Supervised Approach for Indication of Contrast Enhancement in Application of Image Segmentation

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Abstract—**Segmentation methods need a satisfactory input image with a good contrast between Region of Interest and background to provide a high accuracy result. Thus, the application of contrast enhancement before the segmentation is a usual practice. This paper presents a supervised approach to determine if an input image is satisfactory for a specific segmentation approach by using Feature Extraction, Feature Selection and Machine Learning. Experimental results showed the proposed approach ability to indicate the need of contrast enhancement in different segmentation problems with 94 percent accuracy.**

Keywords–Contrast; Image Segmentation; Machine Learning.

I. INTRODUCTION

Image segmentation is one of the most difficult tasks in image processing [1] [2] [3]. In order to provide high accuracy results, segmentation methods need a satisfactory input image with good contrast between Region of Interest (ROI) and background. Due to this fact, application of contrast enhancement before segmentation is an usual practice as shown in [4] [5] [6] [7] [8].

Some contrast enhancement algorithms, such as CLAHE [9], rely on input parameters to be performed. This aspect of contrast enhancement implies that an individual configuration for each image is necessary. A standard configuration for the whole image dataset is impractical in a real application.

Undesirable results, such as noise formation, are obtained in cases where contrast enhancement is used with wrong parameters or in an originally good contrast image, especially when using a simple and general contrast enhancement algorithm like Histogram Equalization (HE). Furthermore, execution time may decrease considerably by removing a useless contrast enhancement step.

The features of an image provide useful information for automatic classification. In this paper, we explore several features, like histogram-based [10], gray-level co-occurrence matrix [11] [12] and Fast Fourier Transform (FFT) [13] [14], which can retrieve contrast and texture information from an image. Our proposal is a supervised approach with image features as input to classify between insufficient and sufficient images contrast, making it possible to decide if a contrast enhancement is necessary before the segmentation step, regardless the problem. The appropriate contrast enhancement step for images with insufficient contrast was not addressed in this paper.

Works related to our proposal are presented in Section II, while a detailed description of our proposed approach is presented in Section III. In Section IV, materials, methods and experiments used to validate our proposed approach are described and in Section V, we show results and discussion of this work. Conclusions are presented in Section VI.

II. RELATED WORK

A good contrast between ROI and background in an input image is essential to provide high accuracy segmentation results. Due to this fact, application of contrast enhancement before segmentation is a usual practice.

In [15], an enhancement approach is presented to address the limitations of medical thermal images such as low contrast, low signal-to-noise ratio, and absence of clear edges. Despite these limitations which usually make the segmentation process difficult, the proposed approach using image enhancement were able to segment the images with an average accuracy of 98%. Similarly, [16] shows that pre-processing can have positive impacts on mammographic segmentation since it improves the contrast of tissue structures in uncompressed breast peripheral areas. Those recent works, and others like [6] and [8], indicate that contrast enhancement before segmentation can be useful to improve segmentation accuracy in gray-scale images.

The CLAHE contrast enhancement algorithm, which relies on input parameters to be performed, is used to improve segmentation as well. In [4], CLAHE was used to successfully improve the accuracy of a fruit segmentation approach. Even if color images were acquired, CLAHE was applied to the Intensity channel (gray-scale) and the enhanced image was segmented by the Hough algorithm. Fixed parameters were used for CLAHE in this approach.

CLAHE was used again in [5], with the goal of improving the segmentation in an intelligent iris recognition system for eye images. Regarding the two main CLAHE parameters, the clip limit parameter was dynamically chosen by the technique proposed in [17], while the sub-region size was fixed to 8x8.

The use of fixed parameters to improve a set of images is not the better solution, since some images may need more enhancement than others. It is possible as well that some images do not require any enhancement (which can be a problem even to contrast enhancement algorithms that do not need parameters). In a real world dataset, in which

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thousands of images will be segmented, enhancing images that do not require any enhancement may represent a huge waste of time depending on the algorithm used. An unnecessary enhancement can also create noise and decrease segmentation accuracy. Thus, it is important to know which images must be enhanced before segmentation.

Some applications use the information contained in multiple channels of an image to perform segmentation. This information is usually related to color. Segmentation and enhancement of color images are not handled in the actual stage of our work, but the idea of enhancing images to improve its segmentation can be applied to color images as well. It can be seen in [7] and [18].

Since features can provide useful information of an image, they may be used for automatic classification. Our proposed approach uses a supervised classifier based on Machine Learning to classify images considering its features.

