Villarey barrack. View of the main courtyard. (Source https://bit.ly/3tTW7kp - CC BY 2.0)

Improving Cultural Heritage conservation: LSTM neural networks to effectively processing end-user's maintenance requests

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Abstract: Preventive conservation of cultural heritage can avoid or minimize future damage, deterioration, loss and consequently, any invasive intervention. Recently, Machine Learning methods were proposed to support preventive conservation and maintenance plans, based on their ability to predict the future state of the built heritage by collected data. Several data sources were used, such as structural data and images depicting the evolution of the deterioration state, but till now textual information, exchanged by people living or working in historical buildings to require maintenance interventions, was not used to support conservation programmes. This work proposes a method to support preventive conservation programs based on the analysis of data collected into CMMS (computer maintenance management software). In a Cultural Heritage building in Italy, hosting a University Campus, data about end-user's maintenance requests collected for 34 months were analysed, and LSTM neural networks were trained to predict the category of each request. Results show a prediction accuracy of 96.6%, thus demonstrating the potentialities of this approach in dynamically adapting the maintenance program to emerging issues.

Keywords: cultural heritage; preventive conservation; maintenance; NLP; neural networks.

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1. Introduction

Built cultural heritage is exposed to various deterioration problems that can be caused by physical, chemical, natural and human actions (Eken *et al.,* 2019; Villafranca Jiménez and Gutiérrez-Carrillo, 2019). To reduce the need for major and invasive interventions (van Balen, 2015), preventive conservation approaches were proposed (van Balen, 2015; Villafranca Jiménez and Gutiérrez-Carrillo, 2019). With a preventive approach, the focus shifts from restoration, intended as all those activities which are needed to repair a serious deterioration, to a more inclusive approach, a proper management strategy, which means implementing a meticulous approach of care, based on data collection, regular monitoring, inspections, control of environmental factors and maintenance activities (Borgarino, 2015).

Indeed, despite the international scientific community's consensus toward a Preventive and Planned Conservation approach (van Balen, 2015; Borgarino, 2015; Villafranca Jiménez and Gutiérrez-Carrillo, 2019), implementation is still partial. In recent years, some researchers have tried to develop effective documentation methods to report the situation of buildings and sites within the scope of preventive conservation. An overview of the strategies processes and operational case studies that support the implementation of preventive and planned conservation in the built heritage sector has been analysed during CHANGES conference in 2017 (van Balen and Vandesande, 2018). Preventive conservation approaches have been already applied in various heritage fields such as archaeology and artefact conservation (Villafranca Jiménez and Gutiérrez-Carrillo, 2019). However, the process for cultural heritage buildings differs from other heritage fields, due to the interaction with humans living and working there (Eken *et al.,* 2019; De Gregorio, 2019). Preventive conservation of the built cultural heritage requires monitoring actions and maintenance interventions in a co-evolutionary approach, because (1) built cultural heritage continues to change; (2) conservation must adapt to the changes, and (3) it should then face many challenges widely relaying with sustainability issues, management strategies, guidelines and, indeed, bureaucracy (Carman, 2019; De Gregorio, 2019; Della Torre, 2010; Villafranca Jiménez and Gutiérrez-Carrillo, 2019).

It has been underlined that maintenance, as the process of "taking care of", is an important element, though not exclusive, of a preventive conservation strategy. Maintenance evolved over time. From a set of corrective actions performed to solve emerging issues, it became a planned approach, based on preventive actions (pre-determined (Hong *et al.,* 2015), condition-based and predictive approach (Dzulkifli *et al.,* 2021) aimed at avoiding failure during operation (Ferreira *et al.,* 2021; Sheu *et al.*, 2015), reducing the possibility of service interruptions and, also, reducing costs (Sourav Das Adhikari *et al.,* 2019). Both in corrective or preventive maintenance approaches, monitoring actions should be regularly performed and data collected (Dzulkifli *et al.,* 2021). Maintenance actions are usually managed through CMMS (Computerized Maintenance Management Systems) (Bortolini and Forcada, 2020; Marocco and Garofolo, 2021; Pishdad-Bozorgi *et al.,* 2018), which also allows to collect end-users' maintenance requests and the related relevant information to generate a corresponding Work Order (WO) (Bortolini and Forcada, 2020; D'Orazio *et al.,* 2022). Then, when existing, CMMS data could be a relevant source of information, not only to act in a "corrective" manner, but also to support "preventive" conservation approaches, based on data collected over longer periods.

