RESEARCH ARTICLE OPEN ACCESS

Skin Pixel Segmentation Using Learning Based Classification: Analysis and Performance Comparison

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ABSTRACT
Skin detection or segmentation is employed in many tasks related to the detection and tracking of humans and human-body parts. The goal of skin pixel detection is locate the pixels of the skins and discard other non-related pixels from regions of the image. Skin area detection has been focus research area in human-computer interactions. Most of the research done in the fields of skin detection has been trained and tested on human images. The approach of this research is to make a comparative analysis of learning classification algorithms to identify the better classifier model for skin pixel detection. Our adopted procedure is based on skin segmentation and human face features which are so called knowledge based approach for skin pixel segmentation. Based on the feature selection of the classified, we found the good detection rate by using the various classification algorithms. We have got the detection rate of above 95.79% in case of J48 algorithm and 95.04% detection rate in case of SMO algorithm. The experiment result shows that, the algorithm gives hopeful results. At last, we concluded this paper and proposed future work.
Keywords-Machine Learning, Pixel Classifications, skin segmentation, Color Space, Image Processing. WEKA

I. INTRODUCTION

Skin color and textures are important cues that people use consciously or unconsciously to infer variety of culture-related aspects about each other. Skin color and texture can be an indication of race, health, age, wealth, beauty, etc. [1] [2]. However, such interpretations vary across cultures and across the history. In images and videos, skin color is an indication of the existence of humans in such media. Therefore, in the last two decades extensive research have focused on skin detection in images. Skin detection means detecting image pixels and regions that contain skin-tone color.Most the research in this area have focused on detecting skin pixels and regions based on their color. Very few approaches attempt to also use texture information to classify skin pixels [1, 2].

Recently tremendous amount of effort has been spent on skin colour modeling and detection methods by several authors. Kakumanu et al.[3,4] have reviewed the articles on skin colour modeling and detection methods and mentioned that the skin colour detection plays an important role in a wide variety of applications ranging from face detection, face tracking, gesture analysis and content based image retrievals to various human computer interaction domains. Skin segmentation deals with detecting human skin areas in an image. It is considered as an important process for face detection, face tracking and CBIR [5]. Skin colour can also be used as complementary information to other features and can be used to build accurate face detection system [6, 7, 8, 9]

In the paper[4], the feature for the detection of skin region is by skin colour so the colour spaces provide the basic framework for feature vector extraction in skin colour detection or segmentation [10,11,12]. Different colour spaces like RGB, Normalized RGB, HSV, YCbCr and CIE L*a*b etc., are used for developing the skin colour detections [13, 14, 15]. Choice of colour space is the main aspect of skin colour feature extraction. It is mentioned in the literature that model based skin segmentation are more efficient than edge-based or histogram based techniques. Here in this paper, we compare the performance evaluation of classifier models based on various learning algorithms which are applied on human image or stack of human images. The features of the human image are being selected manually through rectangular selection of pixels of the image.

The format of the remaining paper is: section 2, defines and explains the skin color models and different classifications of skin colors that has been employed and discusses during the implementations in brief and other detection approaches. Section 3 deliberates the framework design and discusses our detailed design of the implemented system. Section 4 discusses conclusion and future work of the research problem.

II. BACKGROUND AND RELATED WORK

A Skin Classifier

A variety of classification techniques have been used in the literature for the task of skin classification. A skin classifier is a one-class classifier that defines a decision boundary of the skin color class in a feature space. The feature space in the context of skin detection is simply the color space chosen. Any pixel which color falls inside the skin color class boundary is labeled as skin. Therefore, the choice of the skin classifier is directly induced by the shape of the skin class in the color space chosen by a skin detector. The more compact and regularly shaped the skin color class, the more simple the classifier.

The simplest way to decide whether a pixel is skin color or not is to explicitly define a boundary. Brand and Mason [11] constructed a simple one-dimensional skin classifier: a pixel is labeled as a skin if the ratio between its R and G channels is between a lower and an upper bound. They also experimented with one-dimensional threshold on IQ plane of YIQ space where the “I” value is used for thresholding. Other method explicitly defines the skin color class boundary in a two dimensional color space using elliptical boundary models [9]. The parameters of the elliptical boundary can be estimated from the skin database at the raining phase.
A human skin color model requires a color classification algorithm and a color space in which colors of all objects are represented. In order to segment human skin regions from non-skinregions, a reliable skin model is needed that is adaptable todifferent colors and light conditions [?]. The color spaces that arefrequently used in studies are HIS, HSV,, TSL andYUV. In this paper, we choose the color space asthe space of skin detection.

