Gender Detection using Machine Learning Techniques and Delaunay Triangulation

Sarthak Gupta
Guru TeghBahadur Institute of Technology,
GGSIPU, New- Delhi, India

ABSTRACT
Data mining today is being used widely in diverse areas. For example: fraudulent systems, recommender systems, disease prediction, and numerous other applications. One such application is exploited in this article. This paper presents an approach to detect gender of a person through frontal facial image, using techniques of data mining and Delaunay triangulation. Gender prediction can prove to be a very useful technique in HCI (Human Computer Interaction) Systems. Classification, being a very power technique in data mining to group categorical data, is used here to classify a gender as either male, or female. Various classification algorithms such as Functional Trees, AdaBoost, J48, and few others are used to gauge the maximum accuracy. The model used in this paper is robust and attains accuracy level of **93.8283%** along with relative scale invariance. Details of the prediction model and results are reported herein.

General Terms
Data mining, classification algorithms, WEKA tool, gender detection, Machine learning

Keywords
Functional Trees, J48, Naïve Bayes, Machine Learning, Gender Classification, WEKA, Machine learning

1. INTRODUCTION
Gender Classification has become area of extensive research due to it's increasingly powerful applications. Automated gender classification has attracted much attention over the last ten years since augmenting this ability with applications specific to a particular gender can provide a more user-friendly environment and human-like interaction [1], [2].

Till date, the work has been emphasized on gender recognition through visual observation, but now, it has to be emphasized to computer, to perform this task.It is observable that our behavior and social interaction are greatly influenced by genders of people whom we intend to interact with. Hence a successful gender recognition system could have great impact in improving human computer interaction systems in such a way as to make them be more user-friendly and acting more human-like. Over the past decades, there have been significant advances in facial image processing, especially, in a face detection area where a number of fast and robust algorithms [3], [4] have been proposed for practical applications [5]. As a result, a number of research areas attempting to extend the works have been emerging, face recognition, facial expression recognition and gender recognition, for example.

Conforming to the practicality of gender prediction, it is imperative to improve the algorithms from time to time in order to achieve higher accuracy levels and build more robust and accurate systems.

Based on the types of features used, facial feature extraction approaches can be roughly divided into two different categories: geometric feature-based methods and appearance-based methods [6], [7]. Geometric features refer to distance between various facial features such as eyes, nose, chin and lips. Facial features can be extracted from facial image using Viola Jones algorithm that returns the coordinates of various features. Euclidean distance then can be calculated between the detected features, along with Delaunay triangulation calculation. For the sake of accuracy, it has to be taken care of that facial features are detected accurately, and hence, every image from database was manually picked and mined, adhering to proper detection. Few adjustments had to me made in algorithm for some specific images, but every image was manually scrutinized and mined carefully.

In a Delaunay triangulation of facial features for a face, the Delaunay triangles have different sizes in different areas. By classifying the size of the Delaunay triangles, the different facial figures are separated into a number of regions [8]. In a well-separated point set, Delaunay triangles can beclassified into two types. A *foreground triangle* (F-T) is a Delaunay triangle in a cluster [8]a*background triangle (BT)*is a Delaunay triangle outside any cluster. Highly densepoints form F-Ts, while sparse points constitute B-Ts. Clear boundaries can be found to differentiate the two typesof triangles.[8].

Machine Learning is a field of computer science that evolved from field of pattern recognition and computational learning theory in Artificial Intelligence Machine Learning explores the study of algorithms that can learn and make predictions from available raw data. This article has exploited the capabilities of machine learning. Various Machine learning algorithms are deployed for pattern recognition from the data mined from facial images. AdaBoost or adaptive boosting and other algorithms including functional trees are used to measure maximum accuracy levels.

FEI face database [27] database has been used that contains 200 frontal facial images consisting of 100 male faces and 100 female faces. Each subject has a normal expression and a smiling expression associated. The images were preprocessed using MATLAB in order to assure the uniform light effects. Features described in section 3.2 were extracted with the help of MATLAB and loaded into database, from where they were fetched and analyzed. Functional Trees were used to classify the detected gender as either male or female. Highest accuracy of **93.8283%** is achieved in comparison to J48, Random Forest and others summarized in section 4. WEKA (Waikato Environment for Knowledge Analysis) is used as the tool for analysis. The accuracy level is improved in comparison to previous researched performed by [14][24]

Following is the organization of rest of the paper:-

Section 2 describes about literature Survey; the researches that have been performed in this area. Section 3 elucidates the methodology and model proposed in this research. Section 4 and 5 summarizes the results of the research. Section 6 throws light on any future work scope that can augment this research. Concluding the paper with Section 7, it acknowledges the work of various researches that have been conducive in concocting this article.

