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A Novel Neutrosophic-based Machine Learning Approach for Maintenance Prioritization in Healthcare Facilities

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Abstract

The development of decision support tools for use in the maintenance management and renewal prioritization of healthcare facility assets is considered a highly challenging task due to the multiplicity of uncertainties and subjectivity levels available in such a decision-making process. Accordingly, this study utilizes a combination of Neutrosophic logic, Analytic Network Process (ANP) and Multi-Attribute Utility Theory (MAUT) to reduce the subjectivity pertaining to expert-driven decisions and produce a reliable ranking of hospital building assets based on their variable criticality levels and performance deficiencies. This is further integrated with the novel use of machine learning algorithms in this field, namely: Decision Trees, K-Nearest Neighbors and Naïve Bayes to automate the priority setting process and make it reproducible diminishing the need for additional expert judgments. The developed model was applied to Canadian healthcare facilities, and its corresponding predictive performance was validated by means of comparison against a

previously established model, and its excelling capability was clearly demonstrated. Accordingly, the developed integrated framework is expected to aid in creating a consistent, unbiased and automated prioritization scheme for hospital asset renewals, which in turn is expected to contribute to an efficient, informed and sound resources allocation process.

Keywords

Neutrosophic Logic; Analytic Network Process; Multi-Attribute Utility Theory; Decision Tree; K-Nearest Neighbors; Naïve Bayes; Healthcare Facilities

1 Introduction

Asset Management can be defined as the process of evaluating the value of assets within an organizational hierarchy. Maintenance and capital renewals are considered the most crucial functions of an asset management framework and are described by the International Organization for Standardization (ISO 2014) as a mixture of administrative and technical procedures undertaken to allow a building facility along with its underlying components to play the role they are designed for throughout their lifecycle. Thus, the disregard or untimely implementation of such maintenance activities can possibly result in significant process failures that can impose risks to people, revenue losses, or operational interruptions (da Silva et al. 2020).

In healthcare facilities, the traditional maintenance strategies that are used for the upkeep of the building assets and components are either preventive or reactive maintenance. As part of a preventive maintenance program, interventions are done on a timely-based manner. Although this strategy can contribute to the extension of the service life of the assets, it is rather labor-intensive and requires a large initial investment for the maintenance activities to take place on the designated time. Also, this maintenance strategy often leads to the implementation of redundant and/or unnecessary activities that could possibly be omitted without compromising the reliability or performance of the building assets. On the other hand, reactive maintenance is less costly in the beginning as it does not require initial investments to be made, however, it is considered a short-sighted and unsustainable maintenance approach as unexpected failures are highly possible in such a maintenance program which can cause a substantial disruption in a hospital operation as well as elevated cost for maintenance activities due to the ill-planned resources and budget allocation (Ahmed et al. 2020). This led to the evolvement of an updated maintenance program by the Joint Commission on Accreditation of Healthcare Organization (JCAHO 2014), which emphasized on the need for more accurate planning and scheduling of maintenance activities in a healthcare facility taking the variability of asset criticality and risk levels into account. This approach is expected to reduce the cost and labor hours associated with unneeded maintenance activities by reducing the frequency of time-based maintenance and shifting towards a more predictive maintenance approach (Shamayleh et al. 2019).

Moreover, as stated by Elsawah et al. (2014), the estimation of the consequences and probability of failure of the asset components as part of an asset management framework can act as a beneficial aiding tool for municipalities and governments in order to make objective comparisons and prioritize assets with a higher potential failure impact for renewal purposes. The process of predicting the possible consequences and probability of failure is referred to as a Risk Assessment framework (Shahata and Zayed 2015). Risk assessment models that are developed as part of asset management frameworks have recently become a capital mission in healthcare organizations (Jamshidi et al. 2015).

However, the incorporation of such risk-based assessment approaches within healthcare facilities to prioritize the underlying assets has taken a rather subjective form in which experts are required to rank assets' priority levels according to their corresponding expertise and judgement. This can possibly lead to inconsistencies between different experts' opinions as well as uncertainties found as a result of the absence of a systematic methodology for ranking hospital building assets and components.

Accordingly, this paper is realized to provide a systematic means of quantifying the priority levels for different hospital building components depending on the deficiencies detected within their course of operation, as well as their variable risk tendency or failure history experienced. This approach is also enhanced by the use of machine learning algorithms in order to automate the priority setting process reducing the reliance on further expert-based subjective techniques, which improves the overall prioritization process and makes it more consistent and reliable. The proposed framework also aims at providing a fair allocation mechanism of the limited resources and budgets available within healthcare organizations.

2 Literature Review

In the context of healthcare facilities, the asset prioritization topic has been tackled in numerous studies in the literature utilizing variant methodologies as elaborated as part of this section. First, a study by Joseph and Madhukumar (2010) assessed the urgency for conducting the maintenance interventions on medical equipment on the basis of three main criteria, namely: physical condition, function of equipment usage as well as the hazards expected if equipment is kept as is. In their study, the various identified criteria were equally weighted, and the final scores for the equipment were derived based on direct rating. The previous three criteria were also used by Sweis et al. (2014) to determine the priority level of medical equipment as well, however, they evaluated the weights of the criteria on an AHP basis to decrease the subjectivity associated with the ranking process. The previously outlined factors have been expanded by Faisal and Sharawi (2015) where the age of medical equipment since installation was included in the evaluation process, as well as the maintenance cost required to rectify the asset's performance. In their study, the criteria weights were derived on an AHP basis which was found to provide a more objective representation of the real maintenance triggers and drivers. Diverging from the previous frameworks, Shamayleh et al. (2019) omitted the physical condition and the age parameters from their prioritization model and consequently stated that the only indicative factors of the urgency level of the medical equipment to receive a proper maintenance intervention is their relative function within the facility, their failure history, as well as the associated hazards and implications of their breakdown or failure. Adopting a similar understanding, Ahmed and Zayed (2019) assessed the priority level of hospital building components on an AHP basis considering only criticality and risk factors, without including the physical condition into the prioritization process.

On the other hand, Hamdi et al. (2012) and Moscato et al. (2017) determined a different ranking scheme for the assessment of the importance level of assets and their underlying components, namely: function and maintenance requirements. Hamdi et al. assumed that both criteria are of equal importance to the evaluation process of medical equipment, while Moscato et al. analyzed the evaluation criteria for hospital HVAC equipment on a risk matrix format, where the asset maintenance urgency receives a rating ranging from Minimum, Medium, High to Maximum risk level and thus a maximum maintenance consideration is required. Both studies concluded that the equipment's need for maintenance should be included in the priority evaluation process of hospital assets, which entails the quantification of all maintenance and renewal activities employed for the equipment under study in a given period of time illustrating the assets' performance deficiency or vulnerability levels.

