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MACHINE LEARNING MODEL FOR THE PREDICTION OF CONDITION OF MUSEUM OBJECTS

Kurmo KONSA[1,*], Meri Liis TREIMANN[2], Kristiina PIIRISILD[3], Kalev KOPPEL[2]

[1] University of Tartu, Institute of History and Archaeology, Departement of Archival Studies, Jakobi 2, Tartu 51005, Estonia
[2] Software Technology and Applications Competence Center (STACC), Narva mnt. 20, Tartu 51008, Estonia
[3] Estonian National Museum, Conservation Departement–Muuseumi tee 2, Tartu 60532, Estonia

Abstract

An accurate prediction of the future condition of museum objects is crucial for developing appropriate proactive maintenance and preservation strategies. Despite this, there are very few such damage models that can be used in practice. The main reasons, for this lack of deterioration models, include complexity of deterioration problem and lack of understanding of the degradation mechanisms affecting various materials and objects, and lack of reliable quantitative approaches. In the article, we discuss the machine learning model, which predicts the future condition of museum objects. For this purpose, the model uses the data of MuIS (Estonian Museum Information System). To predict deterioration, we experimented primarily with various tree-based machine learning algorithms, such as the decision tree, the random forest, and XGBoost. The best results were obtained using the decision forest algorithm, which was able to identify 92% of deteriorating museum objects with 50% accuracy. The machine learning model provides a way to model ageing processes of museum objects over the course of time and thus better plan the preservation work of museums.

Keywords: *Decision models; Machine learning; Modeling of deterioration; Preservation of museum objects; Museum*

Introduction

The primary task of museums is to preserve information in the form of physical objects [1]. Physical objects are damaged as a result of various processes, which are grouped into physical, chemical, mechanical, and biological [2]. In most cases, different processes work together, damaging the materials and structure of the artifacts. Damage processes are affected by a number of factors, the most important of which are the composition and structure of materials, environmental conditions, and human impacts. It is very difficult and, in most cases, impossible to take all these factors into account [3]. At the same time, modeling the aging of museum objects is very important for their successful preservation. Modeling of damage processes makes it possible to assess the extent of damages (which objects have been damaged and what is the degree of damage), the speed of damage processes and thus changes in the number of damaged objects over time, and finally, the effectiveness of possible management measures [4].

There are three main methods for modelling the aging of museum objects. First, if we know the rate of aging of the materials that make up the object, we can predict the lifespan of the object [5, 6]. The most common way is the application of physicochemical methods after

* Corresponding author: kurmo.konsa@ut.ee

accelerated aging. Some damage rates are known for some materials (e.g., paper, photographic materials, metals) [7-9], but their application to specific objects is again often questionable [10-12]. In most cases, surrogate materials are used in the experiments, and complex, multi-layered materials are often examined in parts. The composition of museum objects is heterogeneous, and different environmental conditions have affected objects during their lifespan. All this makes the transfer of the results of artificial aging experiments to historical sites questionable or at least very difficult [13, 14].

Second, it is possible to use heuristics compiled by experts to predict the aging of objects. These are rules based on some research and practical experience. For example, the fastest aging objects are considered to be wood pulp containing acidic paper, documents damaged by ink corrosion, photographic materials on cellulose nitrate and cellulose acetate substrate, chromogenic color photos, softened polyvinyl chloride, polyurethane foams, vulcanized natural rubber, leather affected by red rot, textiles dyed with iron compounds (black, brown), etc. [15-17] Such heuristics do not take into account the specifics of particular objects and the history of the objects so far. The data depends on the experience of experts and is often too general.

Third, it is possible to use data from collection condition surveys. When we have reliable information about the condition of objects in two different time points, then we are able to model the aging process [18]. But there are many problems with condition surveys. Many damage description systems are characterized by a high degree of subjectivity, and they are not very systematic. Unspecified terminology is used [19]. Very often, the damage is defined by the processes that cause it. In the case of a system with a descriptive level, this is not justified, as it is not clear in each case what is the cause of the damage, and there can be several reasons for one type of damage.

In this article, we provide an overview of the machine learning decision model designed to predict deterioration of museum objects. For this purpose, the model uses the data of MuIS (Estonian Museum Information System). As far as we know, this is the first decision model of its kind.