Machine Learning for Image Classification is widely used in Medical applications [19] [20] [21] [22] [23]. In [24], a survey about Medical image analysis with artificial neural networks is presented. It shows that, besides segmentation, Machine Learning can be useful to classify images and ROI's, providing computer-aided detection and diagnosis.

Machine Learning is also used for aerial and satellite image classification [25] [26] [27], image classification in agriculture applications [28], in astronomical applications [29], image classification in palynology [30] and many other image applications.

Still, contrast enhancement before segmentation can improve accuracy. It may be useful to know which images must be enhanced before segmentation. By extracting the right features, it is possible to classify images using machine learning, which motivates our proposal: a supervised approach to indicate the need of contrast enhancement in applications of image segmentation.

III. Proposed Approach

Inadequate usage of contrast enhancement leads to wrong segmentation and misunderstandings concerning final results, since some features like objects intensity, objects size, area of image occupied by objects and number of different objects are relevant while applying an automatic segmentation approach.

We propose, as shown in Figure 1, an approach to build a model capable of identifying images with insufficient contrast for a specific segmentation task. The built model is created based on feature vectors extracted from a small set of image examples, Image Subset, and it is improved using feature subset selection, considering a supervised labeling process.

A specialist labels each image of the Image Subset as insufficient or sufficient, and this, combined with the extracted features, provide a training set. After performing a feature subset selection, the training set can be used as input to the Classifier Training step, as shown in Figure 1. Labels are applied by visual evaluation from original image and segmentation result. The Training Set is composed of a subset of features that optimally represent the focused segmentation related to the contrast enhancement applied.

In the last step, Supervised Classifier Training, the model for image classification between insufficient or sufficient contrast is created.

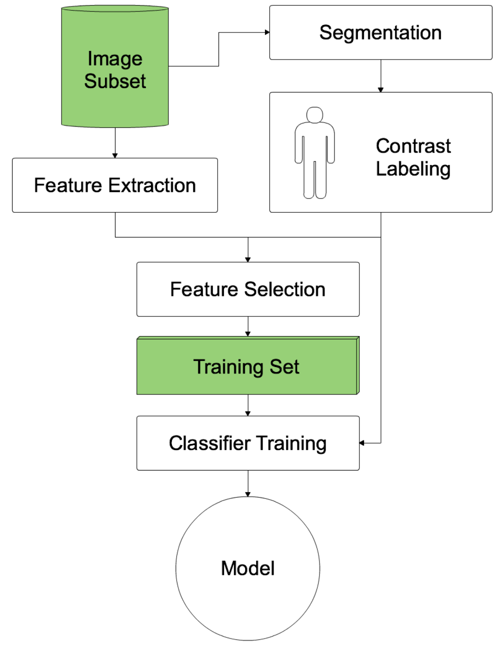

Figure 1. Proposed Approach

A. Image Features

A histogram is a statistical tool that can be used in contrast quality assurance and can represent the mean luminosity of an image. Considering this, we use different metrics from the histogram associated with Texture (Gray-tone spatial dependencies and Spectral Analysis) with the purpose of covering distinct image applications.

Texture is an important characteristic used to identify objects or regions of interest in images. Texture features based on gray-tone spatial dependencies are easily computable and have a general applicability for a wide variety of image-classification applications [11]. Gray-level co-occurrence matrices indicate how often a pixel with gray-tone value i occurs horizontally adjacent to a pixel with value j [12]. On the other hand, texture features based on Spectral Analysis can detect global periodicity on images by finding narrow peaks of high energy in frequency (spectrum) domain and Fourier transform is a common spectral method [13] [14].

We selected several features based on Histogram, Gray-tone spatial dependencies and Image Fourier Domain (shown in Table I). In Figure 2, it is possible to see features P12, P13, P14, P15, P16 and P17 in comparison to a standard histogram, where the x-axis represents gray tones going from 0 to 255 and the y-axis represents the frequency of each tone in an image.

B. Correlation-based Feature Subset Selection

A central problem in machine learning is identifying a representative set of features that best represents a model, increasing precision and reducing dimension. In this paper, we addressed this problem through a correlation based approach, where the main hypothesis is that good feature sets contain features that are highly correlated with the insufficient or sufficient label, yet uncorrelated with each other [31].