Moving forward, Ali and Hegazy (2014) created a different ranking scheme for the prioritization of hospital building assets' renewal. In their framework, multiple rounds of expert surveys were undertaken to arrive at a convenient ranking of the zones, systems and subsystems' importance within a hospital. This was followed by visual inspection to determine the physical condition, sustainability level, risk and level of service associated with the usage of each hospital asset. The priority level was then calculated based on the weighted sum between the weights and scores for the different indicators with respect to each hospital asset.

In the recent years, Salem and ElWakil (2018) introduced a prioritization framework for hospital MEP equipment based on the evaluation of the assets' respective physical condition, safety and infection hazards as well as revenue loss associated with the operation and maintenance of the assets per year. They evaluated the importance of the different criteria as opposed to one another on an AHP basis. Utilizing the same AHP weighting methodology, Abirami and Sudheesh (2020) analyzed the significance level of the medical equipment according to their age, function of usage and the hazards expected in the case maintenance interventions were delayed or disregarded. Similarly, Hernández-López et al. (2020) analyzed the priority of medical equipment using the exact criteria but utilizing a more simplistic approach to the weighting of the prioritization factors where the weights were determined by maintenance personnel on a direct rating basis and a combined score was consequently obtained on a SAW approach.

As previously presented, an extensive number of studies is observable within the asset prioritization field in healthcare facilities, however, the utilization of subjectively deterministic methodologies to arrive at a convenient and representative priority level for assets along with their underlying components is greatly evident. Also, the dearth of an integrated mechanism that combines and agglomerates all the different prioritization factors demonstrating high advantages to the overall prediction process is another limitation realized from reviewing previous studies. In addition to that, the incorporation of multiple-valued logics to facilitate the group-decision-making process has not been explored before in the literature, despite the fact that healthcare facilities are typically referred to as environments involving multiple experts with different views and judgements brought together to arrive at a certain decision. This makes the inclusion of multiple-valued logics in the decision-making process a prospective topic to tackle in future studies. Finally, an important drawback of the previous studies is that the overall healthcare asset prioritization process is judgment-based and experience-dependent. This in turn prevents prospective advantages from employing progressive methodologies like machine learning algorithms to produce a more automated prioritization scheme for assets in healthcare facilities. This observation triggered the exploration of the machine learning utilization within the field of asset maintenance decision-making. Being the largest multidisciplinary database of peer-reviewed literature (Bonato 2016), Scopus was employed for a non-exhaustive search including the following keywords presented in Table 1. The search focused on the studies conducted in the past two decades from the years 2000-2020 as illustrated below to draw conclusions about the sufficiency of machine learning utilization within this field.

Table 1. Number of studies retrieved from Scopus search from the year 2000 to 2020

Search Keywords	No. of Studies
Machine Learning	286,177
Maintenance Management	86,366
Healthcare Maintenance Management	2,088
Maintenance Prioritization	1,474
Maintenance Management ***AND*** Machine Learning	836
Maintenance Prioritization ***AND*** Machine Learning	27
Healthcare Maintenance Prioritization	23
Healthcare Maintenance Management ***AND*** Machine Learning	18
Healthcare Maintenance Prioritization ***AND*** Machine Learning	0

The previous table gives a broad overview of the research status within areas falling under the scope of this paper. First, as it can be noted, the healthcare-related studies can safely be considered limitedly tackled within the areas of maintenance management and prioritization. Moreover, the applications of machine learning techniques for maintenance purposes are evidently scarce with respect to all types of facilities or assets. However, the most obvious drawback in the literature lies within the scarce utilization of machine learning methods to facilitate the maintenance of healthcare assets, which is a gap this paper is aiming to fill and contribute towards its investigation.

3 Methodology

Analyzing the gaps and limitations of the previous literature, this study presents a novel classification-based automated priority setting tool for assets in healthcare facilities. Three algorithms were selected due to their demonstrated popularity and capability in the previous literature, namely: Decision Trees (DT), K-Nearest Neighbors (KNN) and Naïve Bayes (NB). The scope of this study covers the building assets within a healthcare facility including civil, architectural, mechanical, electrical and plumbing systems along with their underlying components. The proposed tool is set to identify the corresponding priority level for the assets based on their criticality or risk rank as well as their performance deficiency with respect to their physical and functionality conditions. Also, for the purpose of minimizing the subjectivity within the decision-making process, an integration between Neutrosophic Logic and Multi-Criteria Decision-Making (MCDM) methods has been employed to arrive at a suitable benchmarking for the hospital building assets. This in turn rectifies the limitations identified within previous studies where most of the studies relied on a direct rating and an equal weighting for all evaluation criteria identified. The detailed steps undertaken within this study are illustrated in Fig. 1.

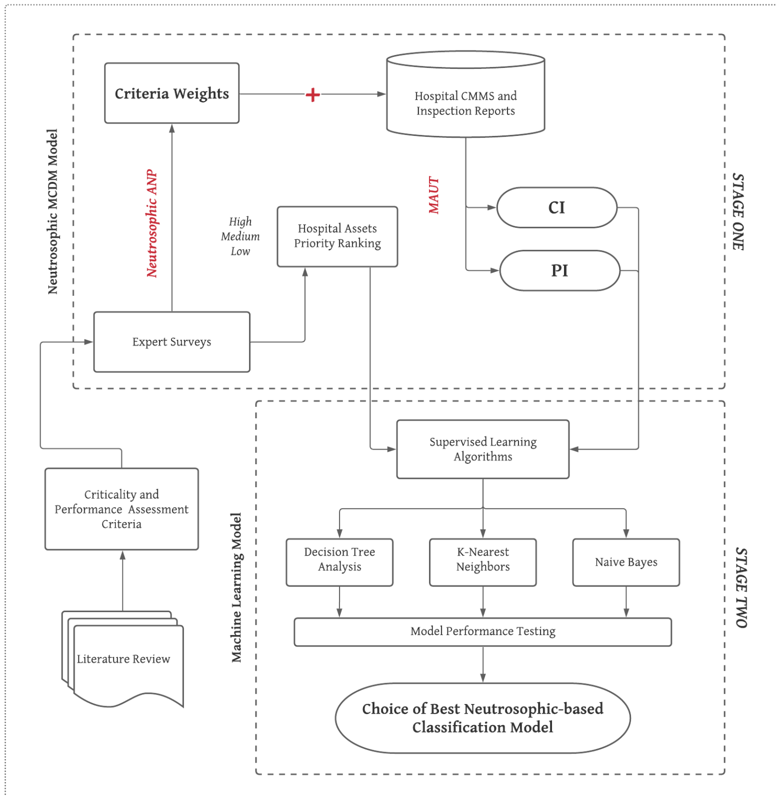

Figure 1 Methodology undertaken to fulfill study objectives

3.1 Multi-Criteria Decision-Making (MCDM)

The first stage is the utilization of MCDM methods to assess the criticality and performance evaluation criteria weights by means of the N-ANP process discussed below, followed by the exploitation of a MAUT to derive the corresponding indices of the hospital building assets.

