# Deep Belief Networks for Multimodal, Images-based Non Contact Material Characterization

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**Abstract.** Our growing cognisance about the chemo-physical properties of electromagnetic waves and of their interaction with various materials provides expanding range of possibilities for quantification and non contact material characterization even in difficult to computation, « non-standard » domains as this of the cultural heritage. This review - thematically part of the IFIDA project dedicated to digitization of archaeometric and conservation-restoration praxis - deals with the possibilities latest neuroinformatic methods offer for a more efficient and fast interrogation, understanding and classification of multi-modal spectral records of paintings on various supports. The workflow followed during their routine non destructive (ND) analysis by human experts is described in terms of specific technical characteristics, research objectives and concrete application for the artworks' characterization as a prototype to simulate artificially. References to techniques for high semantic level information extraction from low-level features are suggested. The strengths and limitations in application of Deep Belief Networks (DBNs) for compression, visualization and data recognition are also considered. Examples of most appropriate architectures and topological maps of Deep Learning Networks for interpretation of UV, IR, XR, β, γ and CT records performing simple characterization and classification tasks - from single layer perceptron to multi-layer deep belief neural networks for unlabelled data - are presented and explained.

**Keywords:** Deep Belief Networks, Knowledge Representation and Reasoning, Knowledge Extraction.

## 1 Introduction

The optical emission (wl from 1-10 nm to 0.1 – 1mm) radiated by every kind of source contains important information about the composition, aggregate state, T, chemical and physical processes running in the studied object. Assessment of thou-sands of multi modal spectral records (MMSR, to which count

Colorimetry (CL); Near UV (NUV); Long UV (LUV); IR reflectography (IRR); IR luminiscence (IRL); Near IR (NIR); Short Wave IR (SWIR); Middle Wave IR (MID-IR); Long Wave IR (LWIRF); IR thermography (IRT); Reflectance Transformation Imaging (RTI); Multi-hyperspectral Imaging (MHI); Spectrophotometry (SP), plain X radiography (XR), beta and gamma radiography, Computed tomography (CT), etc.) of paintings on various supports brought to light dependencies between physic-chemical structure of the artworks and their response to VIS, UV, IR, XR, β and γ radiation in terms of colour, intensity, refractive index, density, etc., that rendered possible the quantification of prior non adapted to computing feature variables (Stoyanova, Spectral investigation of Serbian Baroque icons for their scientific documentation, 2015). Some of these optical phenomena, which are not caused by a chemical change as, for example, those at the origin of selective absorption and reflection, the light polarization or dispersion of combined light, the emission of fluorescence, the shift of max absorption following ionization of molecules of organic compounds, the anomalous dispersion, etc. have already found scientific explanation (Stoyanova, 2015), (Stoyanova, 2014). This created the premises to set up some innovative, non contact, scientifically reliable methods for indicative characterization of the (bio) chemical and physical nature of the materials employed in the studied artworks.

As, with the advent of laser and other new types of radiation sources and receptors, the spectral techniques incremented significantly (Lebedeva, 1986), here will be addressed only multi modal spectral records registered on analogue and digital supports: the most widespread in the routine archaeometric and conservation-restoration praxis. Since decennials they have affirmed as indispensable in the investigation of paintings on various supports because quality and quantity information on the studied materials are expressed through easy measurable characteristics as reflection, absorption, dispersion, emission, etc. of electromagnetic waves, and because automation-friendly and non contact.

MMSR form the first, obligatory step in the protocol for routine human scientific expertise that consists of 3 main phases (Grenberg, 2000):

a) non contact analysis under VIS light, UV, IR, XR, β and γ radiation, carried out prior to any expertise or sampling, by highly experienced restorers (Stoyanova, 2014) (Stoyanova, 2015) (Stoyanova, 2017) (Grenberg, 2000);
b) laboratory investigations needing sampling (Grenberg, 2000);
c) integral assessment of the outcomes resulting from a) and b) (Stoyanova, 2014) (Stoyanova, 2015) (Stoyanova, 2017) (Grenberg, 2000).

