An Evaluation of Parchments' Degradation
A Hybrid Approach

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ABSTRACT

Parchment stands for a multifaceted material made from animal skin, which has been used for centuries as a writing support or as bookbinding. Due to the historic value of objects made of parchment, understanding their degradation and their condition is of utmost importance to archives, libraries and museums, i.e., the assessment of parchment degradation is mandatory, although it is hard to do with traditional methodologies and tools for problem solving. Hence, in this work we will focus on the development of a hybrid decision support system, in terms of its knowledge representation and reasoning procedures, under a formal framework based on Logic Programming, complemented with an approach to computing centered on Artificial Neural Networks, to evaluate Parchment Degradation and the respective Degree-of-Confidence that one has on such a happening.

INTRODUCTION

Parchment denotes a material found in libraries, archives or museums, just to name a few. Maps, liturgical books, charters and other significant medieval manuscripts are examples of parchment artifacts that survived until today. It is an animal skin artifact that has been altered through chemical and physical means to resist putrefaction. It can be made from different animals skins, being produced in different ways and in dissimilar regions and times. These differences may result in disparate aging and reaction characteristics.

Parchment, primarily originating from the hides of cattle, sheep, and goats, is predominantly composed of type I collagen. As the collagen degrades over time, the parchment loses strength, becomes brittle, and deteriorates to the point that it can no longer be used. The basis for the biodegradation of parchment is generally resulting from the biodegradation of collagen, but the presence of a lipid fraction may play an important contribution. The presence of lipids acting as a free radical generator upon interaction with atmospheric sulphur dioxide is suggested as a possible means of the degradation of the collagen. The formation of protein-lipid complexes may be an indication of collagen degradation, as similar conjugates are found in the aging process. Ghioni et al. (2005) suggest a relationship between collagen degradation and the increased lipid content of parchment. In general, the parchments can be degraded by internal and external factors. Internal factors are linked to the composition, types of glues, chemical residues and metal particles, while the external factors can be divided in biological, chemical, physical and mechanical.

One of the factors to be taken into account for the preservation of parchments is the *Relative Humidity* (*RH*) of the storage location. The most commonly encountered recommendations in the conservation literature for the storage and display of parchment are in the region of *50% RH* to *65% RH*. However, recommendations vary and include unspecified levels such as "complete dryness" for the display of parchment. Storage or display below around *25% RH* is not indicated but decreasing the water content reduces (in both cases) the possibility of biodeterioration. A slightly higher value than *30% RH* is suggested like a optimum condition for an object for the long-term preservation leaving intact collagen, the most important structural protein of animal cells (Hansen and Steve 1992). It can finally be referred that below *30%* relative humidity results in the loss of physical properties of the parchments, while above *50%* relative humidity induce

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loss of physical and chemical properties. It is accepted by some authors that the ideal range of relative humidity for storage is the one between *30%* and *50%*.

The degradation of the ink is another factor to pay attention. We can consider three different types of ink degradation. *Haloing* is when a light brown halo spreads out from the inked area. *Burnthrough* is when the ink appears to sink through the parchment and become increasingly visible on the reverse side, and *Lacing* is when the inked areas become so weak and brittle that they crack, crumble and fall out (Reibland and Groot 1999). In this paper we assume that *Haloing* is the level one of degradation, *Burnthrough* is the level two and *Lacing* is the third one and the worst in ink degradation.

Biological attacks can be induced by microorganisms, revealed by the appearance of spots of different colors, intensities and conformations or by insect action that may already be inside where the parchment is filed or may arise from objects already infested. It can also be via the action of rodents that invade the premises through windows, doors or the tubing.

The *chemical attack* may occur by environmental pollution (e.g. dust has a cutting and abrasive action leading to wear and damage on the scrolls). However, dirtiness is the deterioration agent that most affects parchment, that if coupled with inadequate environmental conditions triggers reactions that leads to (parchment) degradation.

The *mechanical degradation* is related to handling and use and assumes the forms of folds, wear, paints stains and gaps.

Solving problems related to *Degradation-of-Parchments* (*DoPs*) requires a proactive strategy. However, the stated above shows that the *DoP* evaluation should be correlated with many variables and require a multidisciplinary approach. Consequently it is difficult to assess the *DoP* since it needs to consider different conditions with intricate relations among them, where the available data may be incomplete, contradictory and/or unknown. In order to overcome these drawbacks, the present work reports the founding of a computational framework that uses knowledge representation and reasoning techniques to set the structure of the information and the associate inference mechanisms. We will centre on a *Logic Programming* (*LP*) approach to knowledge representation and reasoning (Neves, 1984; Neves et al. 2007), complemented with a computational framework based on *Artificial Neural Networks* (*ANNs*) (Cortez et al. 2004).

