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Research paper

Application of machine learning (ML) algorithms in predicting the technical condition of residential buildings

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Abstract: The technical condition of multi-family residential buildings is one of the most important factors determining their aging process. It is most often determined based on the subjective assessment of the assessor without relying on unified criteria. The aim of the article is to propose a systematization of the method of determining the technical condition of buildings using machine learning algorithms. Based on a series of studies in residential buildings erected using traditional technology, a database was created, including characteristic features of individual buildings and their elements, occurring defects and renovation management conducted in individual years. The collected database was used to conduct an analysis using machine learning (ML) algorithms representing various predictive techniques, including Gradient Boosting, Random Forest and k-NN. Statistical analyses were performed for each of the algorithms to confirm the correctness of the estimated models. Variables that have a significant impact on the estimation process for individual algorithms were also determined. The use of machine learning allowed for a significant increase in the objectivity and precision of forecasting the technical condition of buildings. The developed models demonstrate practical potential. It is advisable to extend the research based on a larger database in the future, which may result in even greater accuracy in forecasting the technical condition of residential buildings.

Keywords: technical condition of the building, building renovation, building operation, multi-family residential building, machine learning algorithms, prediction of the technical condition of the building

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1. Introduction

The technical condition of a building is a general description of its current condition, including the various elements of the building, such as foundation walls, structural walls, ceilings, roofs, chimneys, elevations, staircases, basement rooms, technical rooms, installations. This is one of the most important factors determining the aging process of a building. However, it is most often determined by the subjective assessment of the assessor without relying on standardized criteria.

The technical condition directly affects the safety, comfort and value of the property. Correct maintenance of a building's technical condition is important to ensure the safety of residents, users and the environment. Correct maintenance and repairs avoid costly failures, which can also contribute to a building disaster. Regular and thorough building inspections also reduce utility costs in the long term, as early detection of defects allows cheaper repairs. Negligence leads to much more expensive major repairs. A well-maintained building often also consumes less energy, such as through properly installed thermal insulation or efficient heating systems. Maintaining a facility in good technical condition also contributes to the value of the property, as a building in good technical condition is more attractive to buyers or tenants. Keeping a facility in good technical condition and the upgrades performed also raise the standard of the building [1, 2].

Keeping a building in good technical condition also means meeting legal requirements. In Poland, there are regulations that impose an obligation to assess the technical condition of buildings by performing regular technical inspections: annual and five-yearly [3, 4]. Failure to perform them can result in financial penalties or even legal liability for the owners or managers of the facility in the event of an accident. This applies to residential, commercial, industrial and historic buildings. Assessing the current technical condition of a building is a key part of the process of maintaining the property, planning repairs and investments. The purpose of such an assessment is to determine the current condition of the building, identify damage and assess the risk of further operation. This is a complex process, requiring knowledge, experience and the use of modern diagnostic methods. Regular inspections make it possible to detect irregularities at an early stage, avoid serious failures and plan rational renovations.

Most of the scientific research conducted on the assessment of the technical condition of buildings focuses on predicting the aging of a building to determine its changes in performance over time. These studies are aimed at assessing the performance over a specified useful life and allow predicting necessary repairs over time [5–7]. Scientific research attempts to describe the degradation process of residential buildings as a whole or individual components, using, among other things, simulation methods, fuzzy logic, neural networks, stochastic processes and time-based methods for determining technical condition (linear, nonlinear and parabolic methods) [8–23].

The assessment of technical condition is usually carried out based on a visual inspection or on the basis of an expert technical report that includes measurements and diagnostic tests of selected building elements [2, 24]. The visual method is om the basis of an external inspection of the elements in conjunction with the age, durability and degree of use of the building elements. It also takes into account actual damage to elements resulting from improper repairs or vandalism. This relatively quick method yields widely accepted results, although it is on the basis of arbitrary estimates and often the subjective judgment of the assessor. Visual assessment also sometimes uses a weighted average degree of technical deterioration of a building, usually expressed as a percentage. By using this parameter in the estimation, the contribution of the degree of deterioration of individual elements to the weighted degree of deterioration of the building can be taken into account.