The measuring intended in a) uses as a vehicle for information the electromagnetic energy of determined wavelengths and forms of its interaction with the surface of the artefact (emission, reflection, diffusion, refraction, absorption). Its main parameters are defined by:

i) the characteristics of the source of energy (natural or artificial): a relevant aspect because of the resulting physics of the interaction,
ii) the modality of interaction with the surface of the artefact; each type of surface has a different response but there are problems of ambiguity in its interpretation,
iii) type of sensors and detectors: they can be optical, electronic or photographic sensors (emulsions,

vi) the process of assessment and interpretation: at this stage prevails the human component (normally a group of highly specialized experts) because it relies on multidisciplinary knowledge.

The comparative study of all detected elements together (c) has the goal to confirm, precise or reject the indicative hypothesis constructed during the preliminary study (a and b), and to label the abstract results of the scientific analysis, assigning them to determined art-historic phenomena (schools, masters, painting techniques, local traditions etc.), to define the status of conservation, authenticity, presence of post-interventions, etc. (Stoyanova, 2017) and (Stoyanova, 2014). From the point of view of logical reasoning, the interpretation of MMSR is a complex process of the analogue type: the human mind is linked to the ability to adopt generalizations, that is, switch from single information to an abstract model. For this is necessary prior knowledge that can enable the identification of objects, class, etc. by making use of their characteristics of form, size, colour, texture, structure, shade, and location, for ex. (Sheshkus, Limonova, Nikolaev, & Krivtsov, 2016).

## 2 Actually Existing Methods for Image Classification and Interpretation in Arcaeometry and Conservation & Restoration Praxis

The need to assess MMSR of great amount and complexity urges the development of automatic procedures for interpretation in order to contain the processing time within reasonable limits providing complete information on the case study. Moreover, the use of automatic procedures allows to standardize the criteria and to exercise quantitative controls on the accuracy of the results; it also enables the intraoperative use of the data and, in general, contributes to the **setting of a common digital language**.

Reports on the use of digital technologies in museum restoration practice for the past decade demonstrate that transfer and use of digital know – how in national restoration practices is intense but hazardous (Burdajewicz, 2009). This growing collection of methods and computing models (Pyykkö & Głowacka, 2017), (Amin & Zafar, 2014), (Montagnuolo, 2005), (Imran, Hashim, Irtaz, Azhar, & Abdullah, 2017), (Hendriks, 2009) brings with new needs and opportunities, but it produces also a certain fragmentation that hinders **the gradual formation of a common digital language in the CH sector**. From the other side, it is impossible and there is either sense to determine one or some of these methods as fundamental and others as secondary, as each has its own tasks and strengths. An optimal solution warranting interactivity, minimal programming/processing time and costs but also creative approaches, could represent an appositely harnessed software applying flexible e-learning models, able to assess contemporary big amounts of metric and nominal information, working in sufficiently wide and discontinuous thematic ranges and using standard protocols supplied with the typical archaeometric indicators taken into consideration during human examination of specific categories of art objects.

In fact, a German company, Fokus, since 2001 is working on the development of a computer graphic program, the metigoMAP (Burdajewicz, 2009), conceived specifically for art conservators and restorers as an alternative to advanced graphic software available on the market such as the designed for specific aims of graphic conservation CAD and GIS programs. Since its introduction, the software is undergoing constant upgrade according to conservators' suggestions and enables 2D and 3D digital mapping of various phenomena, provides convenient tools for creating, managing, laying out and publishing documentation projects, for precise quantity calculation, and helps to evaluate scope, time and cost of conservation. Its functional domain however, as this of other analogue interpretative soft wares like Morpho+, Octopus Analysis (Rajchenok, et al., 2010), (Van den Bulcke, Boone, Van Acker, & Van Hoorebeke, 2010), (Imran, Hashim, Irtaz, Azhar, & Abdullah, 2017) rests limited to the algorithmic, linear programming and does not offer tools for technical-technological interrogation and interpretation of the visual material. In overall, the process of data comparison and interpretation in the cultural heritage sector still represents a very challenging task due to their non standard scale or non metric character; for the missing ones, for the discontinuity and heterogeneity of cases.