Human skin color has been used to identify and differentiate the skin. This has been proven as useful methods applicable in face recognition, identification of nude and pornographic images (Fleck *et al.*, 1996) (Jones and Rehg, 2002) and also such image processing tasks have been used extensively byintelligence agencies (Ahlberg, 1999).A number of image processing models have been applied for skin detection. The major paradigms included heuristic and recognizing patterns which were used to obtain accurate results. Among various types of skin detection methods, the ones that make use of the skin color as a tool for the detection of skin is considered to be the most effective (Zarit *et al.*, 1999). Human skins have a characteristic color and it was a commonly accepted idea driven by logic to design a method based on skin color identification. The problem arose with the provision of different varieties of human skin found in different parts of the world. A number of published researches included various skin models and detection techniques (Zarit *et al.*, 1999) (Terrillon *et al.*, 2000) (Brand and Mason, 2000), however, none came up with complete accuracy.

There have been many problematic issues in the domain of skin detection. The choice of color space, the model of precise skin color distribution, and the way of mechanizing color segmentation research for the detection of human skin. Most researches have been focused on pixel based skin recognition, classifying each pixel either as skin or non skin. Each pixel is considered to be an individual unit (Brand and Mason, 2000). Pixel-base skin recognition is considered to be one of the finest models that under normal conditions give high level of accuracy at the detection phase of the process. Due to its high applicability and efficiency, some color models are used extensively in the arena of skin detection. These models make use of pixel based skin recognition using a model such as RGB (Albiol et. al., 2001). The RGB model makes use of the three colors red, green and blue to identify the chrominance. Then using an efficient model the necessary range is used and applied to a selected photo to determine the presence of skin. Skin color varies depending on ethnicity and region, therefore additional work must to address the issue.[statistical skin detection]

There is another model called the region based method. This method was applied by (Kruppa, 2002) (Yang and Ahuja, 1999) (Gomez and Morales, 2002). In this method the researchers considered the spatial method of skin pixels, and took them into account during the detection phase with the target of maximizing efficiency. As a contradiction to the fact that different people have different types of skin colors, it is found that the major difference does not lie in their chrominance; rather it is determined by intensity to a large extent. The simplest color models useful for intensity invariant skin detection are HSV (Lee and Yoo, 2002), YUV (Chai and Bouzerdoum, 2000) or YIQ (Martinkauppi and Soriano, 2001). The HSV model is an effective mechanism to determine human skin based on hue and saturation. Other efficient models are YUV and YIQ which follow the same brand of modeling using the RGB color space.[statistical skin detection]

III. Skin Segmentation Classifier Model

A. Learning Based Algorithms

Here we discuss the skin segmentation model based on classification and learning algorithms used in performance comparison evaluation.

1. Data Collection: Data-set in the form of human images are being selected from various sources such as captured the live image from camera or taken the images from internet also.
2. Data-preprocessing & Cleansing: Here the collected data-set will further be processed to

select the accurate and relevant of the images which further need to train the classifier model.

3. Classifications : Based on the training data set, the classification is being performed on the selected human images data set.

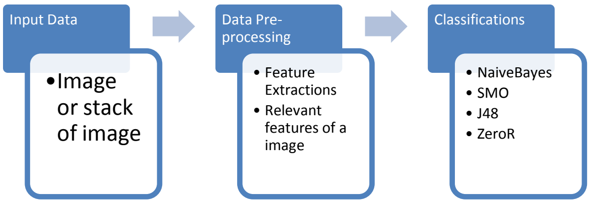


Figure 1: Process flow of the system

Life cycle of machine learning approach

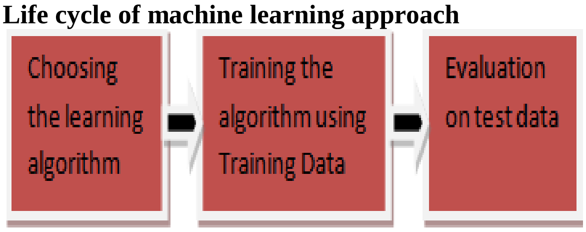
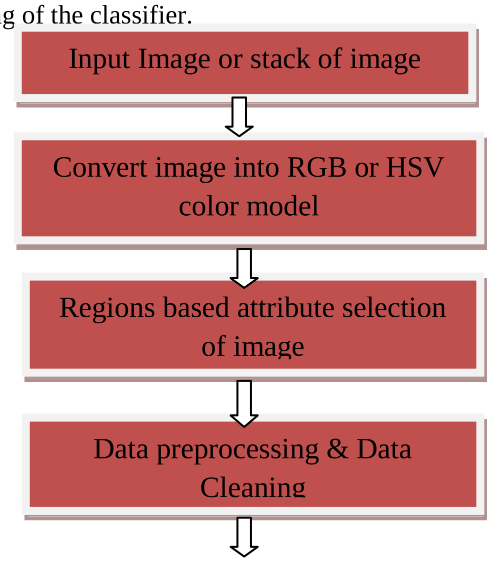