Experimental part

Dataset

The model obtained the data from the museums` information system MuIS (Estonian Museum Information System). MuIS is a web-based environment for keeping records of museum collections, managing them, and making the information in museums available to specialists and all other interested parties. The 60 Estonian museums that have joined MuIS have entered a total of nearly 4.6 million museum objects from the 973 museum collections to MuIS. The database contains a lot of information about museum objects, their context, as well as activities in museums with them. The condition of objects is described in MuIS with four values: good, satisfactory, bad or very bad (Table 1). If the condition is not specified, the value is marked “undefined”.

Almost 3.7 million condition assessments have been entered into MuIS. 62% of museum objects in MuIS have at least one condition assessment, i.e., more than a third of museums have never had their condition assessed. 25% of museum objects have several condition assessments. On average, the condition of museum objects has been assessed every 1210 days, i.e., a little over every three years.

The development of a condition prediction model based on these data requires at least pairs of consecutive condition assessments to try to determine whether one or another event or a property (nature, material, age, techniques) of a museum object or some combination of them correlates with the change in condition. There are more than 1.4 million such pairs among the museum objects with several condition assessments. Almost 32 thousand of them, or a little over 2%, consist of two different condition assessments, i.e., they indicate a change in condition. According to the data entered in MuIS, almost 30 thousand museum objects, i.e., less than one percent of all museum objects, have been subject to a change of condition.

Table 1. Museum objects condition definitions in Museum Information System MuIS

Condition	Definition of condition
Good	The object is in a stable condition, can be used without restrictions, does not require processing. It is exhibitable.
Satisfactory	The object is in a satisfactory condition, distorted in appearance or damaged but stable. It needs conservation for exposure.
Bad	The condition of the object is bad, damaged, and/or unstable; only limited use is allowed and needs processing to achieve a normal condition. Not exhibitable.
Very bad	The condition of the object is extremely unstable, the structure is weak and actively decomposing, affects other objects (e.g., mold, rust), and requires immediate treatment.

Methods

In the project, machine learning methods are used, in which the algorithms learn automatically, without direct human instruction, using existing data. Machine learning algorithms create a model based on a sample (training data) that is used to make predictions or decisions [20]. To predict deterioration, we experimented primarily with various tree-based machine learning algorithms, such as the decision tree, the random forest, and XGBoost.

The data used to train the model is a large table, where each row corresponds to one data point and each column to one attribute/property for that data point. As data points, we used at least two condition assessments for each museum object, to which we added the characteristics of the respective museum object and other features that probably help to predict the deterioration of the condition of the museum object. These data included static data related to the museum object: museum, museum collection, type, material, material group, technology, exhibit ability, date of the object. As additional information, we used the history of the museum object, i.e., a summary of the events related to the museum object (Table 2).

Tabel 2. Data used in the decision model

Data about a museum object	Events connected to the museum object
Museum	How many days the museum object has been in the register
Museum collection	How many days has the current condition of the museum object remained unchanged
Type of object	Has it been to the exhibition
Material	How many times has it been to the exhibition
Material group	How many days has it been at the exhibition
Technology	Has it been at maintenance (incl. conservation/restoration)
Exhibitability	How many times has it been at maintenance
Date of object	How many days has it been at maintenance
	How many times it has been removed from storage
	How many days has it been out of storage

In order to evaluate the results of the model, we divided the existing data into training and test data. The test data is initially discarded, and only training data is shown to the model for learning patterns from the data. Then, based on the model, predictions are made on the test data and compared with reality (we have this information about the test data). This gives a pretty good idea of what results can be expected from the model when it is used in real situation. In order to exclude data leakage, the selection of test data also took into account the fact that it is a time series - the model should be trained on the basis of older condition assessments and then its skill should be evaluated on more recent data. Therefore, we selected random test data only from among the latest condition assessments of museums, while the size of the test set was taken to be 20% of the entire data set.

For classification models, model evaluation usually begins with a confusion or error matrix (Fig. 1), which visualizes how well the predictions correspond to reality and from which various indicators have been derived to evaluate the models.