3.1.1 Neutrosophic Analytic Hierarchy Process (N-ANP)

Neutrosophic logic was introduced by Smarandache (1999) as an extension for intuitionistic and fuzzy logics. Intuitionistic logic is the generalization of Fuzzy logic where two degrees of memberships are involved, namely: degree of Truth (membership) and degree of Falseness (non-membership). However, given that intuitionistic logic can only handle incomplete information, it can be insufficient to deal with inherent inconsistency or indeterminacy levels that are often present in fuzzy systems. Therefore, Neutrosophic sets evolved to overcome this drawback and are represented in the form of a Truth, Indeterminacy, and Falseness degrees of membership. Those three values are independent, and their sum lies between 0 and 3.

Neutrosophic sets are based on a relatively new philosophical branch named Neutrosophy, and are capable of mimicking human knowledge, preference and evaluation scheme by dealing with inherent uncertainties, inconsistencies and indeterminacies in a given set of information. A special case of Neutrosophic sets is a Single Valued Neutrosophic Set (SVNS), which was also proposed by Smarandache (1999) to facilitate the use of Neutrosophic sets in real world applications. Accordingly, this study uses SVNSs to apply the Neutrosophic-based ANP methodology into the assessment and ranking of identified criteria and sub-criteria to measure the criticality, risk and performance levels of hospital building components. The classical form of ANP is regarded as a generalization of the Analytic Hierarchy Process (AHP) and is considered the most comprehensive technique for use in strategic decisions due to its proven capability to handle all tangible and intangible criteria of influence (Saaty 2004). ANP forms a network structure of clusters and nodes to facilitate the decision-making process allowing the existence of complex dependencies and interrelationships between different levels and attributes (Otay and Kahraman 2019).

Decision-makers perform several levels of pair-wise comparisons to derive inner and outer dependencies and preferences of elements in a problem, and priorities derived are accumulated both vertically and horizontally into a matrix known as the Unweighted Super Matrix. Accordingly, a Weighted Super Matrix can be derived from the calculated Unweighted Super Matrix by normalizing each column in the matrix to make it equal to “1.0”. Finally, the priorities for each of the identified elements within the ANP problem can be obtained from the Limit Super Matrix which is attainable upon raising the Weighted Super Matrix to “k” powers.

Therefore, the steps adopted to assess the criteria preferences on an N-ANP basis were adopted from Otay and Kahraman (2019) as described below.

1) Determine the weight given to each of the experts surveyed ew_t as per Eq. 1

$$ew_t = y + a + c \qquad (1)$$

where t is the counter for experts surveyed, y represents the years of experience of the expert, a describes the area of expertise of the expert, and c is the country where the expert gained most of his experience.

2) Design the Influence Matrix of the problem's network composed of 0's and 1's indicating the absence and presence of relationships between factors respectively.

3) Form a comparison matrix for each group of clusters or criteria to represent the preference or influence given by the experts of one element on another.

4) Translate the linguistic terms assigned by experts surveyed to illustrate their inner and outer relationships between different criteria and sub-criteria according to the scale given in Table 2.

Table 2 Linguistic scale, the corresponding Neutrosophic values and Crisp values

Crisp Scale	Linguistic Term	Neutrosophic Set
9	Extremely More Important	(0.90, 0.10, 0.10)
7	Very Strongly More Important	(0.80, 0.25, 0.20)
5	Strongly More Important	(0.70, 0.30, 0.30)
3	Moderately More Important	(0.60, 0.35, 0.40)
1	Equally Important	(0.50, 0.50, 0.50)
1/3	Moderately Less Important	(0.40, 0.65, 0.60)
1/5	Strongly Less Important	(0.30, 0.70, 0.70)
1/7	Very Strongly Less Important	(0.20, 0.75, 0.80)
1/9	Extremely Less Important	(0.10, 0.90, 0.90)

5) Verify the consistency of each of the expert responses by formulating a perfectly consistent Neutrosophic matrix (T'ik, I'ik, F'ik), and then comparing it with the actual responses.

Consistency Ratio (CR) =

$$\frac{1}{2(n-1)(n-2)}\sum_{i=1}^{n}\sum_{k=1}^{n}\left(\left|T'ik-Tik\right|+\left|I'ik-Iik\right|+\left|F'ik-Fik\right|\right) \qquad (2)$$

6) Aggregate all expert responses into one single group decision-making matrix using the Eq. 3. This aggregated matrix is the Unweighted Super Matrix.

For Aj (j=1, 2, 3, … n):

$$Yw=\left(1-\prod_{j=1}^{n}(1-TAj)^{wj},1-\prod_{j=1}^{n}(1-IAj)^{wj},1-\prod_{j=1}^{n}(1-FAj)^{wj}\right) \qquad (3)$$

where j represents the experts' counter; w = (w1, w2, w3, …wn) is the weight vector of experts respectively; and $\sum_{j=1}^{n} wj = 1$

7) Calculate the Weighted Super Matrix by normalizing each column in the Unweighted Super Matrix by means of Eq. 4.

$$xn_{cr}=\frac{x_{cr}}{\sum x_c} \qquad (4)$$

where xn_{cr} is the notation for the normalized element "x" in column "c" and row "r", x_{cr} represents the corresponding element with the same position in the Unweighted Super Matrix which is divided by the sum of all the elements in the same column to obtain the normalized value.

8) De-neutrosophy the three-components weights derived for each element in the Weighted Super Matrix into single crisp numbers Wc using Eq. 5.

$$Wc = \frac{3 + Ti - 2Ii - Fi}{4} \qquad (5)$$

9) Obtain the Limit Super Matrix in which the element weights in the Weighted Super Matrix are raised to power "z" as shown in Eq. 6.

$$Wc^{\infty} = \lim_{z \to \infty} Wc^{z} \quad (6)$$

10) Prioritize the different criteria based on the ranking obtained from the Limit Super Matrix calculated in Step 9.