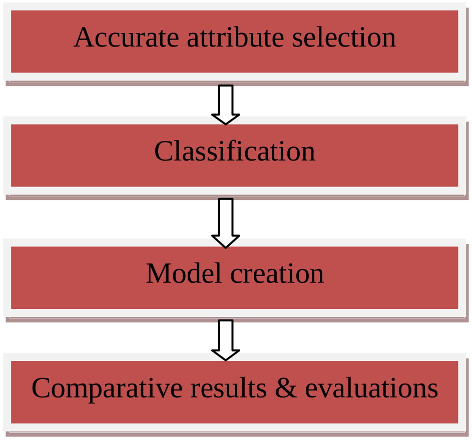
Figure 2: Life cycle of the learning approach

Above figure 2 depicts the life cycle of the machine learning algorithms selected and applied on the human images. As shown first step is to choose the appropriate learning algorithms which need to be applied on the selected features of the human image. Further if the classification by applying the chosen algorithm is giving the good quantified results, then machine has to be trained with the training data set.

B. Operation Flowchart

Below flowchart depict the operation flow in building of the classifier.





Step 1. Feature Extractions (with trainable Weka segmentation)

Feature extraction from the image or stack of image: First step is feature selection; we select the features that we want to use in the building of classifier model for classification of skin pixels. Selection of features of the image with the help of ImageJ open source tool:

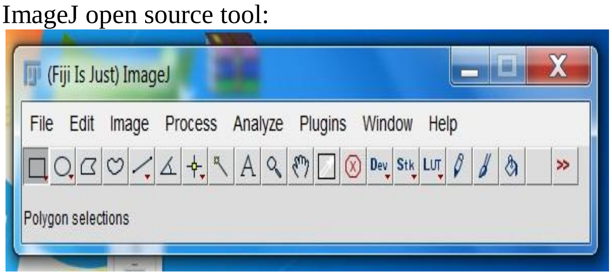


Figure 2: ImageJ snapshot

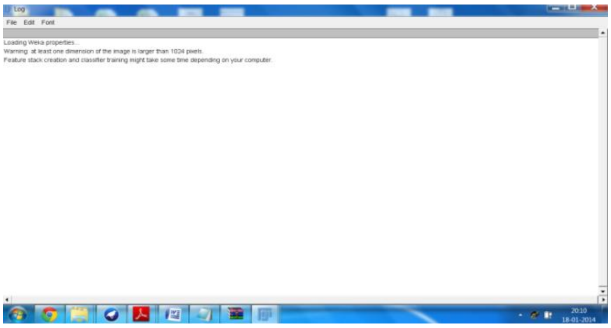


Figure 3: Trainable Weka Plugin

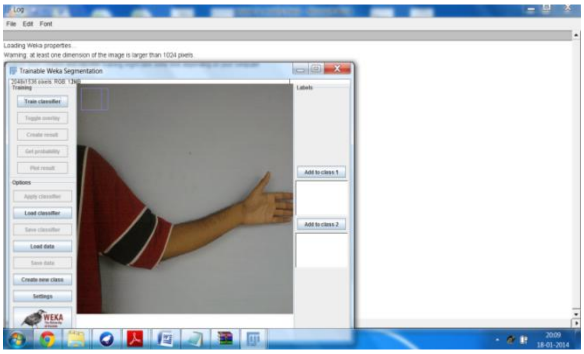


Figure 4: Opening image in trainable Weka.

Applying various algorithms on data set:

Here the selected data set will be loaded into Weka which is machine learning classification tool to classify the data.