A relevant part of the built cultural heritage is managed by public organizations, and included in facility management contracts, then CMMS data are typically available and can be used to implement predictive approaches. However, CMMS data are typically written texts, information exchanged between end-users and technicians, thus requiring natural language processing (NLP) methods for a proper analysis. Previous studies underline the possibility to use CMMS data to improve the maintenance processes. Studies analysed the recognition of the fault (in terms of technical category and priority) and the attribution process (staff assignment) starting from the textual data contained in a CMMS database (Burak Gunay *et al.,* 2019), by using text mining methods (Burak Gunay *et al.,* 2019; D'Orazio *et al.,* 2022; Kim *et al.,* 2022; McArthur *et al.,* 2018). Text-mining methods have also been proposed to analyse CMMS databases and extract information (Gunay *et al.,* 2019) concerning fault frequency of HVAC components (Yang *et al.,* 2018), detect anomalies using neural-based learning methods (Du *et al.,* 2017), automatically detect WOs and faults priority (Bortolini and Forcada, 2020). The possibility to employ sentiment analysis methodologies to detect the priority of end-users' maintenance requests has been also investigated (D'Orazio *et al.,* 2022). The automation of the attribution process through Machine Learning (ML), such as scheduling and staff assignment, or resource optimization, has been recently analysed (El-Dash, 2007; Gutjahr and Reiter, 2010; Wu and Sun, 2006), and a set of classifier models was investigated to predict subcategories based on textual occupant-generated WOs (McArthur *et al.,* 2018). Previous research also provides a prediction model that automatically assigns staff in response to task requests in unstructured textual WOs (Mo *et al.,* 2020), applying different ML methods (Baek *et al.,* 2021; Çınar *et al.,* 2020; McArthur *et al.,* 2018; Mo *et al.,* 2020; Žižka *et al.,* 2019).

However, none of these studies refers to the cultural heritage fields, then further research is necessary to evaluate the applicability of these approaches to cultural heritage buildings, in order to improve the whole maintenance management pursuing a conservation goal. This paper then provides a contribution, by analysing a CMMS dataset referred to a listed Italian building and developing an LSTM Neural Network able to predict the appropriate workforce with the required skills to perform a specific maintenance task, thus reducing service interruptions and improving the general maintenance activity of the building. The proposed approach could also be useful to quickly adapt the maintenance program to emerging issues.

2. Methodology

2.1. The case study

The study refers to the CMMS data collected on a historical building, named "Villarey Barrack", hosting a University Economics Campus, located in Ancona, Italy. The building hosts a population of 250 workers (professors, technicians, administrative personnel) and about 4000 students. The Villarey barrack was built in 1865, when Ancona town was declared "first-class fortress" of the newborn "Regno d'Italia" (Italian Kingdom). The barrack is part of a complex defensive system, based on fortresses, powder magazines and secondary buildings (Altavilla, Cardeto, Scrima), built after the annexation of the town to the kingdom, to host the Italian military fleet on the Adriatic sea, due to the particular position of the town. Giuseppe Morando, a military architect born in Asti (I) in 1822, designed the defensive system. The building is a three-floor masonry building characterized by a square shape (100 × 100 m) with an internal court (62 × 56 m). The building is characterized by mullioned windows and decorations made with a local white stone, named "Conero stone". The building maintained military functions until 1972. After the recognition of its cultural value, the building was introduced in the listed buildings by the Ministry of the Culture, and in 1998 was restored to host the economic faculty of Università Politecnica delle Marche. The building is now part of the "Cardeto Park", a wide urban park facing the sea, comprising other buildings part of the same defensive systems, such as the iconic "Castelfidardo powder magazine", and the ruins of other fortresses and defensive walls built from 14th century in the same area. The Cardeto park comprises also a bastion attributed to the architect Antonio da Sangallo il Giovane.