The processes of interpretation are basically distinguishable into two types: the process of quality interpretation typical of the human mind and the process of quantitative interpreting typical of the machines. These approaches are completely different. The first is entirely crafted by an expert analyst who implements a decision-making process of high-level using with ease available referential information, but is limited in the calculation and mathematical analysis of metric variables (i.e. in the distinction of the levels of grey and colour tones). This is a subjective, concrete and quality-oriented method, but of poor accuracy. The second, related to the automatic interpretation characterized by a decision-making process at the low level, has a limited interaction with the human operator. It does not excel in the understanding of the studied information but allows for a more precise quantitative analysis and produces an accurate assessment of metric data (i.e. the size, gradation of all the grey or of the chromatic levels), therefore can be classified as an objective, abstract and quantitative method.

In the language of informatics, the expertises formulated at the various stages of human analysis refer substantially to the Restricted Bolzmann Machines (RBM) (Golovko, 2015), while the data extraction of MMSR and their interpretation relates to the solution of back propagation tasks, as from the outcomes are calculated the characteristics of the ambient which has caused determined spectral phenomena.

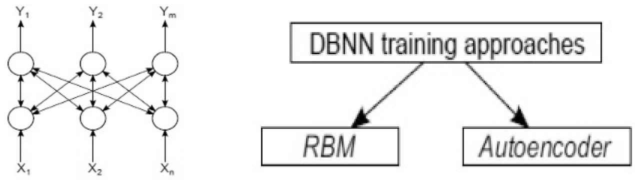



**Fig. 1.** Left: Scheme of a Restricted Bolzmann Machine (RBM); Right: The relation between expertise (RBM) and back propagation tasks in the frame of DBNs training approaches

## 3 DBNs: Strengths and Limitations in Application for Compression, Visualization, Data Recognition and Classification

Neural networks offer a particularly adapted approach for the problematic faced by IFIDA (Stoyanova, Paneva-Marinova, Pavlova, & Pavlov, 2014) for their affinity with the process of human thinking. From the point of view of machine learning, DBNs are considered by some authors special case of the methods of pattern recognition, discriminant analysis, clustering techniques, etc. From a mathematical point of view, the training of neural networks is a multi-parameter non-linear optimization. In comparison to traditional algorithms, well-tuned neural networks have shown to be able at times to overtake any expectations in classification and prediction tasks and are used for the design of various intelligent systems and wherever necessary to solve problems of classification, control and optimization (ANN, n.d.).

Regarding the strengths and limitations of DBNs, the Russian and Angloamerican schools - the most worthy for the development of this sector – in the course of time have defended distant positions (ANN, n.d.). Since 2006 however both converge on the fact that neural networks represent a revolutionary step in intelligent data processing. After Golovko (Golovko, 2015), DBNs can be considered as the latest step in the development of multilayer perceptrons. Such networks integrate different paradigms of neural network learning (Hinton, Osindero, & Teh, 2006) and, thanks to the layered architecture, allow to process and analyse large amount of data or to model the cognitive processes in various areas.

Encog (Heaton, 2015), one of the most popular and probably the most complete systems dedicated to the initialization and testing of neural networks was developed by Jeff Heaton. It contains a huge number of classes, functions and methods for working with neural networks, and is supported by a vast number of neural architectures like the Boltzmann machine, Kohonen self-organizing maps, recurrent networks, Jordan and Elman networks and others. (Heaton, 2015) provides a broad range of activation functions namely sigmoid, linear, sine, Gaussian function, function Elliott, bipolar, competitive, hyperbolic tangent. Also, judging by the available information, in comparison with other similar systems not only the recognition algorithms are associated with neural networks, but also Genetic algorithms, Random Forest and others, which is a strategic factor for optimization of analysis in the CH sector (Stoyanova, Luchev, & Paneva-Marinova, 2016). It has its adaptations to a variety of popular programming languages, such as Java, C#, C++, and also the ability to support parallel computing for multicore processors, as well the possibility of distribution not only on CPU but also on GPU. The latter is quite effective when working with neural networks, as the volume of data is often huge and even really good processors during parallelization will be filled to capacity. However, the library itself has no implementation of convolutional networks.