3.1.2 Multi-Attribute Utility Theory (MAUT)

Consequently, an MAUT method is utilized in order to formulate utility functions used for scoring different alternatives with regards to pre-defined criteria. In a typical MAUT problem, weights for criteria identified are obtained by means of a subjective preference of experts, however, as part of this study, the criteria weights utilized are obtained by means of a Neutrosophic-based ANP as per the previously illustrated methodology. This procedure is performed to reduce the relative subjectivity associated with the typical MAUT and take the uncertainty associated with expert judgements into consideration.

The MAUT is employed in the developed framework to derive a single Criticality Index (CI) or Performance Deficiency Index (PDI) for each asset studied as per Eq. 7 (Kaddoura et al. 2018).

$$CI_m \text{ or } PDI_m = \sum_{c=1}^{n} W_c \times U_c \quad (7)$$

where Wc is the weight for criterion c obtained by means of the N-ANP methodology, Uc is the utility score given by experts in the hospital building inspection process, n is the total number of criteria for assessing either Criticality or Performance Deficiency of building assets represented by the counter m.

3.2 Machine Learning (ML)

In this stage, the performance of three machine learning algorithms in classifying the correct priority levels of assets as per their corresponding CI and PDI is compared to select the most appropriate methodology for future applications on hospital building assets.

3.2.1 Decision Trees (DT)

Decision Trees are supervised machine learning models capable of predicting variable representing a target by analyzing a set of given input variables through a tree-like structure of rules governing the input-output relationship. Training this tree-based model type is first initiated by a root node representing all observations primarily assigned. After that, this initial root node is further divided and split into decision nodes built upon values of variables used for prediction purposes. Those decision nodes are normally represented by a set of branches where the upper branch illustrates the observations count representing cases to be distributed to a lower branch/node. This branching process is carried on repeatedly until a point where all observations within a decision node carry a similar classification is reached (Syachrani et al. 2013). The point that stops the branching and splitting process of decision nodes is called a leaf node as shown in Fig. 2.

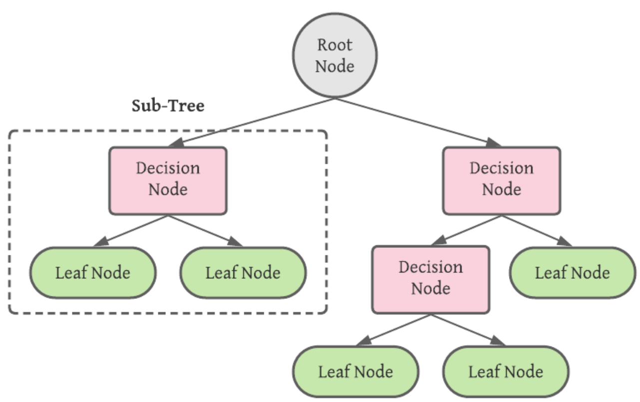

Figure 2 Components of a typical decision tree model

The branching process starts by selecting the most suitable variable from the given input parameters to act as a splitting variable based on a comparison of their relative splitting quality. In the case of a continuous-based predictor variable, all variables can be used as part of the splitting process. On the other hand, in a model with a categorial-based predictor variable, values of target variables present in each category is utilized for the splitting of branches.

The splitting process is performed based on the value obtained from Eq. 8 representing the Pearson Chi-Squared (χ^2) statistical test of predictor variables.

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \qquad (8)$$

where χ^2 represents the Chi-Squared distribution with k – 1 degrees of freedom; O_i is the observed frequency; and E_i is the expected frequency. A larger value for χ^2 indicates a better split between the left and right branches.

The value obtained for χ^2 is consequently converted into a probability value (P_v) by means of comparison of the χ^2 distribution. The P_v represents the likelihood of deriving the observed value with the assumption of having identical target proportions in every direction of the branches. This P_v value can be highly close to 0 if the dataset is largely sized. To facilitate the reporting of the probability value, the logworth of the P_v is used instead of its actual value as shown in Eq. 9.

$$\text{logworth} = -\log(P_v) \qquad (9)$$

The previously elaborated splitting process is recursively repeated until all available variables are surpassed by either of the logworth value or the value of P_v.

The larger size of a decision tree increases its overall complexity and can increase the likelihood of the model’s overfitting thus decreasing its robustness. Accordingly, pruning can be applied to the developed model in order to simplify it without sacrificing the overall accuracy by removing unnecessary leaves from trees to sustain a high accuracy level.

3.2.2 K-Nearest Neighbors (KNN)

KNN is a supervised machine learning algorithm utilized for regression and classification purposes. In general, the KNN is an algorithm of low complexity, and high applicability due to its ability to produce a highly accurate prediction with a little training requirement, and few parameters to tune (Ran et al. 2019).

A typical KNN classification process comprises of the following steps to determine the class of the testing instance by obtaining the class of its neighboring peer instances as demonstrated in Fig. 3.

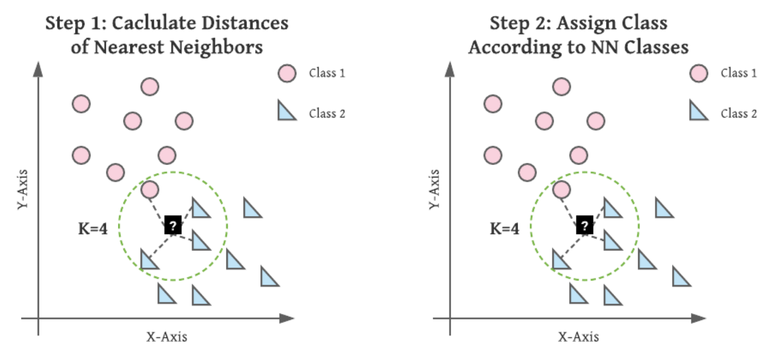

Figure 3 Steps followed as part of a typical KNN classification model

The initial step in a KNN classification is to set a K value that is used to compute distances between a testing instance and all the available input training datapoints. These distances are used to yield the K training instances exhibiting minimal distance calculations in order to assign the testing instance to the most common class demonstrated by its K neighboring points. Furthermore, the assignment of a class to the testing instance is done by calculating the ratio of the different classes available within the neighboring K instances, and the testing instance takes the highest voted class. On a different note, the distances' calculation process in a typical KNN scenario often uses the Minkowski Distance which can take different forms of the generalized form shown in Eq. 10.

$$D=\left(\sum_{i=1}^{n}\left|x_i-y_i\right|^{f}\right)^{\frac{1}{f}} \tag{10}$$

where D is the absolute sum of difference between coordinates; n is the total number of variables; x_i and y_i are the i^{th} variables in the two-dimensional vector space; and f can take three values corresponding to the form of the distance calculated, either 1 for Manhattan Distance, 2 for Euclidean Distance, or ∞ for Chebychev Distance.