2. LITERATURE SURVEY

There have been several efforts towards detecting the gender through facial image. For example, the gender classification based on human faces has been extensively researched in the article [9, 10].Theorypresented two popular methods. The former is proposedby Moghaddam et al. [10] where a Support Vector Machine(SVM) is utilized for gender classification based on thumbnailface images. The latter was presented by Baluja et al.[9] who applied the AdaBoost algorithm for gender prediction.

Gao et al. [11] performed face-based gender classificationon consumer images acquired from a multi-ethnic facedatabase. To overcome the non-uniformity of pose, expression,and illumination changes, they proposed the usage ofActive Shape Models (ASM) to normalize facial texture.The work concluded that the consideration of ethnic factorscan help improve gender classification accuracy in a multiethnicenvironment.

Zehang Sun et al, [12] proposed Gender classification from frontal face images using genetic feature subset selection. They used Principal Component Analysis (PCA) to represent each individual image as a feature vector in a low dimensional space and based on Genetic algorithms, a subset of features are extracted from the low-dimensional representation by ignoring certain eigenvectors which are not needed for classifying facial feature information.

Multi-view gender classification by focusing on shape and texture data for representing facial images was proposed by Hui-Ching Lain and Buo-Liang Lu [13]. In this, the facial area is divided into small regions by using local binary pattern (LBP) histograms.

Md. Hafizur Rahman et al, [14] performed Face Detection and Sex Identification from Color Images using AdaBoost with SVM based Component Classifier and achieved a maximum accuracy level of 89.51% for male prediction and 87.80% for female prediction.

In previous work [15, 16] geometry featureswere used as a priori knowledge to help improve classificationperformance, none of the aforementioned approaches,unlike this work, focused explicitly and solely on facialmetrology as a means for gender classification. Perhaps this research is more closely related to earlier research by **Yi Xiao1**et al. [8] on facial Feature Location with Delaunay Triangulation/Voronoi Diagram Calculation, where theylocate “key points” of facial features using Delaunay Triangulation and Voronoi Diagram technique. However, this article takes a more comprehensive lookat the explicit use of facial geometry in solving the problem.

3. METHODOLOGY

As described in section 1, this article exploits the FEI database [27] that consists of 100 female and 100 male, colored frontal facial images, with each subject having two expressions associated. The geometric feature-based method has been deployed that calculates the Euclidian distance between the detected facial features. The following flowchart in figure 1describes about the general outline:-

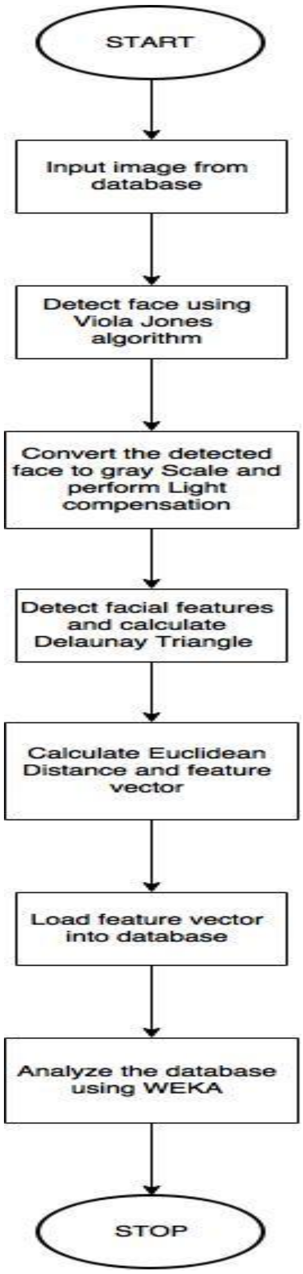

Figure: 1
Flow chart describing flow of model

The above phases are described in following sub-sections.