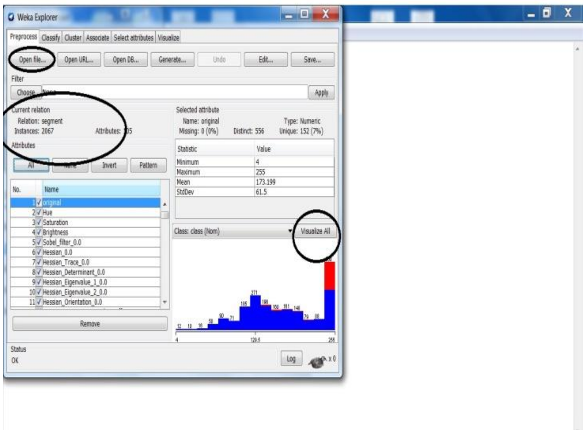


Figure: Loading the data set into weka

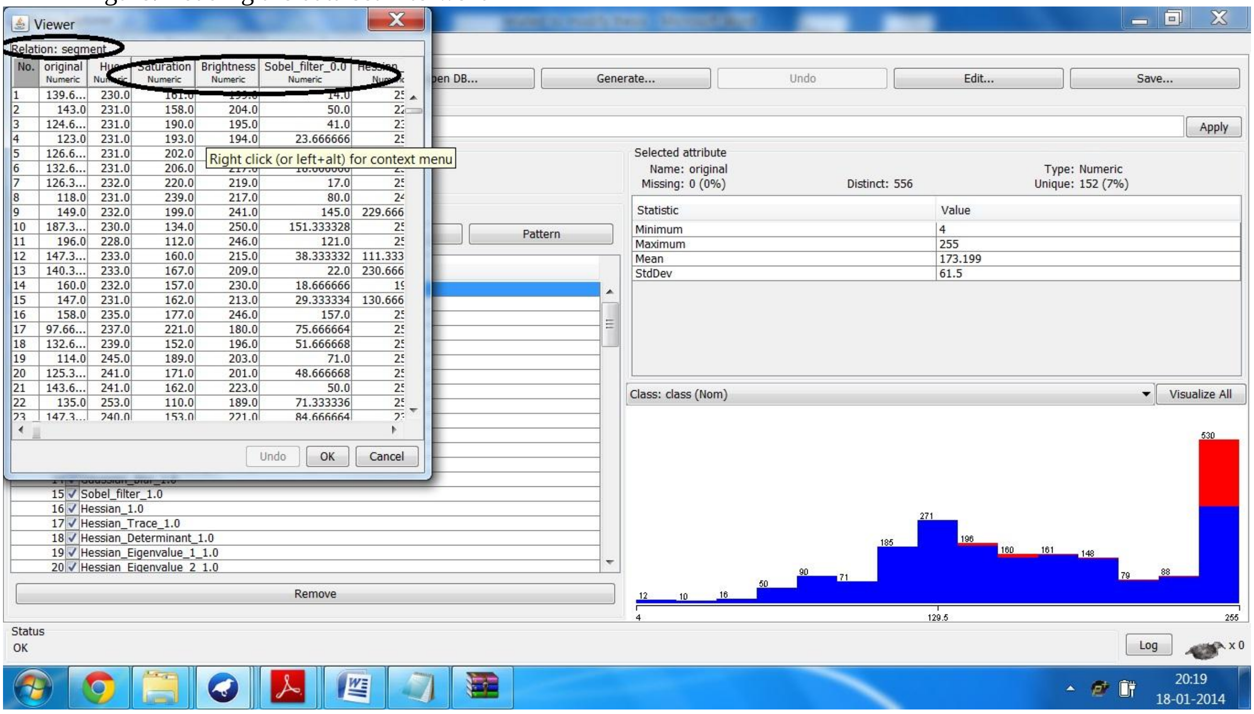


Figure: Features of the image (edit in weka)