The restoration process of the building took several years, due to the conflict between preservation and fire safety laws required for a university building. Three sides of the building (west, south, east) were restored maintaining the original geometry and the integrity of the facades, while the fourth side (north) was rebuilt maintaining only the external facades to host the biggest classrooms and the main stairs. During the restoration process, slabs were substituted, and elevators and new stairs were introduced in the west, south and east blocks. All the doors were changed to grant fire safety, all the windows were substituted, but maintained with the same materials and shapes of the original ones. New electrical, mechanical and fire safety equipment (i.e. sprinklers, evac) were introduced. All internal plasters were replaced. Actually, the building hosts 20 classrooms obtained from the transformation of the original warehouses and horse stables at the ground level. The other levels host department offices and the library of the faculty.

The maintenance of the building, comprising preventive conservation activities is assured by an external contractor with a facility management contract. The facility manager grants the full functionality and safety of the building and of the equipment with preventive and corrective actions. Corrective actions are required by end-users and managed by technicians through a CMMS. It collects texts exchanged by end-users and technicians, the labels attributed by the technicians (priority, intervention category) and the maintenance actions performed.

2.2. The CMMS dataset

Preventive conservation plans are based on the knowledge acquired through monitoring activities. Monitoring actions (structural, image processing), able to depict the evolution of buildings' deterioration state, have been proposed by researchers and implemented in real cases. A CMMS dataset is conceptually similar to the data of structural monitoring, with the substantial difference that the information about the evolution of the decaying state is given not by numbers but by natural language. A CMMS comprises end-users' maintenance requests (sentences) describing the issues and the required actions, labelled by technicians in terms of priority, category and required action. Then, from a CMMS it is possible to acquire information about the decay of building parts, components, systems, and materials, e.g. by analysing the trends of the maintained components over time.

To perform research activities, data contained in the CMMS of Villarey barrack, were acquired by the facility manager. The dataset is composed of 1265 end-user maintenance requests collected in 34 months (from January 2018 to October 2020). The dataset is part of a ten times bigger dataset involving all the buildings of the University (23). Each row of the dataset contains the end-user's maintenance request (provide by an e-mail

Figure 1 | Villarey barrack (on the top – view of the main courtyard) and Castefldardo powder magazine (on the bottom). The two buildings are part of a complex defensive system built in the 19th century after the inclusion of the city of Ancona in the newborn "Regno d'Italia" (source https://bit.ly/3tvTW7kp - CC BY 2.0).

text) and labels: codes and short texts expressing the place, the fault typology and other relevant information useful to assign the proper priority and the required skilled staff to the intervention. The combination of the end-users' requests and labels is named Work Order (WO).

Each end-users' maintenance request is associated with a work category and a specific action. Seven categories are included in the whole University dataset: Building components (doors, windows, walls, floors, ceilings, etc…); Electrical (appliances, electrical components and network devices); Plumbing (water adduction and discharge components); HVAC (Heating and cooling devices and ducts); Fire (fire safety devices); Elevator; Dialer Alarm (comprising textual pre-defined messages generated after an alarm). However, In the subset of data corresponding to the Villarey building, the Dialer Alarm category does not comprise any message during the analysis period, then this category has been excluded from the analysis.

133 actions are then included. Except for actions on technological equipment, those addressed to the building components include: flooring restoration, interior painting, ceilings restoration, doors maintenance, windows maintenance, minute maintenance and assistance for other works. The dataset also includes information about the characteristic of the building and the daily nominal and effective people presence in each day. Effective presence data were collected from the beginning of the pandemic event Covid-19 through tracking systems.

2.3. The research framework

Research activities have been organized in three phases.

Firstly, the dataset was analysed through data mining routines in MATLAB 2021a, to extract information about the statistical distribution of the interventions and to find specific correlations.