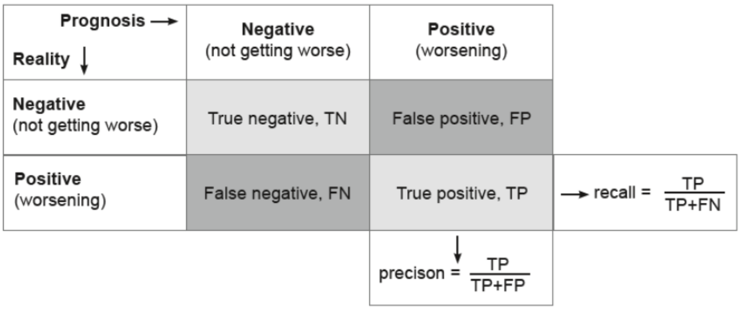

Fig. 1. Confusion or error matrix used for the evaluation of decision model

In the case of modelling deterioration, the most important thing is that the model detects as many deteriorating museum objects as possible, i.e., that there are as few false negatives as possible. A recall, which shows how much of all positives the model finds, is well suited for evaluating this. For example, a recall of 0.9 would mean that the model finds 90% of the deteriorating objects, and 10% is not found (false negatives). The second criterion next to the recall is usually precision, which shows how many of the positive predictions are actually positive. For example, an accuracy of 0.9 would mean that 90% of all cases predicted by the model to deteriorate actually deteriorate, and 10% do not deteriorate (false positives). A higher value is better for both recall and accuracy.

Given the importance of identifying as many deteriorating museum objects as possible, we can give in a little precision if it means higher recalls. We agreed that the accuracy should not be lower than 0.5, i.e., that model could give a false alarm in up to half of the cases.

Results and discussion

Determining the optimal prediction period

As a first experiment, we undertook the task of finding out for which period it would be reasonable to make predictions. Model's task is to predict whether the condition of the museum object will deteriorate during the next n years, where the n that give the best results will be determined experimentally. As a little over ten years have passed since the creation of MuIS and less data has been entered there than before, we considered that we could create a maximum model that predicts the deterioration of the condition over the next ten years. Consequently, we tested periods of 1 to 10 years (Table 3). The aim was to find the period for which the model gave the best results.

Table 3. Determining the optimal prediction period of decision model. N -number of data points, P - number of data points in which case the condition of objects is getting worse

Period (years)	Training data		Test data		Results	
	N	P	N	P	Recall	Accuracy
1	151 001	689	37 751	163	0.644	0.603
2	132 728	998	33 182	218	0.596	0.591
3	112 254	1 108	28 064	305	0.551	0.675
4	100 144	1 212	25 036	311	0.553	0.649
5	84 790	1 290	21 198	346	0.613	0.716
6	71 560	1 414	17 891	332	0.623	0.702
7	56 562	1 464	14 141	358	0.676	0.807
8	46 540	1 457	11 635	399	0.639	0.768
9	37 258	1 535	9 315	369	0.699	0.750
10	31 035	1 533	7 759	404	0.748	0.774

We performed the experiment with a decision tree algorithm. In terms of both recall and accuracy, the usual decision tree on 10-year forecasting achieved the best results: the model found 75% of deteriorating cases from the test data (recall), and 77% of all deteriorating cases were correct (accuracy). When choosing the final period, we also proceeded from practicality, i.e., which period's forecasts would support the planning of museum activities. Museums make long-term work plans years in advance, and in the context of a common repository, 7-year work plans will be drawn up. Based on this, we decided together that we will start forecasting the preservation of museum objects in 10 years.

Finding the optimal decision threshold for the decision model

The model finds the probability that the condition of the museum object will deteriorate in the next ten years. If the probability of deterioration is greater than or equal to a set threshold, the model responds with "deteriorated". By default, the decision threshold for machine learning models is 50%, but depending on the problem to be solved, the algorithm, and the conditions set for it, the optimal threshold may be lower or higher. With a lower threshold, it is possible to obtain more deteriorating museum objects (recall improves), but this also leads to a higher number of false positives (accuracy decreases). Since we agreed that the accuracy could be a minimum of 0.5, we can move the decision threshold down to increase the recall, as long as the accuracy is still greater than 0.5.