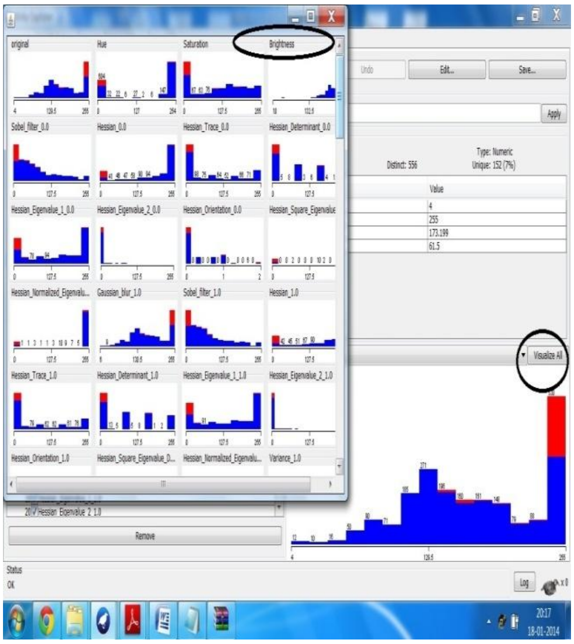


Figure: Visualizing all features using weka

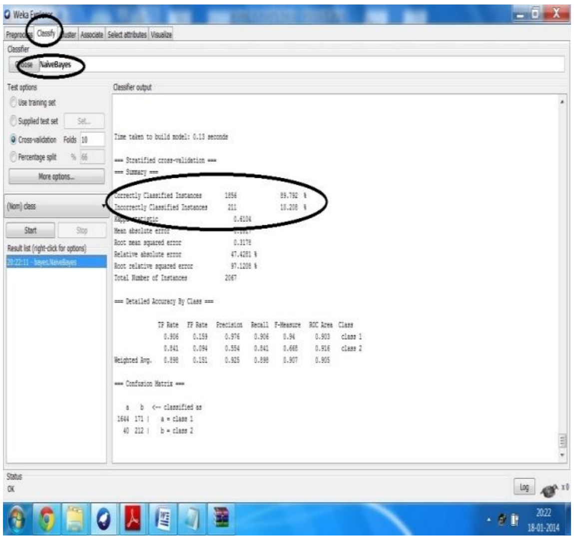


Figure: Using NaiveBayes classification algorithms

Experimental Results and Performances Measurements:

Here we discuss the experimental results and performances of different models applied to selected skin features. For fair performance evaluation of different skin color modelling methods identical testing conditions are preferred. Unfortunately, many skin detection methods provide results on their own, publicly unavailable databases. The most famous training and test database for skin detection is the Compaq database [Jones and Rehg 1999]. In the table below the best results of different methods, reported by applying the different classification algorithms, for the dataset which we have selected from the set of images with the help of trainable weka segmentation on stack of images. Table 1 shows true positives (TP) and false positives (FP) rates for different methods configurations. Although different methods use slightly different separation of the database into training and testing image subsets and employ different learning strategies, the table should give an overall picture of the methods performance. The accuracy of the classifier is also studied for the sample images by using confusion matrix for skin and non-skin regions. Table 2 and table 3 shows the values of TPR, FPR, Precision, Recall and F-measure for skin and non-skin segments of the sample images.

Algorithm	Performance Measures	TP Rate	FP Rate
NaiveBayes	89.792	0.898	0.151
SMO	95.404	0.954	0.194
J48	95.791	0.958	0.187
DecisionTable	94.9202	0.949	0.205

Table 1: Performance Measurements & Detection Rate

Algorithm	Precision	Recall	F-Measure	ROC-area
NaiveBayes	0.925	0.898	0.907	0.905
SMO	0.953	0.954	0.953	0.88
J48	0.957	0.958	0.957	0.948
DecisionTable	0.948	0.949	0.949	0.917