Moreover, the choice of the value of K is either data-driven, where a cross validation approach can result in the selection of the most accurate and representative number of K where higher values can decrease the noise effect but result in a less distinct boundaries within classes (Ran et al. 2019). A more accommodating approach is to experiment the performance of the model using different K values and select the value with the highest performance (Martinez et al. 2019).

3.2.3 Naïve Bayes

A Naïve Bayesian classification is a supervised learning methodology that belongs to the family of probabilistic classification models. The main benefit associated with the utilization of this methodology is its low sensitivity to outliers due to its probabilistic nature, lowering the chances of skewness within the prediction process resulting in a reliable analysis for the given data. Another advantage of this algorithm is the reduced amount of data required for building and training the model due to the exploitation of a utility function that minimizes the relearning process of the conditional probability. Thus, the Naïve Bayesian model is a robust classification tool that involves simple assumptions and algorithms to accordingly produce powerful predictions (Jang et al. 2015).

The Bayesian theory was developed by the English Reverend Thomas Ferguson in 1763 (Bayes 1763). The established theory suggests that a certain likelihood level for a target event Y is expected to occur given that a certain feature event X has been formerly observed. The variable X is represented by Eq. 11.

$$X=(x_1,x_2,x_3,\ldots,x_n) \qquad (11)$$

where the values of $x_{1:n}$ represent all features included in building the predictor model

A simple form of the Bayesian equation is thus given in Eq. 12.

$$P(Y|X)=\frac{P(Y)P(X|Y)}{P(X)} \qquad (12)$$

where P(Y|X) is the probability of observing event Y after the occurrence of event X; P(Y) is the probability of occurrence of event Y; P(X|Y) is the probability of occurrence of event X if Y had already occurred; and P(X) is the probability of event X being observed.

And P(X) can be written as:

$$P(X)=\sum_{Y\in\Upsilon} P(X,Y)=\sum_{Y\in\Upsilon} P(X|Y)P(Y) \qquad (13)$$

where P(X) is considered a normalizing constant for the term P(X|Y) guaranteeing that the sum of P(Y|X) equals to 1 for all possible values of Y belonging to Υ

The optimal target class $\hat{Y}$ can thus be derived based on the values of features or input predictors by using Eq. 14.

$$\hat{Y}=\mathrm{argmax}_Y P(Y)\prod_{i=1}^{n} P(X_i|Y) \qquad (14)$$

where $\hat{Y}$ can either consist of two outcomes in which case the problem is called a “binary” classification problem, or more than two outcomes in which the problem becomes a “multiclass/multilabel” classification problem.

There are three main types of Naïve Bayesian Classifiers, namely: Multinomial, Gaussian and Bernoulli. The Multinomial type is the most popular type of Naïve Bayesian algorithms and is mainly utilized in cases where the features or model predictors are represented in the form of categorial values (i.e. like in rating scales 1 – 5). The Bernoulli type is utilized for the target prediction in problems where the features are illustrated on a Boolean pattern. Finally, Gaussian-based Naïve Bayes is employed where continuous or non-discrete values for predictors are available in a machine learning problem.

3.2.4 Model Performance Evaluation

In order to validate the performance of the machine learning algorithms in accordance with the actual priorities obtained for the hospital building assets, the following tests are deployed. The algorithm with the highest performance is selected as the automated tool for priority setting.

The first test is the Area Under Receiver Operating Characteristic Curve (AUC-ROC). The ROC is utilized to determine the model's capacity to determine classification classes for given assets (Davis and Goadrich 2006), while the AUC is a representation of the aggregated predictive performance of the model across all thresholds. Two parameters are thus evaluated as per Eq. 15 and 16, namely: True Positive Rate (TPR) and False Positive Rate (FPR).

$$\mathrm{TPR}=\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \quad (15)$$

$$\mathrm{FPR}=\frac{\mathrm{FP}}{\mathrm{FP}+\mathrm{TN}} \quad (16)$$

where TP, TN, FP and FP represent the numbers of True Positives, True Negatives, False Positives and False Negatives respectively.

The second testing parameter is the Accuracy of prediction exhibited by the model, calculated as a ratio between correct predictions made and the total number of predictions by means of Eq. 17.

$$AP=\frac{TP+TN}{TP+TN+FP+FN} \tag{17}$$

Additionally, the Precision (P) and Recall (R) provide the relevance of the retrieved values resulting from the model's implementation, as per Eq. 18 and 19.

$$P=\frac{TP}{TP+FP} \tag{18}$$

$$R=\frac{TP}{TP+FN} \tag{19}$$

Upon calculating the values of P and R for every model included, their respective F-Scores are calculated as part of their performance testing. An inverse relationship is often observed between P and R values; therefore, the F-Score measure provides a harmonic mean between P and R as shown in Eq. 20.

$$F=2\times\frac{P\times R}{P+R} \tag{20}$$

4 Implementation

The preliminary step to achieve the sought-after objectives is the identification of criteria and categories used to evaluate the criticality and performance deficiency levels of hospital building assets. The categories and criteria were collected from the literature review formerly presented. Upon criteria identification, their relative importance is validated and weighted by means of the N-ANP expert surveying methodology.

Experts involved within the current study add up to a total of thirty-one sharing similar professional backgrounds relevant to the healthcare facility management fields including hospital operation and maintenance management personnel (30%), maintenance engineers (60%), as well as government officials involved with the planning, auditing and prioritization of infrastructure needs and investments (10%). 58% of the respondents to the developed survey were affiliated with Canadian healthcare facilities with more than 10 years of experience in healthcare organizations in Canada, while the rest were from other parts of the world. Experts were asked to confirm the influence of the identified criteria and factors on the prioritization process of healthcare building assets, and thus were invited for weighting and ranking the superiority of criticality and performance deficiency factors on a pair-wise comparison basis.