In finding the optimal decision threshold, we used a 10-year forecast period, i.e., we trained the model to predict the deterioration of the next ten years. Figure 2 provides an overview of the recall-accuracy curves for all performed experiments.

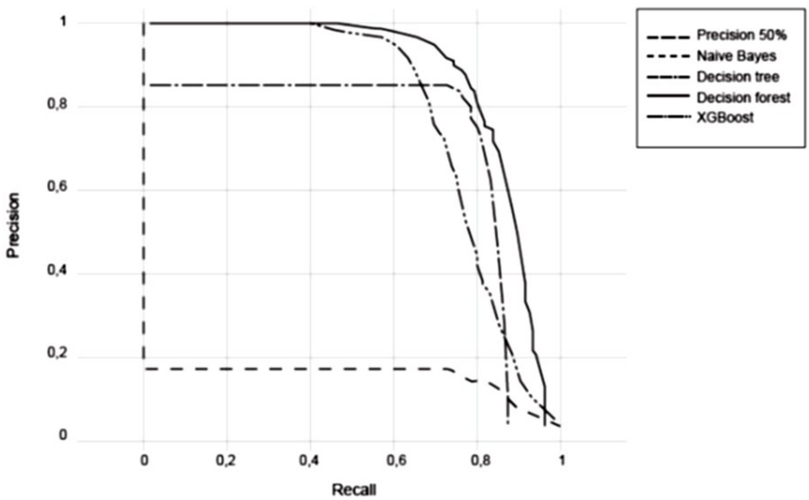

Fig. 2. Precision-recall curves of tested algorithms

Recall-accuracy curves are found by experimenting with different decision thresholds. A lower threshold provides a higher recall, but a lower accuracy (bottom right); raising the threshold improves the accuracy but decreases the recall. In general, the larger the area under the curve, the better the model. We tested the following decision models: Decision tree, Random forest, Gradient boosting (XGBoost), Naive Bayes. The best results were obtained using the decision forest algorithm, which was able to identify 92% of deteriorating museum objects from test data with 50% accuracy.

Evaluation of decision model

Figure 3 displays the results of the model on the test data of 10 pilot museums. Depending on the museum, the model gave different results. The model gives relatively good results, for example, in the Estonian History Museum, where it correctly identified 541 deteriorating museum objects out of 542 in the test data (yield almost 100%), giving only 41 or 7% false positives (accuracy 93%).

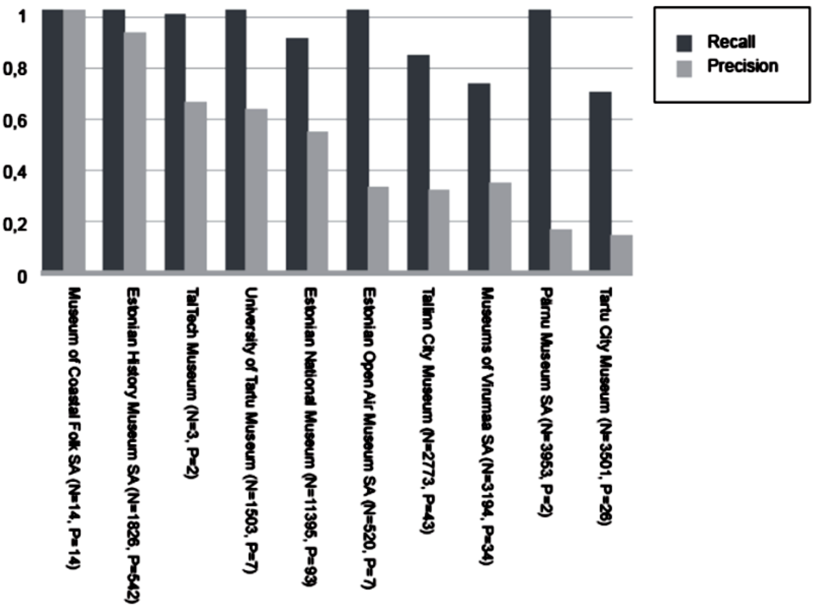

Fig. 3. Results of the final model in pilot museums on test data.
N - number of museum objects in test data,
P - number of deteriorating museum objects in test data

The model achieved rather poor results in several museums with a large number of museum objects, including Tallinn City Museum, Museums of Virumaa, Pärnu Museum, and Tartu City Museum, where over 60% and even over 80% of the positive predictions were false positive. However, this is not such a big problem when the number of deteriorating museum objects is small. For example, there were two deteriorating museum objects in the test data from the Pärnu Museum, and the model found both of them; in addition, the model predicted deterioration for nine more museum objects (of course, there are about 40 times more museum objects in Pärnu Museum and it will take longer to inspect 400 false-positive museum objects). The results are likely to depend significantly on the composition of museum object collections.