Table 2: Performance Evaluation

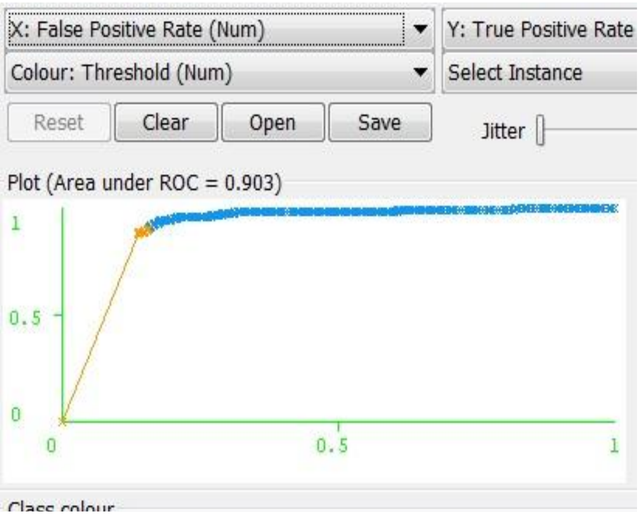


Figure: ROC curve NaiveBayes algorithm

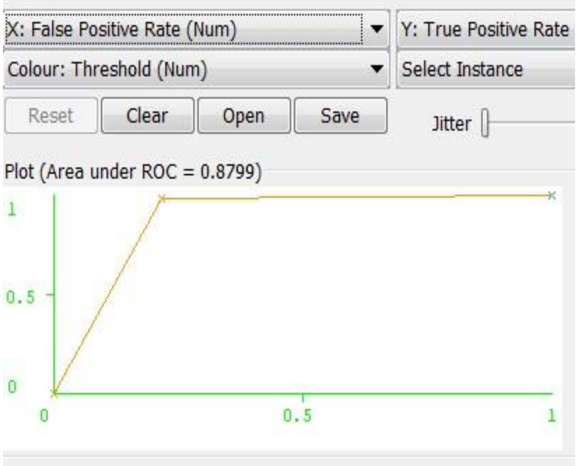


Figure: ROC curve SMO algorithm

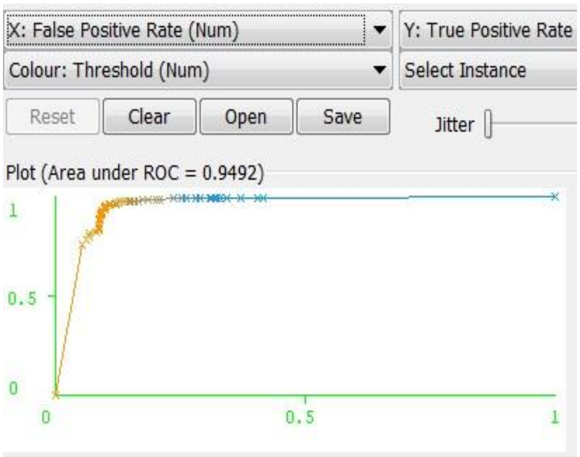


Figure : ROC curve for J48 classification algorithm

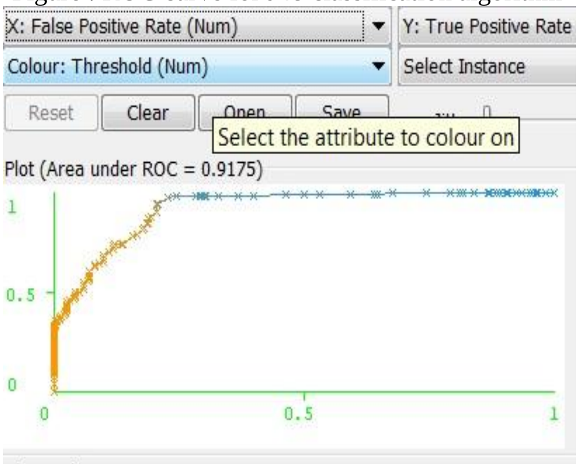


Figure: ROC curve for Decision Tree algorithm

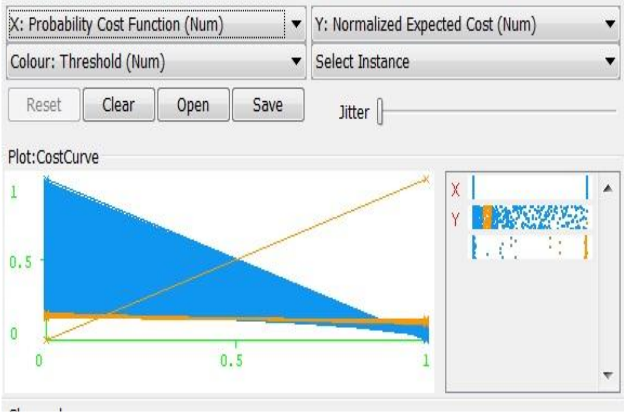


Figure: Cost-benefit curve of NaiveBayes algo

The developed algorithm performance is evaluated by comparing skin colour segmentation algorithm with the Gaussian mixture model. Table 3. present the miss classification rate of the skin pixels of the sample image using various learning algorithms used in the classification model. Here we can see that NaiveBayes algorithm have highest incorrectly classified instances whereas the J48 algorithm have lowest miss-classification rate

Model Name	**Miss Classification Rate**	**Incorrectly Classified Instances**
NaiveBayes	10.208	211
SMO	4.596	95
J48	4.209	87
Decision Tree	5.0798	105

Table 3: Miss-classification Rates of the classifiers.

Methodology Adopted:

Tools and Techniques:

Weka machine learning tool is used during the building of classifier as well as for feature selection of the human image based on trainable weka plug-in.

IV. CONCLUSION

ACKNOWLEDGEMENTS

We would like to sincerely thankful to respected Tajinder Kaur, HoD Department of Computer Science for his contribution and help in writing this paper. We would also thankful to our team-mates and all my friends who involved in the discussions and deliberations during the implementation and development aspects.

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