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A Performance Analysis of Extreme Learning Machine on Skin Segmentation Dataset

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Abstract – Digital image processing has become popular research area recently because of its widespread application compatibility such as security, robotics, quality control, face authentication. Skin segmentation methodology, which is a tool of digital image processing, is useful in nudity alerts and face detection with its flexibility and simplicity. The purpose of the study is to develop general and simple model for skin segmentation with Extreme Learning Machine (ELM). ELM model is applied over Skin Segmentation Database from UCI Learning Repository. The reason for preference of UCI Database is its extensive samples from different age and race group of people.
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Keywords – Skin Segmentation, Extreme Learning Machine, Machine Learning, Classification, Image Processing

I. Introduction

Skin color could be used as discriminative feature in image processing while determining gesture, face and parts of body [1]-[4]. Detecting and distinguishing skin regions over the entire pixels according to color information is called as skin segmentation [5]. Skin segmentation let processing faster and simple by reducing concerned region, therefore it is a preferable image processing tool [5]. However, it has also disadvantages in applications like highlight and shadow results from nonuniform illumination [6]. Also, color variations because of sun exposure and genes difference make skin segmentation process more complicated. The purpose of this study is to construct robust and generalized skin segmentation model based on ELM for future use in image processing applications.

The Skin Segmentation Database in UCI (http://archive.ics.uci.edu/ml/datasets/Skin+Segmentation) is preferred for training model due to samples' skin color diversity according to race, age and gender. Skin textures of dataset is combination of images from both Color FERET Image Database (http://face.nist.gov/colorferet/request.html) and Productive Aging Laboratory Database (http://agingmind.utdallas.edu/facedb/). Dataset consists of color information in Red-Green-Blue (RGB) format and groups them into two classes as skin and non-skin.

ELM is suitable machine learning algorithm for skin segmentation with its low computational cost. This supports skin segmentation's simple and fast nature.

In 2013, Casati and colleagues have applied Artificial Neural Network (ANN) method in SFA & UCI dataset and obtained 92.71% and 88.74% accuracy respectively [7].

In 2014, Uçar [8] has applied Local Color Vector Binary Patterns (LCVBP), Local Binary Patterns (LBP) and Local Color Steerable Pyramid Transform - Extreme Learning Machine (LCSPT-ELM) methods for processed face images in different resolution in AR & FERET dataset. The accuracy results for AR are 97.78%, 98.17%, 99.48% and for FERET are 89.77%, 93.26% ve 94.43%.

Al-Mohair and colleagues have worked on ECU dataset with hybrid model based on Multilayer Perceptron Neural Network (MPNN) and k-means clustering in 2015 [9]. They have transformed color space to YIQ and come up with F_1-measure of 87.82% accuracy.

Jaisakthi et al. [10] have concentrated on color spaces; RGB, HSV, YCbCr, CIElab. They have developed a pixel-based skin segmentation algorithm with ensemble approach using Gaussian Mixture Model (GMM) classifier and applied it to SFA, UCI and ECU dataset. They have indicated that their proposed method is higher in accuracy for UCI dataset than Casati method with 99.55%.

Lei and team have used RGB and HSV color spaces together in Sack AutoEncoders (SAE) method and this combined technic has released 91.00% accuracy for Pratheepan, 93.00% for HGR and 88.00% for ECU dataset [11].

Similarly, Kolkur et al. has focused on combining different color space information by considering not only individual ranges in RGB, HSV, YCbCr but also combinational ranges in determination skin textures [12]. The accuracy result has been indicated as 94.43% for subset of images from Pratheeran dataset.

Dastane and colleagues have used UCI dataset to classify as skin and non-skin by applying two stage pixel neighborhood technic. They have calculated probability of each pixel with Deep Neural Network (DNN), Naïve Bayesian (NB) and Decision Tree (DT). The accuracy result is 97.32%, 93.23% ve 96.35% respectively [13].

Lastly, the authors of this study have applied Complex Valued Neural Network (CVNN) methodology to UCI dataset. They have transformed color space to HSV and obtained 98.60% accuracy result [14].