KNOWLEDGE REPRESENTATION AND REASONING

Many approaches for knowledge representation and reasoning have been proposed using *Logic Programming* (*LP*), namely in the area of *Model Theory* (Gelfon and Lifschitz 1988; Kakas et al. 1998; Pereira and Anh 2009) and *Proof Theory* (Neves 1984; Neves et al. 2007). In this work it is followed the proof theoretical approach in terms of an extension to the *LP* language to knowledge representation and reasoning. An *Extended Logic Program* (*ELP*) is a finite set of clauses in the form:

$$
\begin{array}{l}
\{ \\
\quad p \leftarrow p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m \\
\quad ?\,(p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m) \;\; (n, m \geq 0) \\
\quad exception_{p_1} \\
\quad \cdots \\
\quad exception_{p_j} \;\; (j \leq m, n) \\
\} :: scoring_{value}
\end{array}
$$

where "*?*" is a domain atom denoting falsity, the p_i, q_j, and p are classical ground literals, i.e., either positive atoms or atoms preceded by the classical negation sign $\neg$ (Neves 1984). Under this formalism, every program is associated with a set of abducibles (Kakas et al. 1998; Pereira and Anh 2009) given here in the form of exceptions to the extensions of the predicates that make the program. The term $scoring_{value}$ stands for the relative weight of the extension of a specific $predicate$ with respect to the extensions of the peers ones that make the overall program.

Due to the growing need to offer user support in decision making processes some studies have been presented (Halpern 2005; Kovalerchuck and Resconi 2010) related to the qualitative models and qualitative reasoning in *Database Theory* and in *Artificial Intelligence* research. With respect to the problem of knowledge representation and reasoning in *LP*, a measure of the *Quality-of-Information* (*QoI*) of such programs has been object of some work with promising results (Lucas 2003; Machado et al. 2010). The *QoI* with respect to the extension of a $predicate_i$ will be given by a truth-value in the interval [0,1], i.e., if the information is *known* (*positive*) or *false* (*negative*) the *QoI* for the extension of $predicate_i$ is 1. For situations where the information is unknown, the *QoI* is given by:

$$QoI_i = \lim_{N \to \infty} \frac{1}{N} = 0 \qquad (N \gg 0) \tag{1}$$

where *N* denotes the cardinality of the set of terms or clauses of the extension of $predicate_i$ that stand for the incompleteness under consideration. For situations where the extension of $predicate_i$ is unknown but can be taken from a set of values, the *QoI* is given by:

$$QoI_i = {}^{1}/_{Card} \tag{2}$$

where *Card* denotes the cardinality of the *abducibles* set for i, if the *abducibles* set is disjoint. If the *abducibles* set is not disjoint, the *QoI* is given by:

$$QoI_i = \frac{1}{C_1^{Card} + \cdots + C_{Card}^{Card}} \quad (3)$$

where C_{Card}^{Card} is a card-combination subset, with *Card* elements.

The next element of the model to be considered is the relative importance that a predicate assigns to each of its attributes under observation, i.e., w_i^k, which stands for the relevance of attribute k in the extension of $predicate_i$. It is also assumed that the weights of all the attribute predicates are normalized, i.e.:

$$\sum_{1 \leq k \leq n} w_i^k = 1, \forall_i \quad (4)$$

where $\forall$ denotes the universal quantifier. It is now possible to define a predicate's scoring function $V_i(x)$ so that, for a value $x = (x_1, \cdots, x_n)$, defined in terms of the attributes of $predicate_i$, one may have:

$$V_i(x) = \sum_{1 \leq k \leq n} w_i^k * QoI_i\,(x)/n \quad (5)$$

allowing one to set:

$$predicate_i(x_1, \cdots, x_n) :: V_i(x) \quad (6)$$

that denotes the inclusive quality of $predicate_i$ with respect to all the predicates that make the program. It is now possible to set a logic program (here understood as the predicates' extensions that make the program) scoring function, in the form:

$$LP_{Scoring\ Function} = \sum_{i=1}^{n} V_i\,(x) * p_i \quad (7)$$

where p_i stands for the relevance of the $predicate_i$ in relation to the other predicates whose extensions denote the logic program. It is also assumed that the weights of all the predicates' extensions are normalized, i.e.:

$$\sum_{i=1}^{n} p_i = 1, \forall_i \quad (8)$$

It is now possible to engender the universe of discourse, according to the information given in the logic programs that endorse the information about the problem under consideration, according to productions of the type:

$$extensions - of - predicate_i = \\ = \bigcup_{1 \leq j \leq m} clause_j(x_1, \cdots, x_n) :: QoI_i :: DoC_i \quad (9)$$

where U and m stand, respectively, for set union and the cardinality of the extension of $predicate_i$. On the other hand, DoC_i denotes one's confidence on the attribute's values of a particular term of the extension of $predicate_i$, whose evaluation will be illustrated below. In order to advance with a broad-spectrum, let us suppose that the *Universe of Discourse* is described by the extension of the predicates:

$$f_1(\cdots), f_2(\cdots), \cdots, f_n(\cdots)\ where\ (n \geq 0) \quad (10)$$

Assuming that a clause denotes a happening, a clause has as argument all the attributes that make the event. The argument values may be of the type unknown or members of a set, or may be in the scope of a given interval, or may qualify a particular observation. Let us consider that the case data is given by the extension of predicate f_1, in the form:

$$f_1: x_1, x_2, x_3 \rightarrow \{0, 1\} \quad (11)$$

where "*{*" and "*}*" is one´s notation for sets, and *"0"* and *"1"* denote, respectively, the truth values *false* and *true*.

Taking into account the following clause where the former argument stands for itself, with a domain that ranges in the interval [0, 12], where the value of the second one may fit into the interval [5.5, 7] with a domain that ranges between 2.5 and 10, and the value of the last one is unknown, being represented by the symbol $\perp$, with a domain that ranges in the interval [0, 2]. Therefore, one may have:

$$\{$$
$$\neg f_1(x_1, x_2, x_3) \leftarrow not\ f_1(x_1, x_2, x_3)$$
$$f_1(\underbrace{6,\ \ [5.5, 7],\ \ \perp}_{attribute`s\ values\ for\ x_1, x_2, x_3}) :: 1 :: DoC$$
$$\underbrace{[0, 12][2.5, 10][0, 2]}_{attribute`s\ domains\ for\ x_1, x_2, x_3}$$
$$\} :: 1$$

In this program, the first clause denotes the closure of $predicate\ f_1$. Once the clauses or terms of the extension of the predicate are established, the next step is to set all the arguments, of each clause, into continuous intervals. In this phase, it is essential to consider the domain of the arguments. As the third argument is unknown, its interval will cover all the possibilities of the domain. The first argument speaks for itself. Therefore, one may have:

$$\begin{Bmatrix} \neg f_1(x_1,x_2,x_3) \leftarrow not\ f_1(x_1,x_2,x_3) \\ f_1(\underbrace{[6,6],\ [5.5,7],[0,2]}_{attribute`s\ values\ for\ x_1,x_2,x_3}) :: 1 :: DoC \\ \underbrace{[0,12\ ][2.5,10][0,2]}_{attribute`s\ domains\ for\ x_1,x_2,x_3} \end{Bmatrix} :: 1$$

It is now achievable to calculate the *Degree of Confidence* for each attribute that make the term argument (e.g. with respect to the second attribute it denotes one's confidence that the attribute under consideration fits into the interval [5.5, 7]). Next, we set the boundaries of the arguments intervals to be fitted in the interval [0, 1] according to a normalization procedure given by $(Y - Y_{min})/(Y_{max} - Y_{min})$, where the Y_s stand for themselves. One may have:

$$\begin{Bmatrix} \neg f_1(x_1,x_2,x_3) \leftarrow not\ f_1(x_1,x_2,x_3) \\ x_1 = \left[\frac{6-0}{12-0},\frac{6-0}{12-0}\right]\ x_2 = \left[\frac{5.5-2.5}{10-2.5},\frac{7-2.5}{10-2.5}\right], \\ x_3 = \left[\frac{0-0}{2-0},\frac{2-0}{2-0}\right] \\ f_1(\underbrace{[0.5,0.5],[0.4,0.6],[0,1]}_{\substack{attribute`s\ values\ ranges\ for \\ x_1,x_2,x_3\ once\ normalized}}) :: 1 :: DoC \\ \underbrace{[0,1]\quad [0,1]\quad [0,1]}_{\substack{attribute`s\ domains\ for\ x_1,x_2,x_3 \\ once\ normalized}} \end{Bmatrix} :: 1$$

The *Degree of Confidence* (*DoC*) is evaluated using the theorem of Pitagoras, i.e., $DoC = \sqrt{1 - \Delta l^2}$, as illustrated in Figure 1. Here Δl stands for the length of the arguments intervals, once normalized.