Concretely, a correlation-based approach is an algorithm which evaluates a great number of features subsets in order to

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TABLE I. IMAGE FEATURES: HISTOGRAM, TEXTURE AND SPECTRAL

ID	Description
P1	Entropy of original grayscale image
P2	Entropy of gray-level co-occurrence matrix
P3	Inertia of gray-level co-occurrence matrix
P4	Energy of gray-level co-occurrence matrix
P5	Correlation of gray-level co-occurrence matrix
P6	Homogeneity of gray-level co-occurrence matrix
P7	Entropy of FFT
P8	Energy of FFT
P9	Inertia of FFT
P10	Homogeneity of FFT
P11	Image resolution
P12	Amount of non-zeros index
P13	Amount of non-zeros groups
P14	Largest length group
P15	Smallest length group
P16	Peak of Largest length group
P17	Peak of Smallest length group
P18	Amplitude of mean
P19	Amplitude of median
P20	Histogram Variance
P21	Histogram Standard Deviation

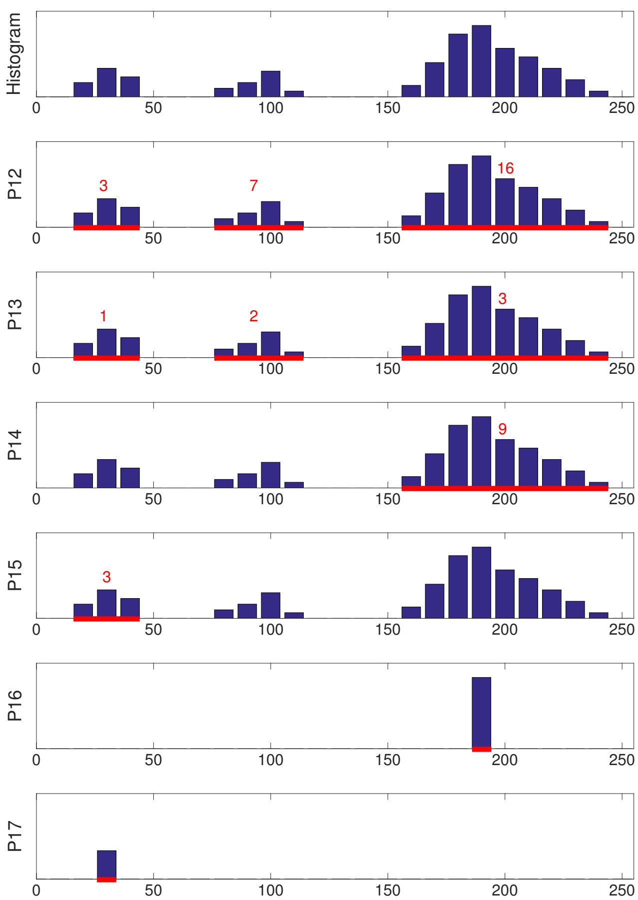

Figure 2. Histogram Based Features

obtain a better set of features than the current one. In order to do so, a correlation-based algorithm is initialized with an empty set of features. Then, with each round, a new feature is added to the set and measures like entropy, relief or merit are used to evaluate how suitable that subset of features has become. The most usual way to add features to the subset is by using a best first search in a feature space [31].

C. Classification

In order to have a suitable approach, which can be used for different segmentation problems and contrast enhancers, a supervised classifier based on Machine Learning is required. This way, it is possible to inform classifiers about what feature can improve ROI segmentation and when the contrast between the ROI and the background is good enough to a specific segmentation process.

Another important characteristic of several Machine Learning approaches, as Artificial Neural Networks (ANN), is online learning [32]. The online learning capacity means that non-stationary processes, which this might well be, can be modelled dynamically based on new image samples. Furthermore, the generalization and scaling feature leads to a model based on fewer samples [33]. In this paper, ANN were chosen as Machine Learning classifiers, since they are widely used in classification problems [24] [34] [35] [36] [37].

IV. Experimental Settings

Two datasets were used in experiments. The first one (Dataset I) was composed of medical images, where the ROI was regarding a wound region. The second dataset (Dataset II) was composed of pork image samples where the ROI was the intramuscular fat (marbling).

Note that the datasets represent different real world problems, specifically regarding ROI, where size, color and contrast with the background is really different between both datasets.

Three experiments were conducted in order to validate our proposed approach.The first experiment was performed using the medical dataset, the second was performed using the pork dataset and the third experiment was performed by combining both datasets in order to verify the robustness of the model to handle two different image scenarios.