However, these calculations only give an approximate value of the degree of wear due to the determination of the components included in the equations, which is at the discretion of the assessor. The nature of the weighted values eliminates some large deviations, i.e., if the assessor underestimates or overestimates the degree of wear of individual components, the result will not be too disturbed. On the other hand, inaccuracy will increase if the degree of wear and tear of elements that contribute significantly to the cost of the entire facility is incorrectly estimated. If an error is made in estimating the wear and tear of both low-cost and more expensive structural elements, the formula will not correct anything, and the whole will be evaluated with a large error. This method requires the expertise of the assessor and is also quite time-consuming.

Currently, the classification of technical condition is not based on standardized criteria. The classification of a building into a particular state is not systematized and depends only on the subjective evaluation of the assessor. In the literature there are also differentiated scales for the division of technical condition classification. The most commonly used are scales of 4, 5 or 6 degrees [25]. This condition is not satisfactory and requires systematization based on clearly defined criteria.

The use of machine learning (ML) algorithms is becoming an increasingly integral part of today's world. Machine learning algorithms are used in various areas of life. They have revolutionized the way we analyze data, make decisions and optimize processes. One area where machine learning is gaining particular importance is also the construction industry. A sector previously traditionally based on experience and manual labor, today it is increasingly supported by digital innovation. Machine learning (ML) algorithms is being used in construction in areas such as [26–31]:

– Design and planning: ML algorithms analyze data from previous construction projects and, based on this data, predict potential problems, costs or lead times. This enables more precise planning and minimizes errors from the concept stage.
– Risk management and safety: ML algorithms help identify high-risk sites for construction site accidents, predict equipment failures or schedule irregularities. Monitoring systems that analyze images in real time can warn of hazards.
– Optimize material consumption: ML algorithms analyze data from IoT sensors and previous implementations to predict material requirements, reducing waste and overproduction. This makes construction sites greener and more economical.
– Process automation: construction machines and robots equipped with ML algorithms can autonomously perform some tasks, such as bricklaying or paving, with high precision and without the need for constant human supervision.
– Prediction and maintenance: in existing buildings, ML algorithms can predict installation failures, plan maintenance and manage energy efficiency based on historical data and operating conditions.

The benefits that ML algorithms bring to the construction industry are too great to ignore. Deeper analysis and better systematization of the results obtained using ML algorithms should also be applied to standardize classification when assessing the technical condition of buildings.

The purpose of this article is to propose a systematization of how to determine the technical condition of buildings using machine learning (ML) algorithms. On the basis of a series of studies in residential buildings erected in traditional brick technology, a database was created covering the characteristics of individual buildings and their elements, the defects occurring and the repair management carried out in each year. The collected database was used to conduct analysis using ML algorithms representing selected predictive techniques including Gradient Boosting, Random Forest and k-NN.

2. Materials

The database, which was used in machine learning, was created on the basis of an analysis of the technical condition of 64 multifamily residential buildings located in the Warsaw agglomeration in Poland. For this purpose, selected buildings built with traditional masonry technology erected between 1928 and 2020 were analyzed. The usable area of the buildings ranged from 497.11 m^2 to 8442.45 m^2. The number of above-ground floors of the buildings ranged from 4 to 14, while the number of underground floors was 1 or 2. The technical condition of the buildings was assessed in 2023 and 2024. The research was performed as part of the annual periodic inspections of buildings as required by the Construction Law [3]. For each building, the project documentation and renovations carried out were also analyzed.

The following elements were visually assessed for each building: foundations, underground walls, basement ceilings, basement floor, overground walls, overground ceilings, roof construction (if there was access), roofs, chimneys above the roof, roof flashings, gutters, downpipes, staircases, elevation, balconies, window and door joinery, flashings (window still), building installations. The qualification of elements for each state was done on the basis of the visual assessment carried out and the number of defects found.

During the visual assessment, the most important defects in the various elements of the building were determined, which should be repaired within 12 months to keep the building in a proper technical condition. After the 12-month period, a re-inspection was conducted to verify the removal of the designated defects. During this inspection, the defects that should be fixed during the next 12 months were also designated.