Secondly, the end-users' maintenance requests were processed through text-mining tools. Pre-processing actions, necessary to arrange the dataset to be trained with LSTM neural network, were performed. The dataset comprises sentences written by the end-users to request a maintenance activity (e-mails texts). Each sentence usually includes meaningful words (necessary to describe what and where happened), strengthening words (introduced by the end-users to add more or less strength to the request), complementary words (i.e «the, in, into, please», etc…), numbers, symbols, and punctuations. Each word can be present in different forms, depending on the structure of the sentence (i.e. urgent, urgently, urgency). Moreover, all these elements can be arranged in different ways, thus providing different possible meanings to sentences, even if composed of the same words. Then the recognition process can be very complex and influenced by the dataset itself.

To improve the ability of LSTM neural networks to properly recognize the type of intervention requested, the original dataset words have been processed. Textual data were filtered, removing the very common words (stopwords), symbols, punctuations, and low-length words (<2). No «stemming» actions were introduced. The «stemming» is a process that reduces each word to the stem (i.e. «Urgen» instead of urgency, urgently, urgent, etc…) (Yan *et al.,* 2020). This choice is justified by the necessity to maintain the lexical richness and variety of the original text. The final dataset comprises 761 unique words. All the activities were performed through text mining routines in MATLAB 2021a. Word clouds of the final dataset were plotted and an LDA (latent Dirichlet allocation) analysis has been performed, to understand how the textual information is arranged in each sentence and which topics are relevant and which words are meaningful for each topic (Žižka *et al.,* 2019).

Finally, in the third phase, an LSTM neural network has been trained and tested to predict the appropriate workforce with the required skills to perform the maintenance tasks.

Neural Network (NN) is a classifier that minimizes the mean quadratic error between the predicted output and the expected value. A neural network is directly trained from the data, based on the prediction errors. RNNs have been introduced because in this case, it was necessary to understand how the prediction is influenced by the sequence of the data, and not only by the data themselves (speech and text recognition). LSTM are RNN that can learn long-term dependencies between time steps of sequence data with loops, allowing information to persist. LSTM has been successfully used for the recognition of speech and natural writing (Burak Gunay *et al.,* 2019).

To perform the training process, the dataset has been divided into three parts. The two main parts are «training» (70%) and «testing» (20%). The third part of the datase (10%) has been used to check the ability of the LSTM for each of the categories. Sentences have been tokenized (each sentence was divided into "tokens": word units) and converted into sequences of numeric indices. Sentences have been truncated (30 words) to have word vectors of the same length. The word embedding layer was put to the dimension of 50 and the number of hidden units was set to 80. 30 epochs were considered. Each «epoch» measures the number of times that the learning algorithm works through the entire training dataset. The last part of the dataset (10%) has been also used to evaluate the results for each category. Results were compared through the following indicators (Gonçalves *et al.,* 2013; Ribeiro *et al.,* 2016): "Accuracy", "Precision", "Recall", "F1-score". "Accuracy", is the number of elements correctly classified with respect to the total number of elements; "Recall", is the ratio of the number of elements correctly classified to the number of known elements in each class; "Precision", is the ratio of the number of elements correctly classified to the total predicted in each class; "F1 measure", is the harmonic mean between both precision and recall.

All the processes have been performed through MATLAB 2021a writing specific code scripts.

3. Results

3.1. Analysis of maintenance interventions

Fig.2 shows the cumulative number of maintenance interventions performed during the considered 34 months.

The trend is almost linear for all the categories, with slope reductions corresponding to the summer periods (2018, 2019) and to the pandemic (2020). The main number of interventions refers to the technological equipment (3/4 of the total), i.e. electrical, plumbing and HVAC. A limited number of interventions has been performed on Fire protection devices and Elevators. The intervention on the building components (1/4 of the total), such as doors, windows, walls, floors, is the second component of the whole dataset.