Below, one has the expected representation of the extensions of the predicates that make the universe of discourse, where all the predicates' arguments are real numbers. They speak for one's confidence that the real values of the arguments fit into the attributes' values ranges referred to above. Therefore, one may have:

$$\begin{Bmatrix} \neg f(x_1,x_2,x_3) \leftarrow not\ f_1(x_1,x_2,x_3) \\ f_1\underbrace{(1,\quad 0.98,\quad 0)}_{\substack{attribute`s\ confidence \\ values\ for\ x_1,x_2,x_3}} :: 1 :: 0.66 \\ \underbrace{[0.5,0.5][0.4,0.6][0,1]}_{\substack{attribute`s\ values\ ranges\ for \\ x_1,x_2,x_3\ once\ normalized}} \\ \underbrace{[0,1]\quad [0,1]\quad [0,1]}_{\substack{attribute`s\ domains\ for\ x_1,x_2,x_3 \\ once\ normalized}} \end{Bmatrix} :: 1$$

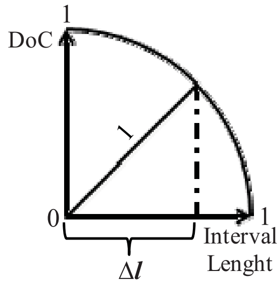

Figure 1: Evaluation of the Degree of Confidence

where the *DoC's* for *f_1(1, 0.98, 0)* is evaluated as (1+0.98+0)/3 = 0.66, assuming that all the argument's attributes have the same weight.

A CASE STUDY

In order to exemplify the applicability of our approach, we will look at an extension of the relational database model, since it provides a basic framework that fits into our expectations (Liu and Sun 2007), and is understood as the genesis of the *LP* approach to knowledge representation and reasoning (Neves 1984).

As a case study, consider the scenario where a relational database is given in terms of the extensions of the relations depicted in Figure 2, which stands for a situation where one has to manage information in order to evaluate the degradation of parchments. Under this scenario some incomplete and/or unknown data is also available. For instance, in *case 1*, the age of the parchment is unknown, while the last intervention occurred between 5 (five) and 10 (ten) years.

In *Light* column of the *Physical Effects* table *0* (zero) and *1* (one) stands for *not exposed* and *exposed*, respectively, while in *Temperature* column *0* (zero) denotes a value into the optimum range of temperature, i.e., between *2 ºC* and *18 ºC* whereas *1* (one) stands for values outside this interval. The *Humidity* column is populated with *0* (zero), *1* (one) or *2* (two) according to the *Relative Humidity* (*RH*) of the storage location. Thus, *0* (zero) denotes *RH < 30%; 1* (one) stands for a *RH* ranging in interval *[30, 50];* and *2* (two) denotes a *RH>50%.*

With respect to the *Mechanical Effects* and the *Biological Attacks*, affirmed on the last two columns of the *General Information* and the first three columns of the *Chemical Effects* tables are filled with *0* (zero) and *1* (one) denoting, respectively, *absence/no* or *presence/yes*. The last column of the *Chemical Effects* table is populated with *0* (zero), *1* (one), *2* (two) or *3* (three) according to the severity of the effects caused by ink degradation. Hence, *0* (zero) stands for *no effects*; *1* (one) denotes *haloing*; *2* (two) stands for *burnthrough* and *3* (three) denotes *lacing*.

General Information				
#	Age	Last Intervention	Inadequate Handling	Occurrence of Disasters
1	$\perp$	[5, 10]	0	0
2	[650, 700]	8	0	1
…	…	…	…	…
40	[400, 425]	$\perp$	1	1

Chemical Effects				
#	Environmental Pollution	Dust	Dirt	Ink
1	$\perp$	1	0	0
2	1	0	0	0
…	…	…	…	…
40	1	0	1	1

Parchment Degradation							
#	Age	Last Intervention	Handling/Disasters	Biological Attacks	Chemical Effects	Mechanical Effects	Physical Effects
1	$\perp$	[5, 10]	0	1	[1, 2]	2	1
2	[650, 700]	8	1	2	1	1	3
…	…	…	…	…	…	…	…
40	[400, 425]	$\perp$	2	1	3	2	1