Based on the diagnosed defects, the technical condition of the buildings was qualified. For this purpose, a four-stage qualification scale was used to represent the wear and tear of buildings: Good condition, Satisfactory condition, Medium condition, Weak condition. The criteria for classification into different categories of technical condition of the whole building are shown in Table 1. In order to more accurately represent the actual technical condition of the analyzed buildings, some of the buildings were classified into intermediate states: Good/Satisfactory, Satisfactory/Medium, Medium/Weak. Table 2 shows the number of buildings classified into each technical condition.

The conducted assessment of the technical condition of buildings was used to develop a database, which was used in machine learning analysis.

Table 1. Criteria for classification into different categories of technical condition of the buildings

Classificationof the technical condition	Evaluation criterion
Good	The building is well-maintained, well-maintained, shows no wear and damage. The characteristics and properties of the built-in materials meet the basic requirements.
Satisfactory	The building is properly maintained. It is expedient to carry out ongoing renovation consisting of minor repairs, additions, maintenance, waterproofing, etc.
Medium	There are minor damages and cavities in the building elements that do not threaten public safety. A partial major overhaul is advisable.
Weak	The building has significant damage, cavities. Features and properties of built-in materials are of a reduced class. Required comprehensive overhaul or replacement of elements.

Table 2. Criteria for classification into different categories of technical condition of the buildings

Typeof the technical condition	The number of buildings
Good	5
Good/Satisfactory	16
Satisfactory	23
Satisfactory/Medium	8
Medium	11
Medium/Weak	1
Weak	0

3. Methods

3.1. Research assumptions

The study aimed to evaluate the effectiveness of selected ML algorithms in the multi-class condition classification of building structures based on their physical characteristics and inspection data. It was hypothesized that complex ensemble models (in particular, Gradient Boosting and Random Forest) would outperform the simpler k-NN algorithm regarding classification performance. In addition, it was hypothesized that certain features – especially those directly describing defects and object condition assessment – would be crucial for condition category prediction.

3.2. Data description and preparation

The analysis was conducted on a dataset containing information about construction objects and their classified technical condition assigned to categories: Good, Good/Satisfactory, Medium, Medium/Weak, Satisfactory, and Satisfactory/Medium (Table 2). The data required preliminary preprocessing: missing values were either imputed or, where necessary, instances with incomplete data were removed. All numerical features were subjected to normalization to ensure that differences in scale would not bias the operation of scale-sensitive algorithms, particularly k-Nearest Neighbors (k-NN). The dataset was partitioned into a training and a testing set in an 80/20 ratio, with stratification applied to preserve class proportions and allow for reliable evaluation of previously unseen data. Additionally, for cross-validation, the training set was further divided into subsets to facilitate model hyperparameter tuning.

3.3. Classification algorithms

The experiment employed three classification algorithms: k-NN, Random Forest and Gradient Boosting. The k-NN algorithm is an instance-based method that classifies a new observation based on the majority class among its k-NN in the feature space [32–34]. Random Forest is an ensemble classifier based on a collection of decision trees constructed using the bagging technique [31, 35]. Gradient Boosting is another ensemble model that sequentially builds decision trees, where each successive tree corrects the errors of the previous iterations [32, 36]. As a result, it produces a robust model capable of capturing complex nonlinear relationships. All models were trained on the same set of features, ensuring a fair comparison of their predictive performance.

3.4. Validation procedure and evaluation metrics

To evaluate the models, 10-fold cross-validation was applied to the training set, followed by a final evaluation on a separate test set. This procedure ensures that the results are not affected by model selection bias and enables reliable estimation of the classifier's generalization performance. A confusion matrix was used for detailed analysis, from which class-specific performance indicators were derived. For the quantitative comparison of overall performance, the following metrics were employed: classification accuracy (CA), precision (Prec), recall, $F1$-score, and the Matthews correlation coefficient (MCC). These metrics enabled a multidimensional assessment of both overall classification effectiveness and class-specific prediction quality. All metrics were derived from the confusion matrix, which organizes the outcomes of classification into four basic categories: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Based on these components, the following performance indicators were calculated [33, 37]:

– Classification Accuracy (CA) expresses the ratio of correctly predicted instances (both true positives and true negatives) to the total number of predictions:

$$CA = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.1}$$

– Precision (Prec) quantifies the proportion of correctly predicted positive cases among all instances predicted as positive:

$$\text{Prec} = \frac{TP}{TP + FP} \tag{3.2}$$

– Recall measures the proportion of actual positive cases that were correctly identified by the model:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3.3}$$

– $F1$-score ($F1$) is the harmonic mean of Precision and Recall, providing a balanced measure that is particularly informative in the presence of class imbalance:

$$F1 = 2 \times \frac{\text{Prec} \times \text{Recall}}{\text{Prec} + \text{Recall}} \tag{3.4}$$

– Matthews Correlation Coefficient (MCC) offers a robust single-value summary of classification performance, incorporating all four values from the confusion matrix. It yields a value between –1 and +1, where +1 indicates perfect prediction, 0 corresponds to performance no better than random, and –1 represents complete disagreement between prediction and observation:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}} \tag{3.5}$$

4. Interpretation of results

The results shown in Table 3 allow a direct comparison of the predictive performance of the models in terms of overall accuracy, class balance and robustness. The Gradient Boosting model achieved the highest performance across all analyzed metrics. Its Area Under the ROC Curve (AUC) reached 0.997, indicating a near-perfect ability to discriminate between the different technical condition classes. This is further reflected in its Classification Accuracy of 0.951, meaning that over 95% of instances were correctly classified. The model also shows balanced performance, with identical values of $F1$-score (0.951), Precision (0.951), and Recall (0.951). These values imply that the model not only correctly identifies the actual class but also avoids false positives at a very low rate. The Matthews Correlation Coefficient of 0.936 further confirms its outstanding performance. MCC, a comprehensive metric that considers all four elements of the confusion matrix, shows that Gradient Boosting achieves high predictive quality across all classes – even under potential class imbalance. The k-NN classifier performed well, though it did not match the accuracy or robustness of Gradient Boosting. Its AUC value of 0.975 still indicates strong discriminative capability. With a CA of 0.938, the model correctly predicted nearly 94% of instances. Its $F1$-score (0.937), Precision (0.938), and Recall (0.938) are nearly identical, which reflects a balanced trade-off between false positives and false negatives. The MCC value of 0.918, while slightly lower than that of Gradient Boosting, still indicates a highly reliable model. Notably, the closeness of the Precision and Recall suggests that k-NN is stable and not biased toward any particular class, although it may be slightly more sensitive to feature scaling and distribution, as typical for distance-based methods. The Random Forest model showed substantially weaker performance compared to the other two algorithms. Its AUC of 0.939, while still acceptable, is significantly lower than that of Gradient Boosting and k-NN. More importantly, its Classification Accuracy (0.738) suggests that more than a quarter of the instances were misclassified. Although the Precision value is relatively high (0.780), the Recall is much lower (0.738), indicating that the model tends to be conservative in its positive predictions – it may avoid false positives at the cost of missing true positives. This imbalance is reflected in the F1-score of 0.728, the lowest among all three models. The MCC of 0.660 confirms that the Random Forest model struggles with consistent prediction across multiple classes.

Table 3. Prediction results

Model	*AUC*	*CA*	*F*1	Prec	Recall	*MCC*
Gradient Boosting	0.997	0.951	0.951	0.951	0.951	0.936
k-NN	0.975	0.938	0.937	0.938	0.938	0.918
Random Forest	0.939	0.738	0.728	0.780	0.738	0.660

As demonstrated in the Confusion Matrix, which presents detailed results for each class and algorithm (Tables 4–6), the disparities in global measures can be understood. Gradient Boosting (Table 4) shows the most precise and consistent classification across all classes. The model identified well the instances belonging to the Good and Medium/Weak categories, with an accuracy of 100% in both cases. This confirms the excellent separability of these extreme classes. For the Good/Satisfactory class, the model achieved 95.9% correct classification, with only a small portion misclassified as Satisfactory (0.7%). The Medium class was also recognized correctly, with 96.8% of cases correctly classified, while minor mistakes occurred in the cases of Satisfactory (4.1%) and Satisfactory/Medium (2.5%). Similarly, for the Satisfactory class, the model achieved a very high classification rate of 91.8%, with only minor misclassifications on the Good/Satisfactory (4.1%) and Medium (1.6%) classes.