The category "dialer alarm" is not present in the observation period. For each category, the mean number of daily interventions ranges from 2.14 to 3.06. The maximum number of daily interventions recorded is 10. Considering the number of interventions and the skills required to solve the specific problems, the analysis of these data is useful to define the general organization required to maintain the building and also grant preventive conservation actions.

The monthly distribution of the categories (Fig. 3) shows that the interventions are concentrated in the class periods, due to the high number of contemporary users. Fig. 4 shows the cloud of words used to require maintenance interventions, confirming that the maintenance is mainly addressed to solve problems on technological equipment, such as electrical appliances (light, neon), and plumbing systems (bathroom). The activity on building components is also relevant, especially on the doors and locking systems.

To understand the existence of specific aggregations between words, a latent Dirichlet allocation analysis has been performed, choosing 6 topics, as the categories (Fig. 5). The first topics correspond to words used to require interventions on the stairs of the building.

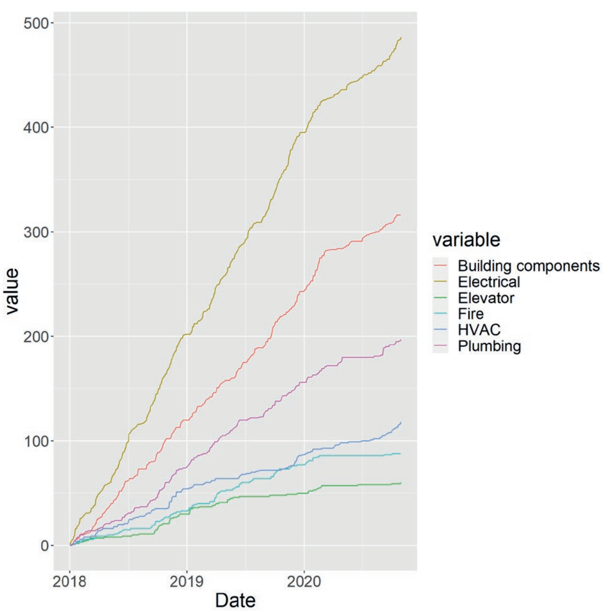

Figure 2 | Cumulative number of maintenance interventions by category. Dialer Alarm category did not entail any maintenance intervention request during the analysed period.

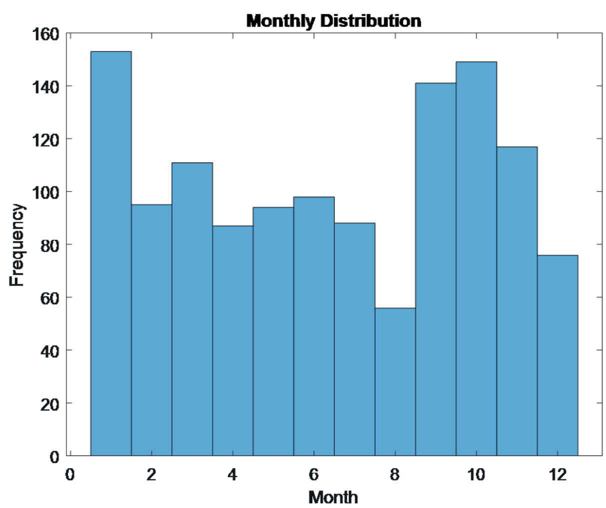

Figure 3 | Monthly distribution of the interventions (all the categories).

Figure 4 | Bag-of-words of the original dataset.

Some topics are clearly related to specific intervention categories. As an example, the first topic aggregates all the interventions on doors to grant the full functionality. The second topic aggregate information about plumbing interventions.

Other topics aggregate information about the place where the issue happened (topics 4,5, 6).

