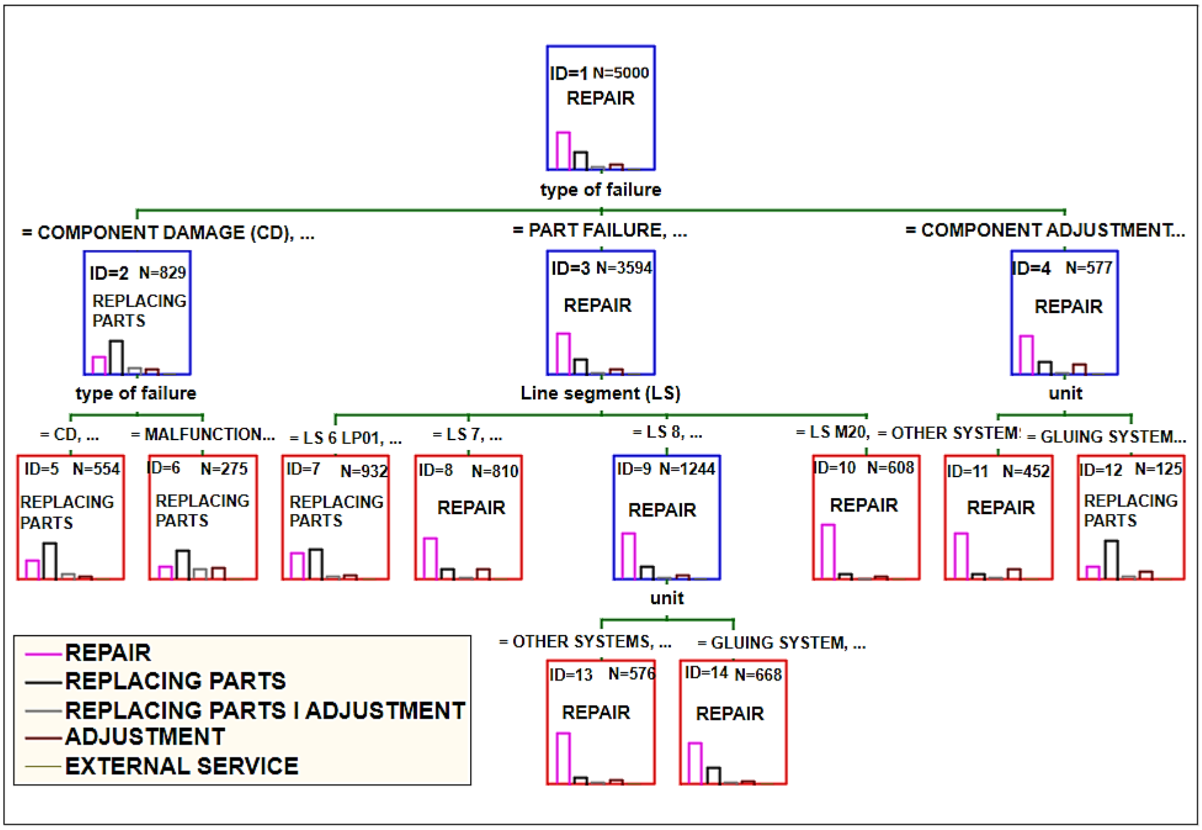

Figure 2. CHAID for “type of task”.

Figure 3 shows the classification matrix showing the frequency of predicted and observed.