The medical images dataset was composed of 100 color images. All files were in Portable Network Graphics format (PNG) and an example image can be seen in Figure 3a. The complete information about the image acquisition for the medical images dataset can be found in [38].

The pork images dataset was composed of 300 gray-scale images containing meat samples (the background was already removed). All files were PNG, as well and an example image can be seen in Figure 4a. The pork images dataset was acquired using a digital single-lens reflex camera and a tripod that supported the device at 37cm above the sample. The camera was configured with automatic settings and had a 16.2 megapixels image sensor and high quality lens, which was optimally engineered to gather more light.

All images were segmented by thresholding, where threshold value was found by max entropy algorithm [39]. The medical images dataset was segmented in the same way as the pork images dataset, but, in order to obtain a better visualization in the labeling process, the original image colors were applied instead of saturation values used in segmentation.

Figure 3 shows the segmentation of images from the medical dataset. Figures 3a and 3b represent samples labeled as 'sufficient contrast' while Figures 3c and 3d represent samples labeled as 'insufficient contrast'.

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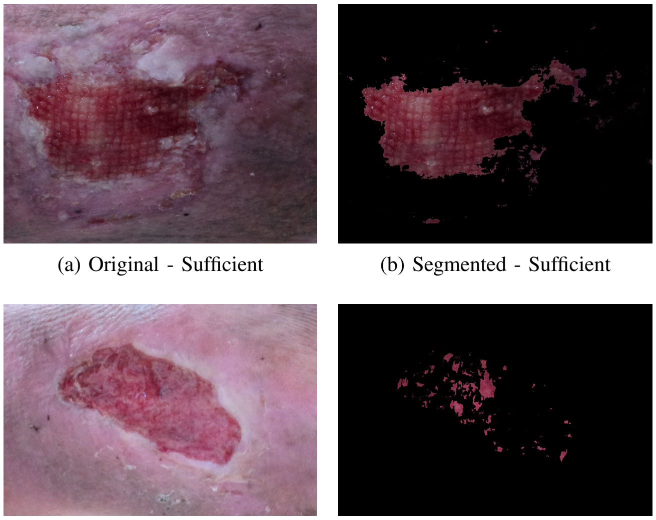
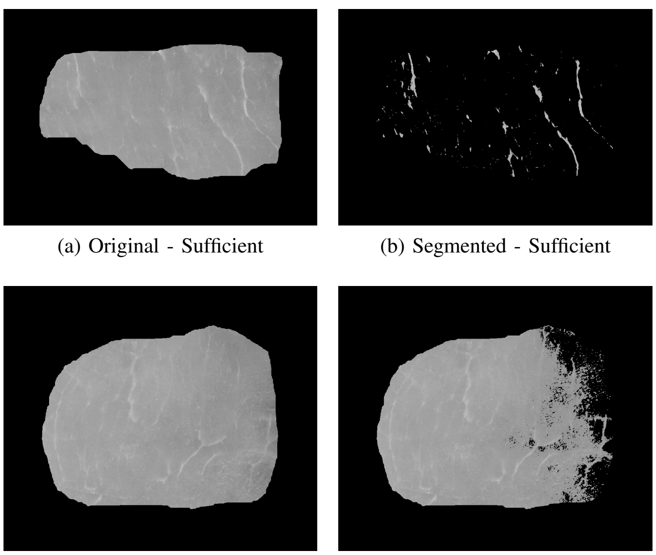


(a) Original - Sufficient (b) Segmented - Sufficient

(c) Original - Insufficient (d) Segmented - Insufficient

Figure 3. Medical dataset - Segmentation and labeling

Figure 4 shows the segmentation of images from the pork dataset. Figures 4a and 4b represent samples labeled as 'sufficient contrast' while Figures 4c and 4d represent samples labeled as 'insufficient contrast'.



(a) Original - Sufficient (b) Segmented - Sufficient

(c) Original - Insufficient (d) Segmented - Insufficient

Figure 4. Pork dataset - Segmentation and labeling

As it can be seen in Figure 3 and Figure 4, the labeling is simple and easy for such images, so only one specialist performed the labeling process. Every image that generated any kind of doubt in the evaluation by the specialist was removed from the dataset.

Before the labeling process, random samples were removed to balance both datasets. Thus, we obtained Dataset I Balanced (Dataset I BA) and Dataset I Imbalanced (Dataset I IM), as well, Dataset II Balanced (Dataset II BA) and Dataset II Imbalanced (Dataset II IM). An extra dataset was created by combining both balanced datasets (Dataset I BA and II BA).