The probability of damage to museum objects over the next ten years predicted on the basis of the model can be called the risk score of the museum object. The distribution of risk scores given by the model is shown in figure 4.

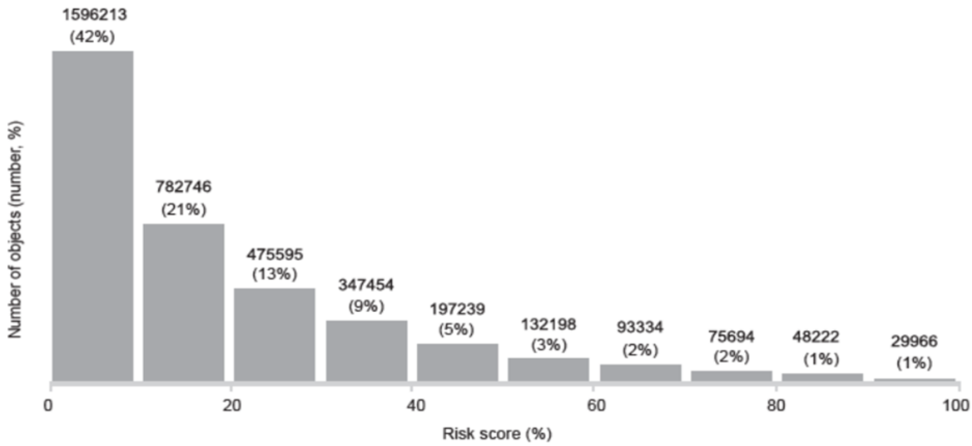

Fig. 4. Distribution of risk scores given by the decision model

The number of objects with the highest risk score (80–100%) is not large, accounting for 2% of the analyzed museum objects.

Conclusions

Unfortunately, the knowledge about the aging rates of most materials is incomplete. Conducting research on collections is also a labor-intensive and time-consuming undertaking. At the same time, museums´ catalogs and information systems contain a wealth of information about objects preserved in museums. A machine learning model that looks for patterns in existing data is currently the only real way to obtain this type of information.

The created machine learning model analyzes the history of condition assessments and changes in the condition of objects and finds which objects have deteriorated more often. Model does not duplicate the data on the condition of museum objects in museum information system, but predicts the condition of the museum objects in the future (in a 10-year perspective) based on the available data. This means, for example, that a museum object that is currently in good condition may be on the list of endangered objects, and at the same time, there may not be museum objects in poor or very poor status on the list, unless model predicts deterioration of their status. Model can give the museum employee a fairly accurate overview of the museum objects of the risk group, and the museum employee does not have to waste resources on monitoring those museum objects whose condition is stable (approximately 95% of the museum objects). A continuous assessment of the condition of the museum object remains necessary, but in the case of stable museum objects, the interval of the condition check could be extended. It would also be possible to prioritize the condition inspection queue, i.e., start with the museum objects with the highest risk of aging.

Described machine learning model could be helpful in museums with large collections and few employees, as well as in museums without preservation specialists. The model could be used, for example, to prioritize the inventory of entire museum collections based on an average risk score. One of the problems with machine learning model is its difficult interpretation, as it is not possible to justify simply and concisely enough why the model gave one or the other score. At the same time, there would be no need for a machine learning model if we knew exactly why and how quickly museum objects were aging.

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References

[1] M.C. Depcinski, *Conservation in museums*, **Encyclopedia of Global Archaeology** (Editor: C. Smith), Springer Nature, 2020, pp. 2645-2648.