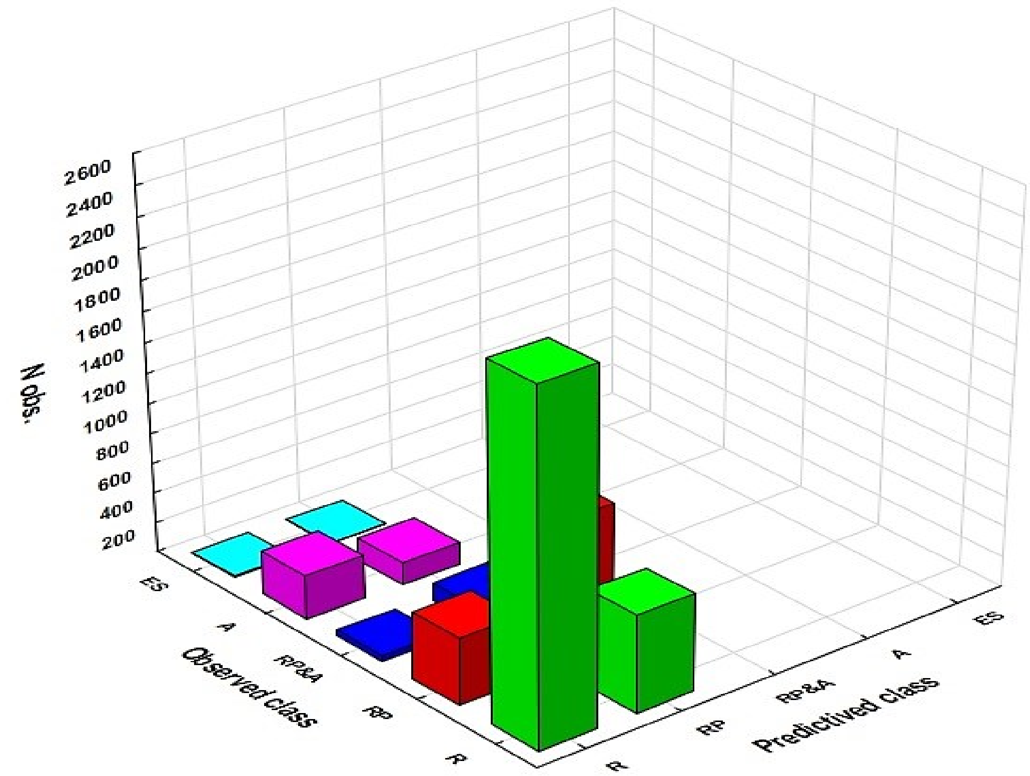

Figure 3. CHAID for “type of task”, where: R- repair, RP – replacing parts, RP&A – replacing parts & adjustment, A – adjustment, ES – external service.

For random forests: the number of trees is 100, maximum tree size is 100 (Figure 4).

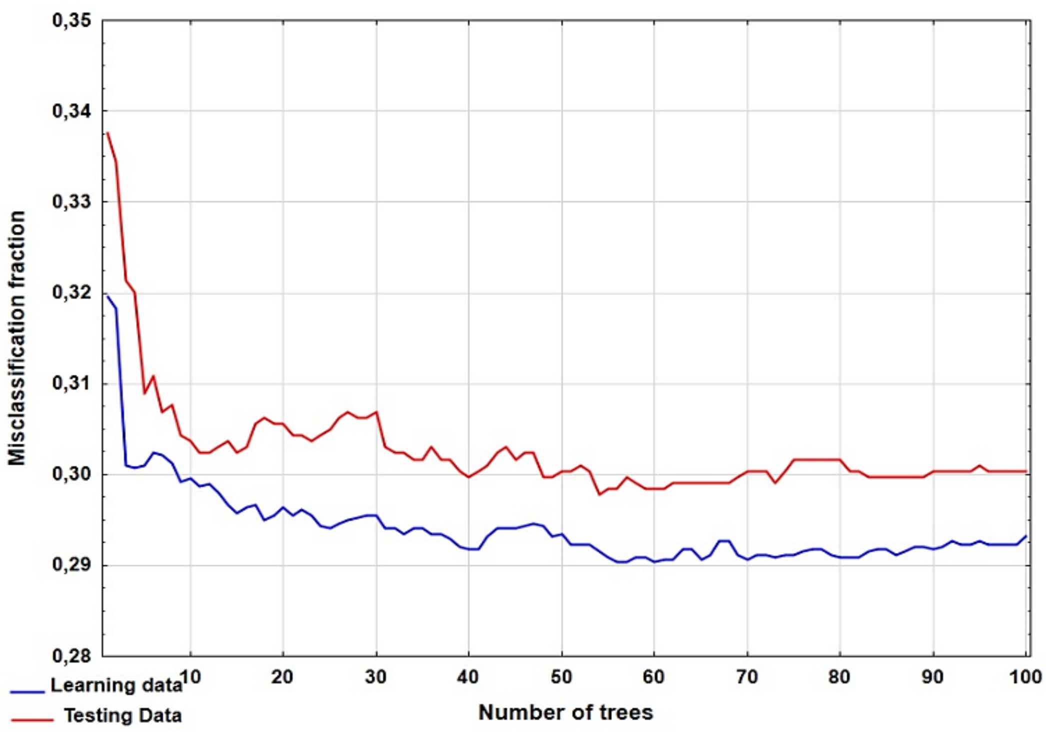

Figure 4. Random forest for “type of task”.