FANN Library (FANN), developed in C++ for working with neural networks, is the main competitor of (Heaton, 2015), opting to reach a wide audience (= huge development environments) with which it can interact. However, the range of classes, methods, functions, is somewhat less, or simply not all presented in the official documentation.

It also contains supports for parallel execution of algorithms for training neural networks. In overall, among the training methods the most interesting result (ANN):

a) Backpropagation
b) Resilient propagation or Rprop
c) Genetic Algorithm

### 3.1 Strengths

Each processor of such network has to deal only with signals that it periodically receives and signals that it periodically sends to other processors. Nevertheless, being connected in a sufficiently large network with controlled interaction, such individually simple processors together are able to perform fairly complex tasks. Neural networks are not programmed in the usual sense of the word, they are trained. The ability of learning is one of the main advantages of neural networks over traditional algorithms. Technical training consists in finding the coefficients of connections between neurons. In the process of training the neural network is able to identify complex relationships between input and output data, and perform generalization. In case of successful training, the network is able to return the correct result based on the data that were absent in the training set, as well as incomplete and/or "noisy", partly distorted data.

**A wealth of opportunities**. Neural networks are a well-developed optimization procedure, allowing the reproduction of extremely complex dependencies (LeCun, Bottou, & Haffner, Gradient-based learning applied to document recognition, 1998) and (LeCun & Bottou, 1998), (Sirotenko, 2009), (Gonsales, 2005), (Mestezkij, 2004). In addition, they represent a very powerful non-linear modelling tool, which copes with the "curse of dimensionality", that obstacles the modeling of linear relationships in the case of large number of variables. As known, in applications where the linear approximation is unsatisfactory – and properly such is the CH sector - linear models do not work well.

**Simplicity of use.** Neural networks learn by examples. The user of a neural network collates representative data and then runs the learning algorithm that automatically adapts to the data structure. Thus the user is required a set of heuristic knowledge about how to select and prepare data, select the desired network architecture and to interpret the results, however, the level of knowledge needed to successfully apply neural networks is much more modest than, for example, when using traditional statistical methods.

Initialization and training of DBNs consists of two main steps

**a) Selection of the initial network configuration** (for example, one intermediate layer with number of elements equal to the sum of the number of inputs and number of outputs - Monitor (Network Advisor).
**b) Selection of the weights (learning examples).**

### 3.2 Limitations

Computation of non-numeric data cause particular difficulties and most often they are presented in the form of nominal variables of type Gender = {Husband, wife}. Variables with nominal values can be represented in numerical form, and in the ST Neural Networks, for ex., exist tools for working with such data. However, neural networks do not give good results when working with nominal variables, which can take many different values.

There are several parameters to set up when working with DNNs, including statistics to monitor the contrastive divergence algorithm, batch sizes, monitoring over-fitting (iterations), learning rate, initial weights, number of hidden units and hidden layers, types of units (e.g. binary or Gaussian), dropout, among others (Hinton, Osindero, & Teh, 2006), (Golovko, 2015), (ANN). The complexity consists also in the fact that normally the input data volume is abnormally great and requires considerable calculative capacities that could not be justified by the impact of the outcomes. A solution to these drawbacks offer the introduction of fiducial points and of colour coding (Stoyanova, Stojanović, & Provorova, 2015). The first replaces big visual volumes with characteristic points, while the second allows to express the interdependences of non numeric data via the chromatic scale (or sfere). But there are also a series of other factors that hinder realisation of similar tasks and namely the non ideal quality of image records or their non-conformity due to different recording systems (hard and soft devices), different formats and measures, incompatibility between analogue and digital records etc. This inevitably constrains to search individual solutions or new, adapted parameters to already established methods.