4.1 Criticality and Performance Deficiency Criteria Evaluation

In order to assess the levels of criticality and risk associated with hospital building assets, four categories were identified and included in the surveying process of the experts in the fields of facility and maintenance management of healthcare facilities to assess their respective priorities and rankings. The four categories describing the vulnerability aspects of the hospital building assets are: Significance of Component (SC) which includes factors that rank the importance level of the asset within the hospital hierarchy and operation, Operational Criticality (OC) which quantifies the risks associated with the failure of the asset on an operational level as well as the previously experienced failure trend of components based on historical records and work orders, the Environmental and Social Criticality (ESF) which is an indicator of the extent of risks and severity of the component's failure to the surrounding environment and hospital building occupants, and finally the Economic Criticality (EC) which includes aspects illustrating the average resources consumed as part of failures experienced within the studied component. Within the aforementioned categories, fourteen criteria were identified and confirmed by experts for their relative importance and influence on ranking the urgency or priority levels of hospital building components as shown in the following table. Table 3 shows the criteria used to evaluate the criticality level of hospital building assets as well as the weights given to them as per the expert survey process previously discussed where more weight was given to responses of experts with more years of experience and higher experience relevance to Canadian-based organizations and facilities.

Table 3 Expert-derived weights for criticality evaluation criteria

Categories	Criteria	Weights
Significance of Component (0.3117)	Purpose of Component Usage (PU)	0.0825
	Location of Component (LC)	0.0971
	Relative Age of Component (RA)	0.0708
	Redundancy Available for Component (RD)	0.0613
Operational Criticality (0.3136)	Presence of Dependent Systems/Components (DS)	0.0673
	Mission Criticality of Component (MC)	0.0898
	Failure Occurrence Rate (OR)	0.0873
	Failure Detectability Level (DL)	0.0692
Environmental and Social Criticality (0.1556)	Failure Effect on Indoor Air Quality (IEQ)	0.0477
	Emissions, Toxic Releases or Contamination Accompanying Failure (ETC)	0.0453
	Failure Effect on Health, Safety and Sanitation of Hospital Occupants (HSS)	0.0626
Economic Criticality (0.2195)	Repair Cost (RC)	0.0670
	Resources Required (RR)	0.0653
	Downtime (DT)	0.0872

According to the gathered responses, the five criteria receiving the highest rating in assessing the criticality level of the hospital building component are: The Location of the building asset within the hospital hierarchy, its Mission Criticality level, the failure Occurrence Rate experienced for that asset, the average Downtime resulting from asset failure, and the Purpose of component usage within the hospital operation.

On the other hand, for the purpose of evaluating the performance deficiency levels of hospital building assets and components, four criteria were identified that are calculated as an inverse of the actual observable condition and performance rating during inspections and facility audit cycles, namely: Physical Condition Deficiency (PC) which is based on the physical observable condition rating received by the component as per the latest inspection or testing, Code Incompliance (CC) which evaluates the level of agreement or disagreement of the component's configuration and usage with the current or future code requirements, Energy and Water Inefficiency (EE) that evaluates the current state of energy and water efficiency within the operation of component being studied, and Capacity Inappropriateness (CA) used to measure the adequacy of the component sizing to serve and maintain the current and seasonal operational condition within the hospital facility. In summary, the PDI is the inverse of the Performance Index (PI) observable within hospital building assets. Table 4 shows the weighting given by the experts to each of the four criteria identified.

Table 4 Performance assessment criteria and their respective weights

Performance Deficiency Criteria	Weights
Physical Condition Deficiency (PC)	0.3761
Code Incompliance (CC)	0.1499
Energy and Water Inefficiency (EE)	0.3418
Capacity Inappropriateness (CA)	0.1321

4.2 CI and PDI Calculation

The succeeding stage is calculating the overall Criticality Index (CI) and Performance Deficiency Index (PDI) for every hospital component studied following the aforementioned MAUT methodology.

The utility scores given to components utilize the weights derived in the previous step, as well as the measuring scales shown in Table 5 to derive the overall indices. The indices are based on the data collected from the inspection records attained from five healthcare facilities in the province of Alberta, Canada. Table 5 shows the measuring scales given to the identified criteria in order to derive their corresponding scores.

Table 5 Measuring scales for the criteria within the Component Significance category

Criteria	Purpose	Location	Relative Age	Redundancy
Measuring Scale (Most to Least Critical)	Life Support and Safety (LSS)	Hospital-Wide (HWD)	> 1	None
	Environmental and Infection Control (EIC)	Acute Care and Emergency (ACE)	0.75 – 1	Partial
	Mobility (MOB)	InPatient Wards (IPW)	0.50 – 0.74	Full
	Communication (COM)	Diagnostics and OutPatient Clinics (DOC)	0.25 – 0.49	Double or More
	Shell and Structure (SST)	Ancillary and Support Departments (ASD)	< 0.25	---

Furthermore, Table 6 demonstrates the calculation methodology of the Component Significance for a group of components and the overall normalized weighted scores given for each evaluation criterion.

Table 6 Component Significance scoring methodology for hospital components

Criteria \ Systems	Roofing	Medical Gas	HVAC
Purpose (PU)	SST	LSS	EIC
Location (LC)	HWD	IPW	ASD
Relative Age (RA)	0.5	0.35	1.1
Redundancy Available (RD)	None	Partial	Full
Weighted Score	=0.0825×0.01 +0.0971×1.00 +0.0708×0.50 +0.0613×1.00 =0.1946	=0.0825×1.00 +0.0971×0.50 +0.0708×0.25 +0.0613×0.67 =0.1896	=0.0825×0.75 +0.0971×0.01 +0.0708×1.00 +0.0613×0.33 =0.1541

Moreover, a similar approach is undertaken to calculate the overall Performance Deficiency Index (PDI) as shown in the following Table 7 that illustrates the calculation procedure of the PI of a sample of hospital building components.

Table 7 Calculation methodology for the Performance evaluation criteria for hospital components

Criteria \ Systems	**Smoke Control**	**Chiller**	**Elevator**
Physical Condition Deficiency (PC)	Excellent	Poor	Marginal
Code Incompliance (CC)	Compliant	Modifications Required	Non-Compliant
Energy and Water Inefficiency (EE)	High Efficiency	Substantial Upgrades Required	Minimal Upgrades Required
Capacity Inappropriateness (CA)	Adequately Sized	Occasional Issues	Inadequately Sized
Overall PDI	$=1 - \text{PI}$ $=1 - (0.3761\times1.00 +0.1499\times1.00 +0.3418\times1.00 +0.1321\times1.00)$ $=0.0000$	$=1 - (0.3761\times0.21 +0.1499\times0.50 +0.3418\times0.01 +0.1321\times0.50)$ $=0.7766$	$=1 - (0.3761\times0.41 +0.1499\times0.01 +0.3418\times0.50 +0.1321\times0.01)$ $=0.6721$

4.3 Machine Learning Methods Implementation

Upon gathering all relevant datasets associated with the 394 different asset types that are present in 5 hospital buildings in the province of Alberta, the methodology was applied for all datapoints to derive the individual CI and PDI of all assets. An overall visualization of the final dataset obtained is shown in Fig. 4.