In our experiment, the max entropy algorithm was used to find a threshold value for image segmentation. It is a simple and fast method, being one of the best solutions to segment meat marbling [39] [40], which is one of our datasets.

In order to evaluate the generalization power of ANN, we experimented with two different networks: Multilayer Perceptron (MLP) and Radial Basis Function (RBF) [19] [41] [42] [43] [44]. We evaluated approximately 22 different MLP and RBF architectures.

Regarding computational complexity, the MLP is $O(n2)$ to train and $O(n)$ to execute while the RBF is $O(n)$ to both train and execute [19] [45]. Fortunately, the specialist only needs to label a small subset of images in order to build the training set, which makes the model viable to be used in real-world computer vision problems with huge datasets.

Towards MLPs, the following settings values were used: learning rate 0.3, momentum 0.2, number of epochs 2500. For MLP, we experimented with different numbers of perceptrons on the hidden layers, ranging from 1 to 22. Settings values towards RBF, on the other hand, were: number of basis functions ranging from 1 to 22, number of iterations on logistic regression until convergence and seeds on k-means as defaults.

The results are mostly discussed in terms of accuracy. However, in special cases, detailed results can be shown in confusion matrices. As it is known in many cases where supervised learning is performed, a confusion matrix is represented by a simple two dimensional matrix. Rows represent the actual classes of each instance, in our case contrast sample labeled. Columns represent the predicted classes, for us: contrast sufficient or insufficient based on the supervised model. This way, ideal results correspond to large numbers on the main diagonal and smaller numbers, hopefully zero, for entries off the main diagonal.

V. Results and Discussion

An overview of the results is shown in Table II. The results of the most accurate architectures are shown for each classifier in each dataset. The results regarding feature selection are also presented.

We first discuss feature selection relevance. As it is possible to note, feature selection matters not only to increase performance by dimensional reduction, but also to help with accuracy. This importance is shown in Table II, where column AF Acc (All Features Accuracy) always presented lower results than column SF Acc (Selected Features Accuracy). In general, as shown in the lower part of Table II, feature selection added an average 6.04% accuracy. There is only one case where using feature selection did not improve classifier accuracy, which is RBF in Dataset II IM. Details considering this special case are properly discussed in Section V-B.

Considering classifiers, it is also possible to realize that the best results from MLP were always higher than the best results from RBF. Details concerning accuracies are shown in Figure 5 and discussed in Section V-B.

A. Feature Selection

Towards selected features, Table III shows results considering all datasets. As it can be seen in the second column

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TABLE II. ACCURACIES OF CLASSIFIERS WITH ALL AND SUBSET FEATURES

Dataset	ANN	AF Acc	SF Acc	Diff.
I IM	MLP	87.21%	88.72%	1.51%
	RBF	81.11%	82.20%	1.09%
I BA	MLP	86.13%	91.08%	4.95%
	RBF	67.32%	80.19%	12.87%
I & II BA	MLP	87.06%	89.55%	2.49%
	RBF	72.13%	82.58%	10.45%
II IM	MLP	83.66%	84.66%	1.00%
	RBF	83.33%	83.33%	0.00%
II BA	MLP	88.00%	94.00%	6.00%
	RBF	70.00%	90.00%	20.00%
			Mean Diff.	6.04%

(quantity of features selected), dimensionality reduction was significant. In the particular case of Dataset II IM, it was possible to reduce the number of features from 22 to just 4. In another case, as seen for Dataset I BA, dimensionality reduction was less expressive, but still, reduced from 22 to just 9 features.

In summary, the features selected for each dataset varied. No feature was present in all cases after feature selection. The most used feature was P12 but this feature was not present in Dataset II BA feature selection.

TABLE III. SUB-SELECTED FEATURES IN EACH EXPERIMENT

DataSet	Quantity	Features Subset
I IM	7	P12, P14, P17, P3, P4, P8 and P7
I BA	9	P1, P12, P14, P17, P2, P3, P4, P6 and P8
I & II BA	5	P1, P12, P13, P2 and P3
II IM	4	P12, P13, P17 and P2
II BA	6	P11, P16, P17, P18, P21 and P9

B. *Classifiers*

Regarding classifiers, Figure 5 shows box-plots for both MLP and RBF on each dataset when using feature selection. MLP, plotted as blue box-plots, shows much greater accuracy than RBF in all five datasets. Although MLP presented lower outliers in some cases, they were still better than the RBF results. This fact is notable on Dataset I IM and Dataset I & II BA where the lowest results from MLP are still higher than the median results from RBF. Another outstanding result achieved by MLP on experiments is the difference from third quartile and the first quartile in all datasets. In practice, this is shown on the smaller box size from MLP plots which results in a very stable classifier on experiments.