The efficiency of DBNs, whose initialization and training is time-consuming process depends very much on the appropriated choice of parameters. The discontinuity of the data characteristic for the CH sector also imposes some limitations regarding the approach: practically the only adapted results the minibatch approach, which works with small packages of training samples to divide the calculations across multiple machines. In the ST Neural Networks package, i.e., there are tools allowing for classification of images by a relatively modern method as the method of convolutional neural networks.

## 4 Multimodal Spectral Analysis: Objectives and Tools

In overall, the main objective of multimodal spectral analysis is the material characterization of the artwork. The archaeometric indicators established in the course of preliminary assessment of data serve the encoding of the abstract outputs. In each spectral mode these indicators (features) are different, and this determines the need to select the most adapted architecture/topological map of the single perceptrons and of all together. Some insides:

### 4.1 The Investigation in VIS/Raking Light

In the context of this first survey are explored the status of conservation; damage caused by environmental factors – crackles; the characteristics of the author's manner and their identity with the connotations of determined masters/school; the methods and sequence in the realization of the work; the painting technique(s) and materials; the relation between support, gesso layer, paint and protective layers; the technical methods, the consistence of the paints, the configuration of the brushes; type(s) of crackles, particularities of employed materials. Basing on comparisons with archaeometric indicators, it is possible to elaborate hypothesis on the pigment compositions and on the presence of certain not common compounds/materials. The pattern recognition, a subarea of machine learning that, like DNNs, search to emulate the typical process of human mind, is the most effective at this step: several programs serve the recognition of objects, identification of the pattern or the models to the in-side of the data at the end of the classification. In &5 below are included some possible applications of single perceptrons for "deciphering" the material nature of coatings.

### 4.2 The Investigation in the UV Register

Most important feature variables of paintings under UV lighting represent **intensity, color, density, homogeneity of MMSR**, the presence of dark areas as sign of posterior interventions; deposits or missing protective layer; the reaction of gesso, paint and varnish layers together as well as separately to UV radiation. Fluorescent analysis (identification of a substance by the color of its fluorescence under ultraviolet radiation) has very high sensitivity: a fairly negligible amount of the substance (up to 10 $g^{-1}$), so that it is detected. Previously collected data of archaeometric value (low content features) allow to individualize, for example, presence of glues, egg, old Pb white, cinnabar or madder; to extract important information about the status of conservation (about losses and restorations); reconstruct faded inscriptions made with iron-gall inks or with Hg, Pb, Cr and Fe containing pigments; ascertain the position in-depth of the inscriptions (under the varnish, between two layers of varnish, over them or on their place; over restored parts).

DBNs can be of particular help in the accurate calculation of the chromatic levels and in the comparison of the outcomes in the different fidutial points. The extreme sensitivity of the luminescence, for example, of the receptors and formats in which it is recorded, is a valuable tool for discovering differences not noticeable in normal light. In particular, in the study of details of the painting that, apparently mono-chrome in normal light, in UV produce different glow, if they are painted with colours of different composition.

### 4.3 The Investigations in the IR Register

IR screening is a facility in discovering of restorations on the surface or in-depth, of inscriptions or autographs, and is also a reliable tool in the reconstruction of those made with carbon-containing substances. Varnish, deposits and subtle paint layers result transparent for IR radiation, while soot, carbon, graphite pencil, china ink and other carbon containing materials are well recognizable. The most important information it offers regards however the preparatory design.

The investigation in the IR register, in conformity with the applied wave length, allows to see the underlying layers of the painting, eventual modifications in the composition or *pentimenti*; to recognize the preparatory design: a hidden element, of particular importance in the attribution and dating. Fundamental for the indicative material characterization is also the colour of NIR records registered on analogue supports.