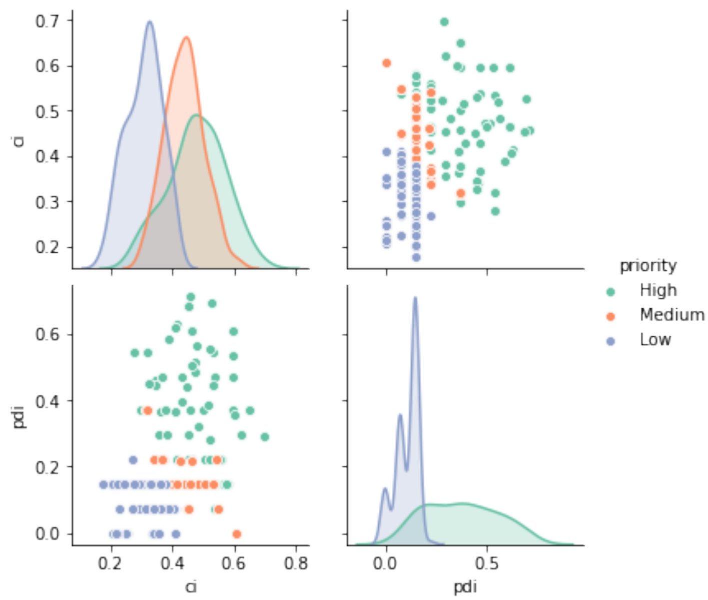

Figure 4 Visualization of the collected datasets

Decision Tree, K-NN and Naïve Bayesian analyses codes were consequently built on a Python environment in order to evaluate their respective performance in predicting a correct priority level for hospital building assets based on their criticality and deficiency levels.

For the purpose of building optimal classification models, all possible parameter combinations were investigated by means of an integration between Grid Search and Ten-Fold Cross-Validation. This was performed to obtain the highest Information Gain that represents a successful splitting/classification scheme. In each fold, the AUC-ROC is calculated, and the average is then used to indicate the overall model performance.

For the decision tree model, the optimal combination of parameters derived from the search process resulted in an AUC-ROC score of 0.917339 on the training portion of the dataset. The effect of each of the CI and PDI of assets on the overall assigned priority level was also evaluated, and their relative importance levels were 0.563194 and 0.436806 respectively. Fig. 5 shows the developed tree as per the pruned parameters chosen.

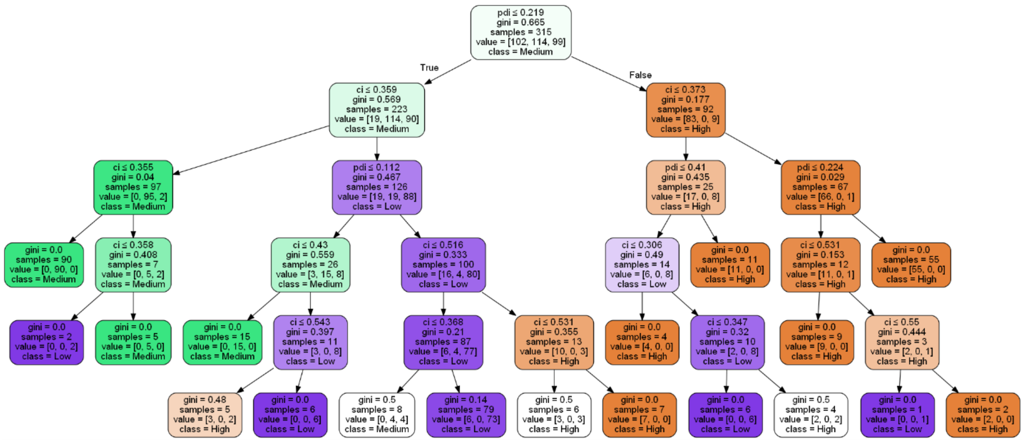

Figure 5 Decision Tree classification model visualization

Accordingly, the predictor model was formed, and it received an overall AUC-ROC score of 0.862709 based on weighting the results of the One-vs-One and One-vs-Rest tests by prevalence. Moreover, the overall Accuracy was calculated to be 0.90 which indicates a high performing model. Precision, Recall and F-Scores were calculated for each individual class, and their weighted average was obtained as per Table 8.

Table 8 Decision Tree model performance evaluation results

Class	Precision	Recall	F-Score
High Priority	0.93	0.83	0.88
Medium Priority	1.00	0.91	0.95
Low Priority	0.71	1.00	0.83
Weighted Average	0.92	0.90	0.90

Secondly, the best estimator model parameters for the K-NN algorithm resulted in an AUC-ROC score of 0.947011. A visualization of the KNN with the chosen number of neighbors is provided in Fig.6.

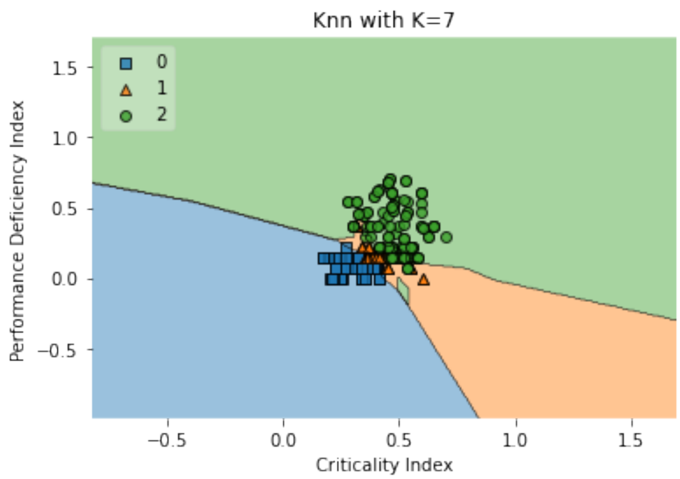

Figure 6 K-Nearest Neighbors classification model visualization

Accordingly, the predictor model was built by using the best combination of parameters and the corresponding AUC-ROC scores of 0.825764 and 0.825234 for the One-vs-One and One-vs-Rest methodologies were obtained respectively. The overall Accuracy was then calculated it received a value of 0.86 which is less than the score achieved by the Decision Tree Analysis, however it also indicates a high performing model. Precision, Recall and F-Scores were calculated for each individual class, and their weighted average was obtained as per Table 9.