Biological Attacks								
#	Bacterias	Fungi	Moths	Cockroaches	Termites	Larvae	Lice	Rodents
1	0	1	0	0	0	0	0	0
2	0	0	0	0	1	1	0	0
…	…	…	…	…	…	…	…	…
40	0	0	1	0	0	0	0	0

Physical Effects			
#	Light	Temperature	Humidity
1	0	0	1
2	1	1	1
…	…	…	…
40	0	1	0

Mechanical Effects				
#	Gaps	Wear	Folds	Paint Stain
1	0	1	1	0
2	0	1	0	1
…	…	…	…	…
40	0	1	1	0

Figure 2: An Extension of the Relational Database Model

The values presented in the *Handling/Disasters*, *Biological Attack*, *Chemical*, *Mechanical* and *Physical Effects* columns of *Parchment Degradation* table are the sum of the correspondent columns or tables, ranging between [0, 2] [0, 8], [0, 6], [0, 4] and [0, 4], respectively.

Now, we may consider the relations given in Figure 2, in terms of a *parch_degrad* predicate, depicted in the form:

$$parch\_degrad: Age,\ L_{ast}I_{ntervention},\ H_{andling}/D_{isasters},\ B_{iological}A_{ttacks},\ C_{hemical}E_{ffects},\ M_{echanical}E_{ffects},\ P_{hysical}E_{ffects} \rightarrow \{0,1\}$$

where *parch_degrad* stands for the predicate *parchment degradation*, *where 0* (zero) and *1* (one) denote, respectively, the truth values *false* and *true*. It is now possible to give the extension of the predicate *parch_degrad*, in the form:

$$
\begin{array}{l}
\{ \\
\quad \neg parch\_degrad(Age, LI, H/D, BA, CE, ME, PE) \leftarrow not\ parch\_degrad(Age, LI, H/D, BA, CE, ME, PE) \\
\quad parch\_degrad(\underbrace{\perp,\ [5,10],\ 0,\ 1,\ [1,2],\ 2,\ 1}_{attribute`s\ values}) :: 1 :: DoC \\
\qquad \qquad \underbrace{[400,700][0,100][0,2][0,8][0,6]\ [0,4][0,4]}_{attribute`s\ domains} \\
\} :: 1
\end{array}
$$

In this program, the former clause denotes the closure of predicate *parch_degrad*, and the next, taken from the extension of the *parchment degradation* relation shown in Figure 2, presents the information regarding *case 1* (one). Moving on, the next step is to transform all the argument values into continuous intervals, and then move to normalize the predicate´s arguments. One may have:

$$
\begin{array}{l}
\{ \\
\quad \neg parch\_degrad(Age, LI, H/D, BA, CE, ME, PE) \leftarrow not\; parch\_degrad(Age, LI, H/D, BA, CE, ME, PE) \\
\quad parch\_degrad(\underbrace{0,\quad 0.999,\quad 1,\quad 1,\quad 0.986,\quad 1,\quad 1}_{attribute`s\ confidence\ values}) :: 1 :: 0.855 \\
\qquad\qquad \underbrace{[0,1][0.05,0.1][0,0]\,[0.125,0.125][0.17,0.33][0.5,0.5][0.25,0.25]}_{attribute`s\ values\ once\ normalized} \\
\qquad\qquad \underbrace{[0,1]\quad [0,1]\quad [0,1]\quad [0,1]\quad [0,1]\quad [0,1]\quad [0,1]}_{attribute`s\ domains\ once\ normalized} \\
\} :: 1
\end{array}
$$

where its terms make the training and test sets of the Artificial Neural Network given in Figure 3.

ARTIFICIAL NEURAL NETWORKS

Several studies have shown how *Artificial Neural Networks* (*ANNs*) could be successfully used to structure data and capture complex relationships between inputs and outputs (Caldeira et al. 2011; Salvador et al. 2013; Vicente et al. 2012). *ANNs* simulate the structure of the human brain, being populated by multiple layers of neurons, with a valuable set of activation functions. As an example, let us consider the former case presented in Figure 2, where one may have a situation in which the evaluation of the parchments' degradation is needed. In Figure 3 it is shown how the normalized values of the interval boundaries and their *DoC* and *QoI* values work as inputs to the *ANN*. The output translates the parchments' degradation and the confidence that one has on such a happening. In addition, it also contributes to build a database of study cases that may be used to train and test the *ANN*.