### 4.4 The Radiological (Plain XR, β, γ and CT) Investigation

**Plain XR**. When a beam of rays gets through an object (e.g. painting), soft rays are delayed to a greater extent than the hard, so that there is not only a general quantitative easing, but the ratio of soft and hard rays in the beam changes. Practically, the attenuation of the intensity (the difference between the intensity of the beam with which they came out of the tube, and the one with which they, having passed through a subject, will act on a photographic film) depends on the chemical composition of the object and on its thickness: the weakening is proportional to the 4th degree of the element number in the Periodic Table and to the 3rd degree of the wavelength; the attenuation increases rapidly with increasing the thickness of the substance through which the ray pass, especially when this are soft rays (Sil'chenko, 1955).

**β radiation** is applied with success in investigation of old books and paper documents (Erastov, 1997).

**γ radiation** is used mainly for defectoscopy of metal supports.

**Computer Tomography**. The recently developed computer tomography (CT) and bifocal raking radiography have assumed the role of a kind of spatial ND techniques in the investigation of art objects. In difference to traditional X-ray, CT gives information on the spatial position of details up to 0,5 mm, in sections of 1 to 12 mm depth, and allows to measure with great precision the density (Rho) of the wooden support, capturing even less pronounced differences. This enables the qualitative esteem of the radiological properties of the different elements (fresh or mature, core or peripheral part, etc.) the type of section and its orientation, and - considering the specific material characteristics – the dating of the support (Schüller, 1997).

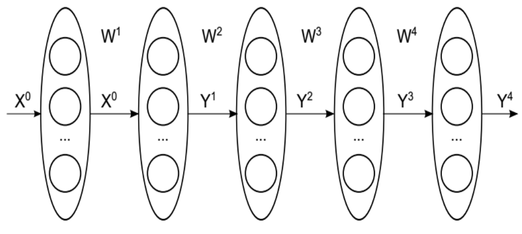



**Fig. 2.** Topological map of an integrated interpretation of MMSR where $x^0$, $y^1$, $y^2$, $y^3$, $y^4$ represent respectively the VIS, UV, IR, and XR (β,γ, CT) spectral records.

Icons, thanks to the lack of Pb containing substances in the preparative (gesso) layer, offer good possibility to study not only the wooden support but also the plaster, to note eventual presence of canvas; to ascertain their integrity or to individualize interventions carried out over crackled surface. CT and raking X-rays can also reveal important facts regarding renewals of the paint layer, particularly with Pb, Zn, Hg containing pigments.

# 5 Examples of Most Appropriate Architectures and Topological Maps of Deep Learning Networks for Interpretation of MMSR

## 5.1 Architecture and Topological Map of DBNs for Material Classification & Characterization Based on the Properties of Dispersed Combined Light

As mineral pigments are denser substances than natural dyestuffs, with much greater specific mass, in easel painting they can be easily distinguished from natural dyes changing the position/angle of the painted surface in respect to the light source and verifying eventual presence of changes in the intensity of refraction. One layer perceptron can be effectively applied to the characterization/classification of the materials employed in the paint and protective layers interpolating the input (x) with the refractive index of selected fidutial points not covered with varnish; the hidden layer - with eventual presence of glazing under the protective varnish; the output (y) – with the refractive index measured on the varnished surface. The value of $w_{ki}$ and $w_{kj}$ is established by other perceptrons assessing the UV and IR records (Fig. 2).

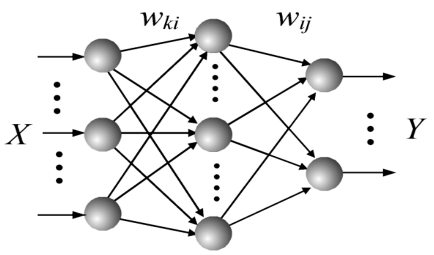



**Fig. 3.** Perceptron with one hidden layer

The encoding (Back Prop) of the outcomes bases on the fact that when a light ray passes from one medium to another with different density at an angle, it is refracted (bent) and its speed changes. At the interface (pigment layer, gum, glue, varnish or oil protection ), it is bent in one direction if the material it enters is denser (when light slows down) and in the other direction if the material is less dense (when light speeds up). Because different wavelengths (colors) of light travel through a medium at different speeds, the amount of bending is different for different wavelengths.