Table 9 KNN model performance evaluation results

Class	Precision	Recall	F-Score
High Priority	0.76	0.83	0.79
Medium Priority	0.80	0.77	0.78
Low Priority	1.00	0.97	0.98
Weighted Average	0.88	0.87	0.87

Lastly, for the purpose of building a Naïve Bayes-based classification model, a Grid Search methodology is found inapplicable, due to the absence of parameters to tune within Naïve-Bayes models. Accordingly, considering the nature of data features included within the datasets, a Gaussian Naïve Bayes (GNB) model was formulated, and a label encoding was applied to the classes to transform string class labels, namely: High, Medium and Low priority levels into numerical ones, namely: 0, 1 and 2. This process was performed using the Label Encoder library in Scikit-Learn in Python. The preliminary AUC-ROC is found to be 0.855329. Visualizing the estimator model, Fig. 7 was generated.

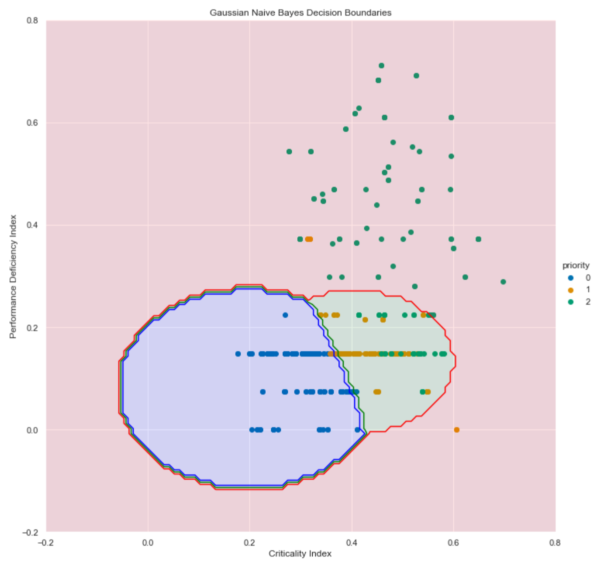

Figure 7 Naive Bayes classification model visualization

Consequently, the modified AUC-ROC scores were derived for the predictor model upon employing One-vs-One and One-vs-Rest evaluation procedures resulting in scores of 0.669037 and 0.625558 respectively and the overall Accuracy was found to be 0.49. This score is outperformed by both the Decision Tree Analysis and K-Nearest Neighbors models. Furthermore, the Precision, Recall and F-Scores were calculated for each class as per Table 10.

Table 10 Naive Bayes model performance evaluation results

Class	Precision	Recall	F-Score
High Priority	1.00	0.33	0.50
Medium Priority	0.00	0.00	0.00
Low Priority	0.46	1.00	0.63
Weighted Average	0.39	0.49	0.37

As illustrated by the previously presented investigation results of the three machine learning algorithms employed, two conclusions were deduced which are: 1) Criticality and Performance Deficiency levels of hospital building components provide a valid foundation for predicting the appropriate components' priority level; which was verified by the high capability demonstrated by the algorithms given the CI and PDI scores as input parameters, and 2) Decision Tree was the highest performing algorithm in predicting the appropriate priority level; which suggests that further future predictions would best be made using the developed N-ANP-MAUT Decision Tree methodology for an automated, less-subjective and more data-driven prioritization mechanism.

4.4 Model Validation

For the purpose of providing a further validation of the proposed model, the capability of the proposed Decision Tree model was compared to results derived from applying a previously established model in the literature. The model chosen for verification is the one by Ali and Hegazy (2014), due to its relative popularity and applicability in the case study hospital chosen within the scope of this study. Assuming the accuracy of expert judgemeents regarding the prioritization of hospital assets, the developed model and the verification model were both compared against expert-driven decisions.

Applying the methodology of Ali and Hegazy (2014), the same weights for systems, subsystems and zones were utilized in the case study hospital to arrive at the relative Overall System Importance (OSI) for every asset analyzed. Moreover, this value was multiplied by the Overall System Deficiency (OSD) scores calculated following the exact pattern outlined as part of their study. Since their weighted sum-based final score ranged from 0 to 10000, a "Low" priority was assumed for scores less than 3333, "Medium" priority for scores less than 6666 and "High" priority was for assets receiving higher score values. Consequently, the level of agreement between their ranking scheme, the proposed model as part of this study and the actual priority level arrived at by means of expert opinions was calculated as shown in Table. The conformance level represents the accuracy of the models in identifying correct priority levels for given instances.

Table 11 Level of conformance between proposed model, model from the literature and actual priority levels

Class	**Actual Priority Levels**	**Proposed N-ANP-DT Model**	**Ali and Hegazy (2014)**
High Priority	117	111	115
Medium Priority	129	120	98
Low Priority	148	125	99
Conformance Level		0.9058%	0.7937%

As it can be noted from Table 11, the model from the literature exceeded the proposed model in correctly identifying the high priority instances. However, the proposed model's capability significantly surpassed the model from the literature in the two other priority classes. Also, the overall conformance level of the proposed model outweighed the model by Ali and Hegazy (2014) by almost 11% in correctly identifying priority classes which validates the proposed model as a beneficial tool for the automated priority setting of hospital building assets for renewal purposes.

5 Conclusion

As proved by the recent COVID-19 pandemic, the continuous availability and operability of healthcare facilities and their underlying assets are considered of utmost importance. This triggered the need to develop efficient methodologies to prioritize the healthcare assets' renewal to face the continuously deteriorating condition levels of facilities as well as the limited budgets and resources available to meet their corresponding maintenance and renewal requirements. In this study, a prioritization model is developed where the variable asset failure consequences and mission-dependability influence their priority level as opposed to the models in the literature mostly relying on physical condition for such purpose. The developed model utilizes an integration between Neutrosophic Logic and Multi-Criteria Decision-Making techniques to result in an objective and reliable priority level for hospital assets. A combination of machine learning algorithms was also introduced for the first time in the asset prioritization field where Decision Trees, K-Nearest Neighbors and Naïve Bayesian classification algorithms were experimented, and the highest performing algorithm was outlined. Furthermore, the developed model was validated by means of a comparison with a previously established model against the actual priority levels derived for components and it exhibited a higher predictive performance by around 11% which makes it suitable for the automated and efficient prioritization of hospital building assets for renewal purposes. The proposed model was applied on Canadian healthcare facilities which proposes a possible path for further research by expanding the application of the model on different parts of the world mimicking their respective prioritization mechanisms. The criticality and performance deficiency-based priority levels derived can also be used in future models to rank and evaluate the applicability of different maintenance strategies to each building asset. The identification and analysis of more criteria to evaluate the priority and urgency of hospital assets, as well as the experimentation of different algorithms can also work as an interesting expansion endeavor.

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