Considering balanced and imbalanced instances, it is also possible to realize that MLP achieved higher results when the dataset is balanced, as seen from Dataset I BA to Dataset I IM and from Dataset II BA to Dataset II IM. However, this is not the case for RBF. Actually, on Dataset I IM, RBF achieved better results than in Dataset I BA, where instances are balanced.

A third situation is shown by results on Dataset I & II BA, a situation where both scenarios are tested at once. This time, MLP also performed better than RBF regarding stability and higher accuracy results. Considering stability, MLP presented only one outlier, while RBF presented several. Considering higher accuracy results, the entire box from MLP is plotted above the best results from RBF.

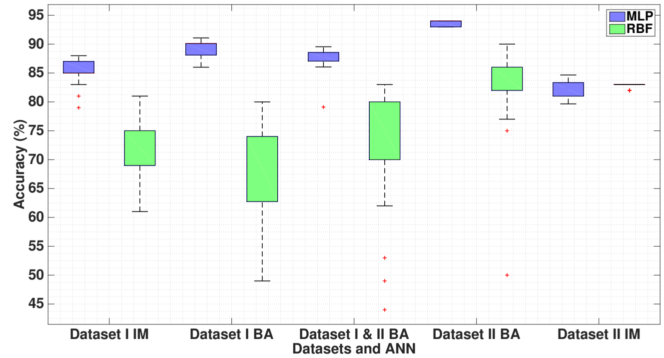

Figure 5. Boxplot of MLP and RBF accuracies

TABLE IV. CONFUSION MATRIX OF DATASET II IM PERFORMED BY RBF

		Predicted		
		Sufficient	Insufficient	Total
Actual	Sufficient	250	0	250
	Insufficient	50	0	50
	Total	300	0	300

TABLE V. CONFUSION MATRIX OF DATASET II BA PERFORMED BY MLP

		Predicted		
		Sufficient	Insufficient	Total
Actual	Sufficient	46	4	50
	Insufficient	2	48	50
	Total	48	52	100

A special case is shown in the case of Dataset II IM, where RBF seemed stable by presenting a very small box. However, it is not a true sign of success. As shown in Table IV, the results imply that, actually, the classifier presented a very high rate of error. Therefore, in different datasets and different ways of evaluation, MLP presented more desirable results than RBF. In order to show that results in other cases were satisfactory in terms of generalization, we show the prediction results to another classifier on Dataset II BA. Table V shows predictions with settings which achieved 94% accuracy to classify instances.

VI. CONCLUSION

In this paper, we proposed a supervised approach able to indicate the need of contrast enhancement in images, specifically before segmentation process. Experimental results showed high accuracy when dealing with two different datasets, especially when using feature selection and MLP classifier. As well, it exposed some features that best represent contrast in digital images.

The proposed approach can be used in computer vision systems that can afford a segmentation step, avoiding undesirable noise and wasted time by an incorrect or useless application of a contrast enhancement method.

Addressing feature discussions, dimensional reduction was an important issue on our approach in terms of performance. As discussed in Section V-A, in a particular case, feature selection enabled reduction from 22 to only 4 features.

ANN accuracy was also discussed and experiments showed that, mostly, MLP performed better than RBF in terms of maxi-

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mum accuracy, outliers values and stability. Details concerning such issue were presented in Section V-B. Still, RBF presented a very peculiar case in which no generalization was performed correctly, as seen in Table IV.

In summary, supervised learning approach for indication of contrast enhancement in image segmentation was successfully achieved. Different datasets were tested and 94% accuracy was achieved in a case where different datasets were tested at the same time. The proposed approach performed well not only when the dataset consisted of a single scenario, but also when the dataset consisted of different image scenarios.

As future work, we will employ contrast enhancement approach in order to observe the behavior of the classifier and analyze if the model will be able to handle the adjusted contrast. We also intend to use color information as features besides segmenting the images with more complex algorithms, e. g. watershed and decision trees.

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