[2] D.P. Kronkright, *Deterioration of artifacts made from plant materials*, **The Conservation of Artifacts Made from Plant Materials** (Editors: M-L.E. Florian, D.P. Kronkright and R. E. Norton), The Getty Conservation Institute, 1990, pp. 139-193.

[3] B. Fabbri (editor), **Science and Conservation for Museum Collections,** Nardini Editore, 2012, pp. 1-470.

[4] T. Grøntoft, L.P. Stoveland, T. Frøysaker, *Predicting future condition and conservation costs from modeling improvements to the indoor environment: The monumental Munch-paintings in the University of Oslo's Aula assembly Hall*, **Journal of Conservation and Museum Studies**, **17**(5), 2019, pp. 1-15.

[5] M. Frigione, A. Rodríguez-Prieto, *Can accelerated aging procedures predict the long term behavior of polymers exposed to different environments?*, **Polymers**, **13**(16), 2021, Article Number: 2688.
[6] D. Erhardt, M. F. Mecklenburg, *Accelerated vs natural aging: effect of aging conditions on the aging process of cellulose*, **Materials Issues in Art and Archaeology,** Vol. IV (Editors: P. B. Vandiver, J.R. Druzik, J.L. Galvan Madrid, I.C. Freestone and G.S. Wheeler), Materials Research Society, 1995, pp. 247-270.
[7] E. Menart, G. de Bruin, G., M. Strlic, *Dose-response functions for historic paper*, **Polymer Degradation and Stability**, **96**(12), 2011, pp. 2029-2039.
[8] F. Coppola, A. Modelli, M. Strlič, M. Andretta, F. Scagnolari, *Kinetics of degradation of non-recycled and recycled contemporary paper*, **Cellulose**, **25**(9), 2018, pp. 5337-5347.
[9] A. Fenech, C. Dillon, K. Ntanos, N. Bell, M. Barrett, M. Strlič, *Modelling the lifetime of color photographs in archival collections*, **Studies in Conservation**, **58**(2), 2013, pp. 107-116.
[10] R.L. Feller, **Accelerated Aging. Photochemical and Thermal Aspects**, The Getty Conservation Institute, 1994, p. 280.
[11] R.P. Brown, *Survey of the status of test methods for accelerated durability testing*, **Polymer Testing**, **10**(1), 1991, pp. 3-30.
[12] P. Dellaportas, E. Papageorgiou, G. Panagiaris, *Museum factors affecting the aging process of organic materials: review on experimental designs and the INVENVORG project as a pilot study*, **Heritage Science**, **2**(2), 2014, pp. 1-11.
[13] N. Luxford, D. Thickett, *Monitoring complex objects in real display environments – how helpful is it?* **Climate for Collections: Standards andUuncertainties** (Editors: J. Ashley-Smith, A. Burmester and M. Eibl), Archetype Publications Ltd, 2013, pp. 257-269.
[14] G. Leijonhufvud, E. Kjellström, T. Broström, J. Ashley-Smith, D. Camuffo, *Uncertainties in damage assessments of future indoor climates*, **Climate for Collections: Standards and Uncertainties** (Editors: J. Ashley-Smith, A. Burmester, M. Eibl), Archetype Publications Ltd, 2013, pp. 405-418.
[15] **NPS Museum Handbook, Part I**, Museum Management Program, 1999, pp. 4:6-4:8. https://www.nps.gov/museum/publications/handbook.html
[16] M. Demeroukas, *Condition reporting*, **MRM6: Museum Registration Methods** (Editors: J.E. Simmons and T.M. Kiser), The Rowman & Littlefield Publishing Group, Inc., 2020, pp. 400-413.
[17] K. DePauw, *Deterioration: environmental versus inherent vice*, **Indiana Historical Society Collections Advisor**, **93**, 2019. https://indianahistory.org/wp-content/uploads/2019.07-Deterioration.pdf
[18] K. Konsa, *Conservation strategies: A deterioration model of printed materials*, **Papier Restaurierung**, **2**(2), 2008, pp. 29-33.
[19] J. Taylor, D. Watkinson, *Indexing reliability for condition survey data*, **The Conservator**, **30**(1), 2007, pp. 49-62.
[20] T. Mitchell, **Machine Learning**, McGraw Hill, New York, 1997, pp. 49-62.

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