Table 4. Confusion matrix for Gradient Boosting

		Predicted						
		Good	Good/ Satisfactory	Medium	Medium/ Weak	Satisfactory	Satisfactory/ Medium	Σ
Actual	Good	100%	0.0%	0.0%	0.0%	0.0%	0.0%	38
	Good/ Satisfactory	0.0%	95.9%	0.0%	0.0%	0.7%	0.0%	167
	Medium	0.0%	0.0%	96.8%	0.0%	4.1%	2.5%	254
	Medium/ Weak	0.0%	0.0%	0.0%	100%	0.0%	0.0%	23
	Satisfactory	0.0%	4.1%	1.6%	0.0%	91.8%	1.6%	283
	Satisfactory/ Medium	0.0%	0.0%	1.6%	0.0%	3.4%	95.9%	131
Σ		38	172	247	23	294	122	896

Satisfactory class, the model achieved a very high classification rate of 91.8%, with minor misclassifications on Good/Satisfactory (4.1%) and Medium (1.6%). Finally, the Satisfactory/Medium class was also highly distinguishable, with 95.9% of its instances correctly classified and only minor leakages to Medium (1.6%) and Satisfactory (3.4%). Gradient Boosting not only offers high overall accuracy but also minimizes confusion between neighboring classes, especially those in the Medium, which are often more challenging to separate.

The k-NN model (Table 5) performs well overall, correctly identifying 97.4% of Good and 100% of Medium/Weak instances. Its classification of Medium (93.7%), Satisfactory (90.9%), and Satisfactory/Medium (95.8%) was also strong, although it showed slightly more confusion between neighboring classes such as Medium and Satisfactory. Despite this, the model maintained balanced Precision and recall across categories, making it a reliable but slightly less discriminative alternative to Gradient Boosting.

Table 5. Confusion matrix for Gradient Boosting

		Predicted						Σ
		Good	Good/ Satisfactory	Medium	Medium/ Weak	Satisfactory	Satisfactory/ Medium	
Actual	Good	97.4%	0.0%	0.0%	0.0%	0.0%	0.0%	38
	Good/ Satisfactory	0.0%	95.3%	0.0%	0.0%	1.0%	0.0%	167
	Medium	0.0%	0.0%	93.7%	0.0%	4.2%	2.5%	254
	Medium/ Weak	0.0%	0.0%	0.0%	100%	0.0%	0.0%	23
	Satisfactory	2.6%	4.7%	4.3%	0.0%	90.9%	1.7%	283
	Satisfactory/ Medium	0.0%	0.0%	2.0%	0.0%	3.8%	95.8%	131
Σ		39	172	255	23	287	120	896

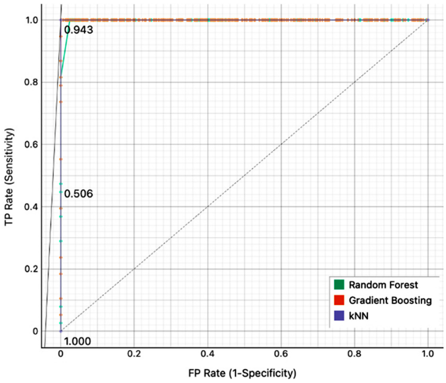
Table 6. Confusion matrix for Gradient Boosting

		Predicted						Σ
		Good	Good/ Satisfactory	Medium	Medium/ Weak	Satisfactory	Satisfactory/ Medium	
Actual	Good	100%	0.9%	0.0%	0.0%	6.1%	0.0%	38
	Good/ Satisfactory	0.0%	89.1%	3.4%	0.0%	17.5%	6.2%	167
	Medium	0.0%	0.0%	66.0%	0.0%	0.7%	0.0%	254
	Medium/ Weak	0.0%	0.0%	0.0%	100%	0.0%	0.0%	23
	Satisfactory	0.0%	10.0%	16.8%	0.0%	70.0%	0.0%	283
	Satisfactory/ Medium	0.0%	0.0%	13.9%	0.0%	5.7%	93.8%	131
Σ		19	110	382	23	297	65	896