Figure 4 shows the basic mechanism to prevent overfitting. In general, as the model is expanded with additional trees, the share of false predictions in the training sample decreases, and after reaching a certain number of trees, stabilization may occur. However, in the test sample, as the number of trees increases, the share of incorrect predictions first decreases and then may begin to increase. The beginning of an increase in error in the test sample signals overfitting of the model and allows us to select the appropriate level of model complexity. In particular, if the error in the test sample stops decreasing as more trees are added, we may consider stopping the training process.

4.2. Results for “type of repair”

Based on the CHAID tree for “type of repair”, the number of split nodes was 14, and the number of end nodes was 17.

Based on random forests, 100 trees were built, number of branches: 100. Comparison of the classification matrix between CHAID and random forests showed an advantage of the latter method in terms of predicting all “types of repairs” with lower assessment risk (0.262 vs. 0.356), but a larger error (0.007- 0.011 vs. 0.006).

4.3. Comparison of both approaches

The study realized a comparison of the effectiveness of the two approaches (CHAID, random forests) based on a pre-specified set of criteria: accuracy, risk assessment, and error for tasks and repairs. The comparison showed an advantage of random forests in terms of risk assessment, with an advantage of CHAID in terms of error for tasks and repairs for the classified output values: “task type” and “repair type”. The accuracies obtained were similar: 70.75% for “repair type” and 71.46% for “task type”, with the inclusion of feature validity resulting in the previously predicted reduction in classification accuracy to 62.53% for “repair type” and 67.31% for “task type”, but may speed up action (obtaining a decision) where this is critical.

It should be noted that the final solution is the sum of the classifiers' responses by aggregating the solution for both output values: “task type” and “repair type”.

5. Notes in the main text

Modern manufacturing systems are very complex and involve interconnected machines, and an accidental machine failure will not only stop production on a single machine but will also spread throughout the system and cause other machines to be unable to perform their functions at the expected level. Each failure results in downtime and is a loss. If a failure occurs, appropriate action and maintenance must be performed to restore the required machine functions. The downtime depends on how quickly and accurately the cause of the failure is determined. Based on the research, we have shown that using ML techniques can improve the accuracy of decisions regarding the type of maintenance work that should be carried out to efficiently and effectively remove failures and reduce losses caused by machine downtime.

Relatively simple AI-based solutions such as CHAID and random forests have yielded fairly high accuracy with very short execution times, which, within edge processing, fulfills the complex trade-off between accuracy and speed in predictive maintenance applications. The presented families of simple algorithms should be developed as a transparent source of opinion for industrial decision-making processes.

Due to enterprises' need to effectively use their resources and reduce losses, automating the decision-making process regarding identifying the causes of emergency events and determining maintenance works may be of key importance for improving the efficiency of processes in the enterprise. Although the issue of "failure prediction" dominates the literature, we cannot forget about enterprises in which the use of the predictive maintenance approach is limited due to, among others, machine age and implementation costs. However, it should be noted that failures occur in every enterprise, regardless of the chosen maintenance strategy, and the approach presented in the article can reduce losses.

Current research focuses on eliminating the most important limitations of the described solutions, occurring to varying extents and intensity in both described solutions (CHAID and random forests):

- The impact of data set quality and size, particularly by limiting employees' ability to select classifications to drop-down menu items or numerical values.
- Unbalanced data set in classes, especially in the case of training, when one group of failures occurs more often than others or some components are new and simply do not fail for a long time.
- Risk of overfitting, which can be reduced by using hybrid solutions, including random forests.
- Some approaches require real-time response due to data entry and classification duration.

Further research will focus on:

- Comparison of the effectiveness of various ML methods and techniques that can be used to develop the above-mentioned solutions.
- Standardization of data acquisition, collection, and analysis, both from employees and using IIoT.
- Flexibility, adaptation, and combination of solutions according to needs, including depending on the area of application or the form of data (numerical, descriptive) or their characteristics (e.g., predominance of one type of damage).
- Imaging the results of analyses as part of human-machine interaction.

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