II. MATERIALS AND METHOD

A. ELM

It is a feedforward neural network having one hidden layer topology given in Fig.1 that focused on output layer's weight rather than iteration. It was proposed by Huang and colleagues as a new learning algorithm in 2006 [15]. In Artificial Neural Network (ANN), backpropagation learning algorithm based on gradient-descent based calculations is massive and time consuming. ELM model prefers to determine the output layer's weights for expected outputs rather than learning algorithm. New methodology of selecting hidden layer's weights randomly but calculating output layer's weights analytically has speed up ANN model learning algorithm with skipping iterative tuning of excessive parameters [15]. Moreover; ELM is less likely to converge in local minima than ANN [15], [16].

Huang summed up learning principle of ELM in three principles [17]:

1. In addition to linear activation functions and nonlinear activation functions, discrete and non-differential activation functions are applicable for hidden nodes of ELM by hidden neuron's independence of training samples and learning conditions [16], [17].
2. ELM is good in generalization with minimal training error and output weights' norm [16], [17], [18].
3. Although outputs of hidden layer need to be biased in ANN methodology, biasing should not be biased ELM approach due to optimization constraints. [17], [18].

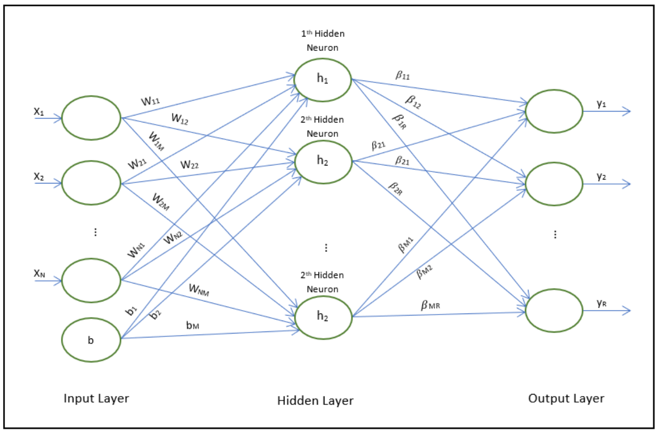

Fig. 1. Network topology

For N feature input, M hidden layer neurons and R class outputs, the system outputs can be determined as;

$$\bar{y}_r = f_r(X) = \sum_{j=1}^{M} \beta_{jr} \sum_{i=1}^{N} g\left(W_{ij}X_i + b_j\right) \qquad (1)$$

where $r = 1,2,3 \dots R$, $g(.)$ is the activation function, $\bar{Y} = (\bar{y}_1, \bar{y}_2, \cdots, \bar{y}_R)$ is the network outputs, $\beta = (\beta_1, \beta_2, \cdots, \beta_R)$ is output weights, $W = (W_1, W_2, \cdots, W_M)$ is hidden layer weights, $X = (X_1, X_2, \cdots, X_N)$ is inputs and $b = (b_1, b_2, \cdots, b_M)$ is hidden layer biases.

If $H = (h_1, h_2, \cdots, h_M)$ is substituted for hidden layers' output;

$$\bar{Y} = H\beta \qquad (2)$$

Error in network can be expressed as;

$$\mathrm{E} = \min\|H\beta - T\|^2 \qquad (3)$$

where $T = (t_1, t_2, \cdots, t_R)$ is targets that observed outputs.

While error is converging to zero for error minimization, ELM network equation has become straightforward:

$$H\beta = T \qquad (4)$$

By matrix algebra optimum output layer's weights could be calculated as;

$$\beta^* = H^{\dagger}T \qquad (5)$$

$H^{\dagger}$, is called as the "Moore-Penrose" generalized inverse matrix and Huang's study can be examined for detailed information [15].

ELM is simple and fast way to find the optimum solution for calculated β^* output layer weight. The robust of network is based on massive neuron number in hidden layer. Randomness of hidden layer's weight results in the less over-regularization and the more accurate prediction [18].

As a summary, for N input ELM having M neuron in hidden layer and activation function $g(x)$ Huang and team works can be summarized in 3 steps:

1. Randomly assigned W (weights) and b (biases)
2. Calculated hidden layer's output matrix H.
3. Analytically calculated output layer weight β^* is to for optimal solution.