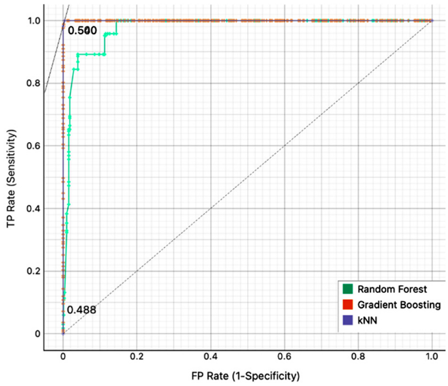
Random Forest (Table 6) shows strong performance for Good and Medium/Weak (100%) but struggles considerably with middle-spectrum classes. Only 66.0% of Medium and 70.0% of Satisfactory cases were correctly classified, with high misclassification into adjacent categories like Good/Satisfactory and Satisfactory/Medium. This indicates that the model has difficulty capturing nuanced boundaries between closely related classes, leading to reduced Precision and lower overall reliability compared to the other algorithms.

Analysis of the ROC curves (Fig. 1) for all classes indicates the excellent discriminatory ability of the Gradient Boosting classifier. The model consistently achieves the steepest ROC curves and highest AUC values, which indicates a high level of sensitivity and specificity in both distinct and transitional categories. It is worth noting that the model performs exceptionally well in classes such as Good and Medium/Weak, where class boundaries are well-defined. In addition, it shows solid support for more ambiguous categories such as Satisfactory and Satisfactory/Medium. The k-Nearest Neighbors algorithm also shows good performance, maintaining high AUC values and curve trajectories that are similar to those of Gradient Boosting, suggesting strong generalization despite sensitivity to feature scaling. In contrast, Random Forest shows relatively limited discriminatory power, with noticeably flatter ROC curves and reduced AUC values, especially in intermediate classes characterized by feature overlap. Taken together, the ROC-based assessment supports Gradient Boosting as the most effective and reliable model in this multi-class classification task, followed by k-NN, while Random Forest shows the most significant variability and susceptibility to class bias.

The comparative feature importance analysis (Fig. 2) reveals substantial differences in how individual classifiers prioritize input variables when predicting the technical condition of buildings. For the Gradient Boosting model, the most influential factor is the number of defects designated for completion during the previous inspection, which causes the largest decrease in AUC when permuted, indicating its dominant role in shaping the model's decision boundaries. This is followed by aesthetics of the facility and surroundings, usable Area, and year of construction, all of which contribute meaningfully, but to a lesser extent. The remaining variables exhibit minimal impact, suggesting either redundancy or limited predictive signal under this model's structure. In the case of Random Forest, a different pattern emerges: aesthetics is ranked as the most critical feature, followed closely by defects from the previous inspection and year of construction. Notably, annual inspection of the building and number of residential units appear more relevant here than in Gradient Boosting, which may reflect Random Forest sensitivity to discrete, categorical characteristics. The spread of importance values is also more even, suggesting less sharp feature prioritization and possibly contributing to the model's lower discriminative power observed earlier. Conversely, the k-NN classifier attributes the highest importance to the usable and development areas, producing substantial drops in AUC when perturbed. This aligns with the nature of instance-based algorithms, which rely heavily on spatial relationships in the feature space. Interestingly, several defects and aesthetics are markedly reduced in this model, indicating that contextual and semantic information may be underutilized by k-NN relative to ensemble tree methods.



(a)



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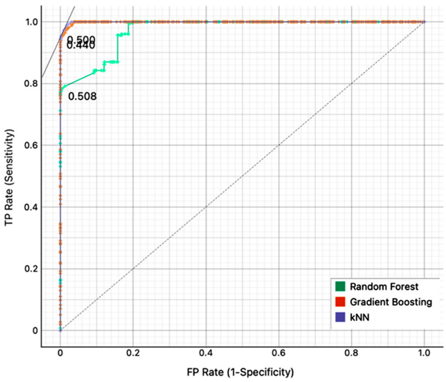