3.2. LSTM Accuracy results

LSTM Neural Networks have been trained and tested, in order to predict the appropriate workforce with the required skills to perform a specific maintenance task on the Villarey Barrack. Fig. 6 shows the confusion matrix obtained at the end of the training process. The confusion matrix shows the number of predicted sentences for

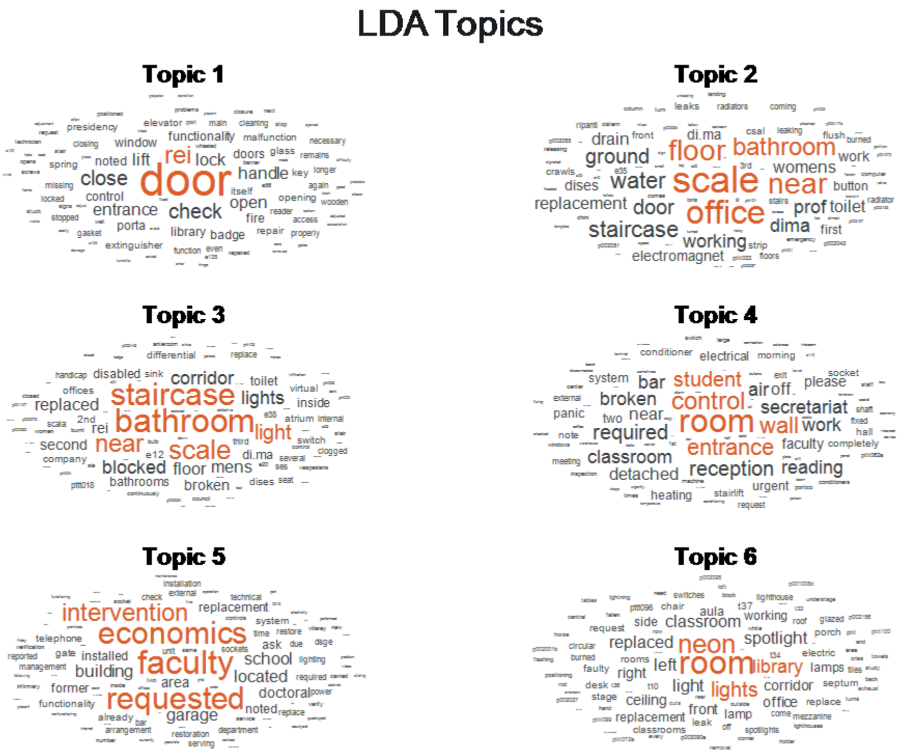

Figure 5 | LDA results.

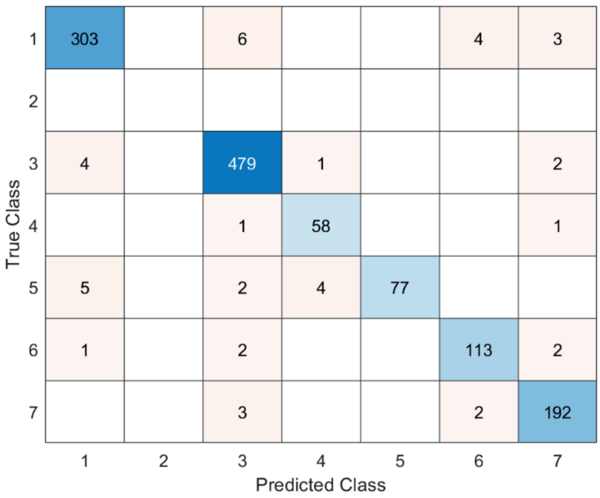

Figure 6 | Confusion matrix. 1:Building Components; 2: Dialer Alarm; 3: Electrical; 4: elevator; 5: Fire; 6: HVAC; 7: Plumbing. Dialer Alarm category did not entail any maintenance intervention request during the analysed period.

each category against the real categories (attributed by the technicians). The final accuracy obtained is 96.6%. The accuracy is obtained by summing the correct predictions (values on the diagonal of the matrix) and dividing them by the total sum of the sentences. The white line corresponds to a category included in the global CMMS dataset, but without interventions in the considered period (dialer alarm).