The dataset holds information about the factors considered critical in the prediction of degradation state of parchments. Twenty three variables were selected allowing one to have a multivariable dataset with 40 records (Figure 2). These variables were grouped into five main categories, i.e., *General Information*, *Biological Attacks*, and *Chemical*, *Physical* and *Mechanical Effects*. Thus, the number of variables used as input of the ANN model was reduced to seven, i.e., the predicate´s arguments were workout according to a process of sensibility analysis, based on their *DoC*s values. A technique used to determine how different values of an independent variable will impact a particular dependent variable under a given set of assumptions.

The dataset used in the training phase it was divided in exclusive subsets through the 4-folds cross validation. In the implementation of the respective dividing procedures, ten executions were performed for each one of them. To ensure statistical significance of the attained results, 30 (thirty) experiments were applied in all tests. The back propagation algorithm was used in the learning process of the *ANN*. As the output function in the pre-processing layer it was used the identity one. In the other layers we used the sigmoid function.

A common tool to evaluate the results presented by the classification models is the coincidence matrix, a matrix of size $L \times L$, where L denotes the number of possible classes. This matrix is created by matching the predicted and target values. L was set to 2 (two) in the present case. Table 1 present the coincidence matrix (the values denote the average of the 30 experiments). It shows that the model accuracy was 87.5% (35 instances correctly classified in 40). Thus, the predictions made by the *ANN* model are satisfactory and therefore, the generated model is able to predict degradation state of parchments.

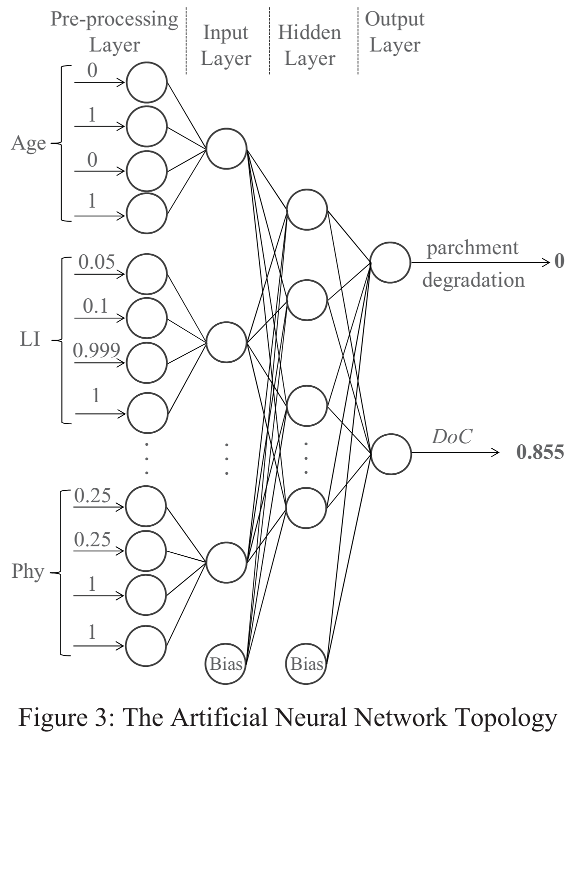

Figure 3: The Artificial Neural Network Topology

Table 1: The Coincidence Matrix for the ANN Model

Target	Predictive	
	False (0)	True (1)
False (0)	18	4
True (1)	1	17

CONCLUSIONS AND FUTURE WORK

To set a timeline to the maintenance of parchments is a hard and complex task, which needs to consider many different conditions. On the other hand, once the parameters to assess *DoP* are not fully represented by objective data (i.e., are of types *unknown* or *not permitted*, taken from a set or even from an interval), the problem was put into the area of problems that must be tackled by *Artificial Intelligence* based methodologies and techniques for problem solving. In fact, the computational framework presented above uses powerful knowledge representation and reasoning methods to set the structure of the information and the associate inference mechanisms. One's approach may revolutionize prediction tools in all its variants, making it more complete than the existing ones. It enables the use of normalized values of the interval boundaries and their respective *QoI* and *DoC* values, as input to the *ANN*. The output translates the *DoP* and the confidence that one has on such a happening. Indeed, the main contribution of this work is to be understood in terms of the evaluation of the *DoC*, and the possibility to address the issue of incomplete information.

Future work may recommend that the same problem must be approached using others computational frameworks like Case Based Reasoning, Genetic Programming or Particle Swarm, just to name a few.

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