If the painting is varnished or covered with a film of gums or glue that reflects stronger than egg binder & pigments, the light ray reacts to it as to an interface. When these reflecting layers encountered by the light are more and their surfaces are not parallel to each other as it is usually in manufacts, the colors separated at that inter-face continue along different paths upon leaving the medium.

Refraction of light when it passes from one medium to the other obeys Snell's law, which states:

$$n1 \sin(1) = n2 \sin(2)$$

where n1 and n2 are the indices of refraction of the two media, and 1 and 2 is the angle the ray of light makes with the normal to the surface in the two media. The index of refraction for air is (almost) 1, while for glass it is about 1.5 (or so), for painting materials instead exist detailed database with refractive indexes.

### 5.2 Perceptron for (Binary) Classification of Natural Resins Varnish Based on their Reaction to Polarized Light

Natural resins extracted from the Cypresiacee class rotate polarized light clockwise (here $x_1$), while those deriving from Pinacee rotate it counterclockwise ($x_2$). The training of DBN with opportune examples can help to distinguish automatically the appurtennance of a varnish to one of the groups (y). For each configuration, one should run some experiments, for not to obtain erroneous results due to the fact that the learning process is caught in a local minimum. The ST Neural Networks package, i.e., supports automatic memorization of the best network during the experiment (in terms of control errors).

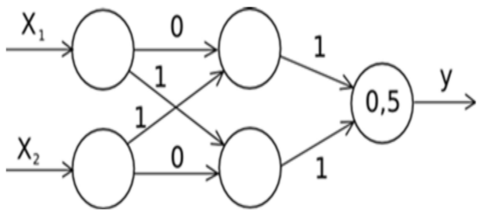
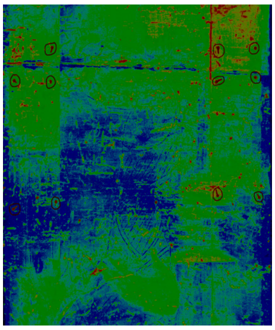



**Fig. 4.** Configuration of a perceptron with two hidden layers for solution of binary classification tasks

### 5.3 Adaptation of Image Processing Software Filters for Elemental Tracing with DBNs

The colour of the iron nails in this icon has been used as a reference for to ascertain the eventual presence of rust (the red points near the circumscribed nails) in the ground preparation due to water infiltrations. To the end has been adapted a very common in image processing software filter that turns the interrelation between the grey values in a tunable chromatic map, and a reference bar with samples of different elements (Fe in this case). For to give reliable indications, the DBN architecture of such a test must include VIS, UV and IR levels, as illustrated in Fig.2.



| Element periodic N (EPN) | EPN : Pb N | $EPN^4$ : Pb $N^4$ |
|---|---|---|
| Ca (20) | 1:4,1 | 1:282,5 |
| Fe (26) | 1:3 | 1:110 |
| Cu (29) | 1:2,1 | 1:64 |
| Zn(30) | 1:2,73 | 1:56 |
| Ag (47) | 1:1,8 | 1:9,5 |
| Ba (56) | 1:1,464 | 1:1,7 |
| Au (79) | 1:1,037 | 1:1,2 |
| Hg (80) | 1:1,025 | 1:1,1 |

**Fig. 5.** Left: the "posterization" of the XR of an icon (Stoyanova, 2017) assigns to the B/W gradation chromatic values, which allow to distinguish better the grey layers and, basing on the outcomes of the VIS, UV, and IR spectroscopies, to associate them to determined elements. For the encoding are used the dependencies described in &4.4. Right: the radiotrasparency of selected elements expressed in respect to Pb.

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