

# Estimating image quality for bone scintigraphy using machine learning

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Nuclear medicine is a less known sector of the healthcare industry which allows to visualize metabolic processes in contrast to standard MRT and CT scans. For a nuclear medicine examinations it is necessary to inject organ specific radiopharmaceuticals into the vein of the patient. <sup>[1]</sup>

Bone scintigraphy is globally the most frequently used nuclear medical examination. It enables the diagnosis of rheumatism, endoprosthesis loosening and small bone metastases earlier than other imaging methods. Bone scintigraphy is divided into three phases: the perfusion, the bloodpool and the mineralisation phase. In the mineralisation phase the gamma camera captures the emitted radiation from the bones and creates a two-dimensional image of a skeleton. But there are some issues which can influence the quality of this image. For example the scintigraphy can be noisy or partly pale due to a low dose of the radiopharmaceutical. Moreover, possible movement and contamination artefacts can degrade the quality. These are some issues which can lead to inaccurate or wrong diagnoses. Therefore a precise and objective analysis of the images could potentially lower the rate of wrong diagnoses. In this bachelor thesis, the mineralisation phases of bone scintigraphies are analysed and categorized with respect to their quality. <sup>[2]</sup>

In a previous project work, different methods have been implemented. These methods translate visual features like blur and edges into numeric data to facilitate machine learning. <sup>[3]</sup>

Machine learning methods are computer systems which can learn automatically and make predictions based on data. There are numerous variations of learning algorithms. Some of them are used to distinguish between six levels of image quality. The algorithms access the dataset of the implemented methods and compare their results with the classification of a nuclear medicine specialist concerning the image quality. <sup>[4]</sup>

Overall, seven image properties were analysed with thirteen implemented methods: the information entropy, the proportional black content, the line profiles, the image noise, the sum of edges, the compactness of the depicted object and some histogram attributes. Before the algorithm can gather the image properties the scintigraphies should be edited. Many raw bone scintigraphies have poor contrast and make a diagnosis impossible. In practice the radiology assistants typically adjust the contrast for each image individually. The use of these manually edited images would distort the results. Consequently the raw scintigraphies are optimized using histogram equalization. Moreover, the images should have the size of the depicted skeleton because superfluous pixels would alter the results of some implemented methods. The proportional black content, the line profile and the noise would be much smaller. Additionally the edge detection and the histogram would be affected. Only the information entropy and the compactness of the depicted object are consistent. Nevertheless not every image property makes sense to determine image quality. 26 bone scintigraphies – thirteen good and thirteen bad samples – are used to analyse the methods. Ideally, the values of the good samples should be notably different from the results of the bad ones. In our experimental evaluation this hypothesis has not been confirmed. But some image properties are still useful to distinguish image quality.

The ratio of the white pixels, the image focus, the noise, the compactness of the depicted skeleton and the sum of the edges are used as features for the dataset. The sixth attribute is the individually given grade by the nuclear medicine specialist for every scintigraphy.

Selected machine learning algorithms are using this dataset to distinguish between relative good and bad scintigraphies. To gain as much information as possible five rather different algorithms were tested.

- **The naive Bayes** classifier is based on applying Bayes' theorem with strong (naive) independence assumptions between the features. It calculates any type of probability within the dataset and formulates prior probabilities to classify new objects.<sup>[4]</sup>
- The **k-nearest neighbours** algorithm (*k*-NN) categorizes an object by a majority vote of its neighbours. Imagine the training objects are plotted in a coordinate system depending on their features. To classify a new object, it must be added to this mental coordinate system. Afterwards the algorithm analyse the membership of its *k*-nearest neighbours and assigns the new object to the class most common among them.<sup>[4]</sup>
- A **decision tree** is built of leaves and branches. The leaves represent class labels and branches represent the conjunction of features that lead to those class labels. This algorithm arranges the features by importance and divides the dataset regarding the end property. For classifying new objects, the algorithm runs through the decision tree along the branches.<sup>[4]</sup>
- **Support vector machines** separate two classes with a linear discriminant function. Very often it is impossible to divide the dataset in the original feature space. Thus the kernel trick is used to map the inputs into high-dimensional feature spaces. A new object is classified by adding it to this space and determining its position with respect to the hyperplane.<sup>[5]</sup>
- A **perceptron** transforms the basic functions of a nerve cell into a mathematical model. It consists of an input function which is affected by weighting factors and an activation function. The activation function determines if there should be an output signal or not. Several linked perceptrons are called multilayer perceptrons which form more complicated neural networks. By traversing the multilayer perceptron an object can be classified.<sup>[5]</sup>

With the given dataset the different machine learning algorithms achieve quite similar results. The Support vector machine can classify 34.42% of the scintigraphies according to their predetermined quality. The k-nearest neighbour algorithm matches the image quality slightly better with 37.21%. According to our experimental results, the evaluated algorithms are almost equally suited for this problem. Nonetheless, there are still options optimize on various settings of the algorithms. Furthermore, the dataset could be more optimized as well. For example, it can be larger and more balanced in quality because most available images of the dataset were good examples.

This bachelor thesis offers an introduction to the automated determination of image quality. Several similar black and white images were analysed with the possibility of six grades. Five different machine learning algorithms can categorize about 36% images correctly. This demonstrates the complexity of this topic and shall motivate to proceed with further research.

## References

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