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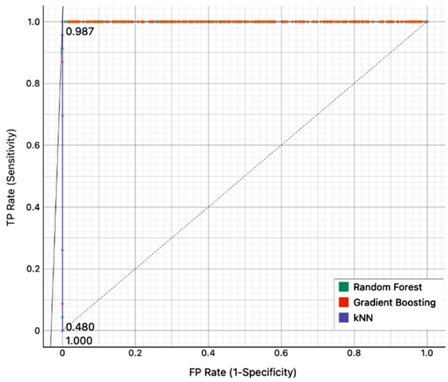

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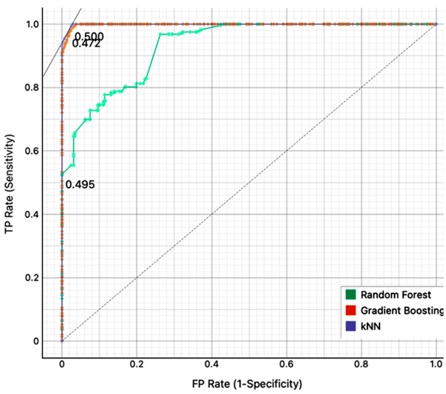
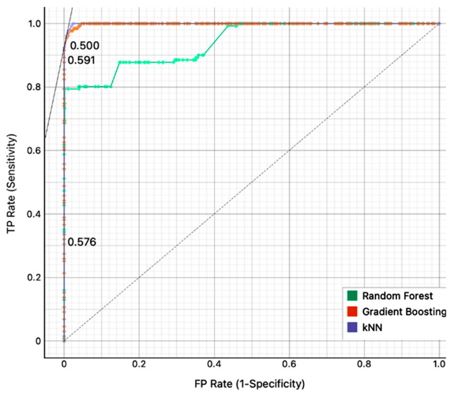


(e)



(f)

Fig. 1. ROC curves for all classes: (a) Good, (b) Good/Satisfactory, (c) Medium, (d) Medium/Weak, (e) Satisfactory, (f) Satisfactory/Medium