B. Confusion Matrix

Confusion matrix is an useful method in performance analysis for visualization. Confusion matrix group the samples according to actual class and predicted class. As shown in Table 1, C_{xy} is the number of samples that belongs to X but predicted as Y [19].

Table 1. Example of Confusion Matrix for 2 class data

Predicted Class	**Observed Class**	
	X	**Y**
X	C_{xx}	C_{yx}
Y	C_{xy}	C_{yy}

C. Sensitivity- Specificity

Sensitivity is the positive predictive rate that points the accuracy in predicting j^{th} class samples in j^{th} class while specificity is negative predictive rate that points prediction accuracy in distinguishing non-j^{th} class samples.

For X class;

$$Sensitivity = \frac{C_{xx}}{(C_{xx} + C_{xy})} \tag{6}$$

$$Specificity = \frac{C_{yy}}{(C_{yx} + C_{yy})} \tag{7}$$

D. *Prediction Accuracy*

Classifier accuracy or prediction accuracy is the overall strength in classifying as ratio of true predictions to false predictions.

$$Accuracy = \frac{(C_{yy} + C_{xx})}{(C_{yx} + C_{yy} + C_{xx} + C_{xy})} \tag{8}$$

E. K-Fold Cross Validation

In classification studies, dataset is separeted into two subsets (training and testing). The training set is for constructing the system and the testing set is for measuring the performance of system. Randomness of splitting is crucial to evaluate the system performance and test system through all consequences. CV is a useful statistical tool for random division of datasets by rotating specified number of subsets as training and testing in order. Thus, all samples have the chance both to train the system and to validate classifiers as well [20], [21]. For example, for k-fold-cross-validation, dataset is divided into k random sets one of which includes all classifier equally. $(k-1)$ sets are used for training, k^{th} set is used for testing in each iteration. Iteration is repeated k times by changing the testing subset. The overall performance is the average of k iterations [21], [22].

III. Experimental Result

In this study, ELM methodology is applied to skin segmentation data set for six different activation functions in hidden layer (sigmoid, sinusoidal, radial basis, tangential sigmoid, triangular basis transfer and hard limit) four different hidden layer neuron number – 100, 500, 1000, 2000 – with RGB color space.

The 10-fold cross validation accuracy results are in Table 2 below.

Table 2. Results of Proposed Method for RGB Color Space

Activation Function	**Hidden Layer Neuron Number**			
	100	500	1000	2000
Sigmoid	**99.00%**	**99.77%**	**99.81%**	**99.85%**
Sinusoidal	68.75%	78.24%	83.57%	87.93%
Hard Limit	98.84%	99.65%	99.74%	99.80%
Triangular Basis	62.04%	91.20%	95.67%	97.69%
Radial Basis	93.92%	96.20%	97.83%	98.76%
Tangential Sigmoid	98.96%	99.72%	99.79%	99.82%
Max. Accuracy	99.00%	99.77%	99.81%	99.85%

The more hidden layer neuron number the more accurate the test result as expected.

For proceeding step specificity - sensitivity performance analyses have been applied. The overall average of 10-fold Confusion Matrix is given in Table 3.

Table 3. Confusion Matrix for RGB Color Space for 2000 hidden layer neuron and Sigmoid Activation Function.

Predicted Class	**Observed Class**	
	Skin	**Non-Skin**
Skin	50838	21
Non-Skin	379	193819

The obtained sensitivity and specificity values are 99.26% and 99.99% which are highly satisfactory results.

IV. DISCUSSION AND CONCLUSION

As a result, ELM have result in high accuracy for UCI skin segmentation dataset. For even small number of neuron in hidden layer, ELM predicted skin textures successfully.

Comparison with studies in literature shown in Table 4, ELM could be summarized as convenient, fast and applicable model with high reliability for skin segmentation. This result yields the study for further steps as improving and testing ELM model with other skin datasets and applying this model in real time process.

Table 4. Comparison of Proposed Method with Research on UCI Database

Authors	**Method**	**Accuracy**
Casati et al	ANN	88.74 %
Jaisakthi et al	Ensemble GMM Classifier	99.55%
Dastane et al	DNN	97.32%
Dastane et al	NB	93.23%
Dastane et al	DT	96.35%
Kiziltas et al	CVNN	98.60%
	Proposed Method	99.85%

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