3.3. Precision, Recall and F1-score for each category

The ability of the LSTM neural network trained for each category has been checked through «Precision», «Recall» and «F1-score» values, which are shown in Tab. 2. The precision score obtained (ratio of the number of elements correctly classified to the total predicted in each class), is very high, reaching values near the unity. Almost all the sentences are correctly predicted by the trained LSTM neural network. Consequently also Recall (ratio of the number of elements correctly classified to the number of known elements in each class) is very high. The lowest value is 0.920. F1-score (harmonic mean between both precision and recall) shows the optimal agreement obtained in each class. The lowest value is 0.933, meaning that almost all the sentences are correctly recognized.

4. Discussions

Results underline the capabilities of the proposed approach in automatically recognizing maintenance needs from written natural language communications received by end-users of the investigated building heritage.

First, the LDA (latent Dirichlet allocation) analysis succeeded in understanding the topics of interest for each of the end-users' sentences, confirming the outcomes of previous works (Žižka *et al.,* 2019). In this sense, the most important topic in terms of maintenance requests is represented by the building components, thus stressing the impact of such work categories on the building heritage maintenance, especially in respect of the users' actions. Similarly, other equipment involving direct use by occupants shows a paramount impact on the maintenance tasks, as expected also in view of the interventions on the building heritage over time. The LDA analysis could support facility managers in understanding which are the core words of each topic of interest in the building heritage maintenance, by also pointing out the level of knowledge and perception of building components and equipment by non-expert end-users.

Second, the LSTM neural network has been trained and tested, and results shows that it can reliably predict the appropriate workforce with the required skills to perform the maintenance tasks corresponding to the aformentione topics highlighted in the LDA analysis.

Table 1 | Precision, Recall and F1-score for each category. Dialer Alarm category did not entail any maintenance intervention request during the analysed period.

Class ID	Name	Precision	Recall	F1-score
1	Building Components	0.958	0.968	0.963
2	Dialer Alarm	-	-	-
3	Electrical	0.985	0.971	0.978
4	Elevator	0.966	0.920	0.943
5	Fire	0.875	1	0.933
6	HVAC	0.957	0.949	0.953
7	Plumbing	0.974	0.960	0.967

In this sense, previous works insights are confirmed (Burak Gunay *et al.,* 2019), verifying the validity of the adopted tools in the analysis of communications in building heritage too. According to the indicators provided by literature (Gonçalves *et al.,* 2013; Ribeiro *et al.,* 2016), all the intervention categories have been properly recognized. For instance, considering the F1-score as the indicator combining precision and recall, obtained values are always > 0.93, thus implicating the relevant prediction capabilities of the method. Such a result encourages the use of these techniques also in sensitive and complex contexts such as building heritage, despite their specificities in terms of construction and use issues. Since this work focuses on maintenance topics recognition, the same approach could be also adapted to other related assignment activities, such as those concerning the priority of end-users' requests, so as to timely react in the relevant context of building heritage. Such actions will move towards a more effective Preventive and Planned Conservation approach (van Balen, 2015; Borgarino, 2015; Villafranca Jiménez and Gutiérrez-Carrillo, 2019) by fully merging operation, maintenance and general conservation/restoration tasks in building heritage.

5. Conclusions

This work proposes a method to support preventive conservation programs based on data collected in a CMMS (computer maintenance management software). Data about end-user's maintenance requests collected for 34 months and stored in a CMMS in a heritage building hosting a University Campus in Italy were analysed. In particular, LSTM neural networks were trained to predict the category of each maintenance request, thus reducing the intervention time. The proposed model can predict, with high accuracy levels (96%), the technical category of each new end-user's maintenance request and automatically select the correct staff. In this way, the CMMS become able to dynamically adapt the maintenance program to emerging issues, thus improving the management process of the built cultural heritage.

Future research should further investigate proper analysis methods of maintenance intervention trends (e.g. the concentration of interventions belonging to certain categories during certain periods) in order to further develop preventive approaches. In future applications, technicians could be supported by such methods and tools to reduce assignment times for maintenance requests, since the proposed approach could provide a preliminary and reliable screen of the end-users' communications. By this way, facility management could be more focused on the implementation of maintenance tasks with the workforce rather than on the simple assessment of needed skills, and the whole intervention process could be hence speeded up.

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