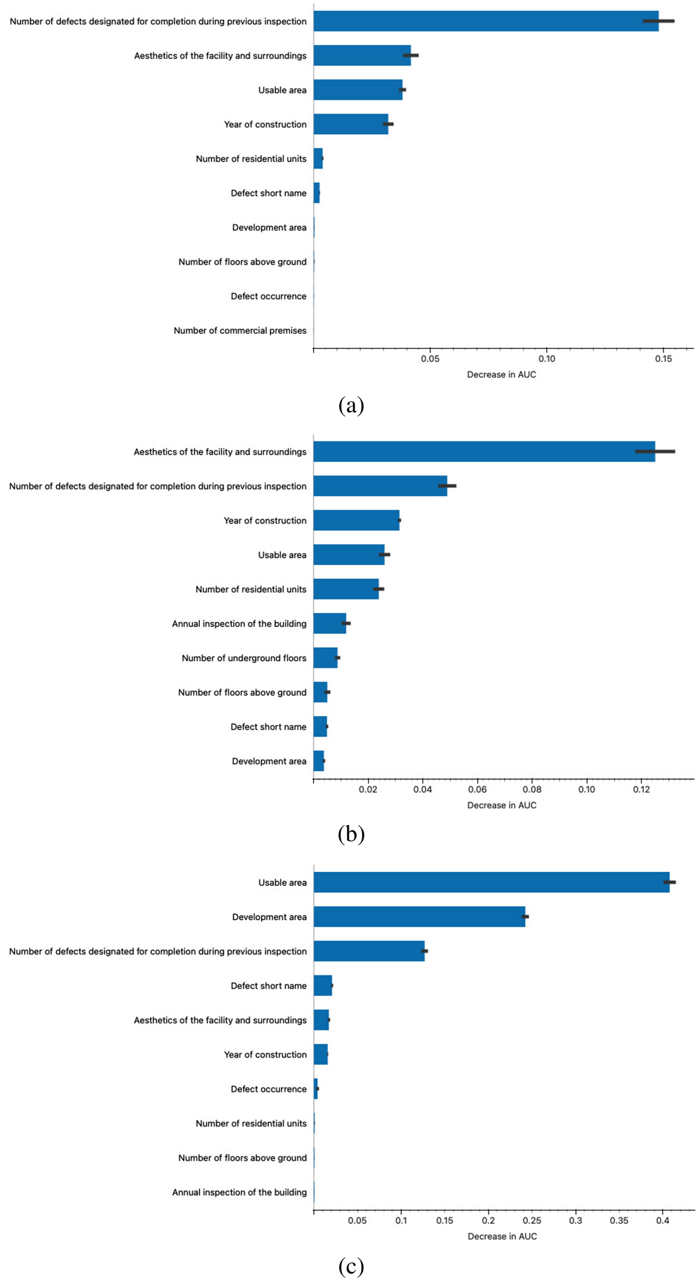


Fig. 2. The comparative feature importance analysis: (a) Gradient Boosting, (b) Random Forest, (c) k-NN

5. Conclusions

The article examines the possibility of applying machine learning (ML) algorithms in the prediction of the technical condition of multifamily residential buildings. For this purpose, tests were conducted on selected buildings, which were used to develop a database. In the conducted analyses the following algorithms were used and compared: Gradient Boosting, Random Forest, k-NN. Statistical analyses were performed for each algorithm, confirming the correctness of the estimated models. Variables that significantly affect the estimation process for each algorithm were also identified.

Analyses show that the Gradient Boosting algorithm shows the most accurate prediction in classifying the technical condition of buildings. In the tests conducted, it achieves a score of 91.8% to 100%. Gradient Boosting shows high overall accuracy and minimizes confusion between neighboring building condition classes. The k-NN algorithm classifies building states equally well (from 90.9% to 100%), but shows more confusion between neighboring classes. Despite this, the model maintained a balanced precision and recall rate across all categories, making it a reliable but slightly less selective alternative to the Gradient Boosting method. In contrast, the Random Forest algorithm ranks the condition of buildings from 66% to 100%. This indicates that the algorithm has difficulty capturing the nuances of boundaries between closely related classes, leading to reduced precision and lower overall reliability compared to other algorithms.

The results of the analysis suggest that the methods of ML algorithms show potential for use in the prediction of the technical condition of multifamily residential buildings. The use of machine learning algorithms has significantly improved the objectivity and precision of building condition prediction. The presented models show practical potential, while in the future it is advisable to expand the research on the basis of a larger database, which can affect even greater accuracy in predicting the technical condition of residential buildings.

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Zastosowanie algorytmów uczenia maszynowego (ML) w prognozowaniu stanu technicznego budynków mieszkalnych

Słowa kluczowe: algorytmy uczenia maszynowego, budynek mieszkalny wielorodzinny, eksploatacja budynku, predykcja stanu technicznego budynku, remont budynku, stan techniczny budynku

Streszczenie:

Stan techniczny budynków mieszkalnych wielorodzinnych jest jednym z najistotniejszych czynników determinujących proces ich starzenia się. Najczęściej jest on określany na podstawie subiektywnej oceny osoby oceniającej bez opierania się o ujednolicone kryteria. Celem artykułu jest zaproponowanie usystematyzowania sposobu wyznaczania stanu technicznego budynków z wykorzystaniem algorytmów uczenia maszynowego. Na podstawie szeregu badań w budynkach mieszkalnych wzniesionych w technologii tradycyjnej stworzono bazę danych obejmującą cechy charakterystyczne poszczególnych budynków i ich elementów, występujące usterki oraz prowadzoną gospodarkę remontową w poszczególnych latach. Zgromadzona baza danych posłużyła do przeprowadzenia analizy z zastosowaniem algorytmów uczenia maszynowego reprezentujących różne techniki predykcyjne w tym Gradient Boosting, Random Forest oraz k-NN. Dla każdego z algorytmów wykonano analizy statystyczne, potwierdzające poprawność szacowanych modeli. Zostały także określone zmienne mające istotny wpływ na proces estymacji dla poszczególnych algorytmów. Zastosowanie uczenia maszynowego pozwoliło na istotne zwiększenie obiektywności i precyzji prognozowania stanu technicznego budynków. Opracowane modele wykazują potencjał praktyczny, natomiast w przyszłości wskazane jest rozszerzenie badań w oparciu o większą bazę danych co może wpłynąć na jeszcze większą dokładność prognozowania stanu technicznego obiektów mieszkalnych.

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