3.1 Light Compensation

All too often, pictures takes from digital cameras produce undesirable light effects, contributing to light and dark bands in some images. Hence, the need arises for Light Compensation in order to detect features correctly. The problem of elimination of non-standard illumination is one of the most complicated problems in the area of computer vision. Due to the complex illuminated environment in the real world. According to [17, 18, 19, 20 and 21], the lighting compensation (LC) algorithm is very efficient in enhancing and restoring the natural colors into the images which are taken in darker and varying lighting conditions. The implemented LC algorithm is based on the assumption that the spatial average of surface reflectance in a scene is achromatic. Since the light reflected from an achromatic surface is changed equally at all wavelengths, it follows that the spatial average of the light leaving the scene will be the color of the incident illumination [22]. The Light Compensation algorithm can be defined as described below:

$$S_c = \frac{C_{std}}{C_{avg}}$$

$$C_{avg} = \frac{\sum_{i=1}^{i=m} (C_i)_{C_i>0}}{\sum_{i=1}^{i=m} (1)_{C_i > 0}}$$

$$C_{std} = \frac{\sum_{i-1}^{i=m} \left[\max\left(R_i, G_i, B_i\right) + \min\left(R_i, G_i, B_i\right)\right]}{2 \times n}$$

$$n = m - \sum_{i=1}^{i=m} \left(1\right)_{R_i=G_i=B_i=0}$$

Where, S_c stands for the scale factor for one specific channel of R, G or B. The C_{std} and C_{avg} separately stand for the standard mean gray value of the specific channel and the mean value non-black pixels in the same channel[22]. The m stands for the number of pixels in the image, n stands for the number of non-black pixels in the image [22]. This is to solve the over compensation problem for images with dark background, i.e., images taken at night [22]. By calculating the average of the maximum and minimum channel percentage, an adaptive mean gray value of the whole image is gained. [22]

3.2 Face Detection and Feature Extraction

For detection of facial features, it is first necessary to detect face from the input image. Therefore, Viola Jones Algorithm is deployed to detect face as well as facial features from the input image. It is a robust algorithm for detecting faces, proposed by Paul Viola and Michael J. Jones. Face detection is shown in figure 2a.The detected facial image was then, converted into Grayscale counterpart, for better performance.

Figure: 2a
Face detected from input image using Viola-Jones Algorithm

Here is the list of features extracted from facial image for analysis:-

Table: 1
Features vector extracted from facial image

S.NO	NAME	DESCRIPTION
1	EE	Euclidean distance between eyes
2	LEFC	Euclidean distance between Left-eye and face center
3	REFC	Euclidean distance between Right-eye and face center
4	LENC	Euclidean distance between Left-eye and Nose center
5	RENC	Euclidean distance between Right-eye and Nose center
6	LEMC	Euclidean distance between Left-eye and center of Lips
7	REMC	Euclidean distance between right-eye and center of Lips
8	NCMC	Euclidean distance between center of Nose and Lips
9	FCNC	Euclidean distance between Face center and Nose center

Euclidean distance is defined as: -

$$D\left(p, q\right) = D\left(q, p\right) = \sqrt{\left(q_1 - p_1\right)^2 + \left(q_2 - p_2\right)^2 + \ldots + \left(q_n - p_n\right)^2}$$

Where, In Cartesian Coordinates, $p = \left(p_1, p_2, p_3, \ldots, p_n\right)$ and $q = \left(q_1, q_2, q_3, \ldots, q_n\right)$ are two points in Euclidean n-space, $D\left(p, q\right) = D\left(q, p\right) =$ Euclidean distance between points p and q.

3.3 Delaunay Triangulation

In a point set P, its Delaunay Triangulation is defined as[8]:-

$$DT = \left\{ \begin{matrix} T\left(p_i, p_j, p_k\right) \mid p_i \in P, p_j \in P, p_k \in P, \\ C\left(p_i, p_j, p_k\right) \cap P \setminus \left(p_i, p_j, p_k\right) = \phi \end{matrix} \right\}$$

Where, $C\left(p_i, p_j, p_k\right)$ is the circle circumscribed by thethree vertices p_i,p_j,p_k, which form a Delaunay triangle T (p_i, p_j,p_k). A **Delaunay triangulation** is a triangulation DT(**P**) such that no point in **P** is inside the circum-hypersphere of any simplex in DT(**P**). It is known that there exists a unique Delaunay triangulation for **P** if **P** is a set of points in *general position*; that is, the affine hull of **P** is *d*-dimensional and no set of $d + 2$ points in **P**lie on the boundary of a ball whose interior does not intersect **P**. Delaunay Triangulation is then calculated for the Euclidean distances calculated before. The image 2b[23] shows Delaunay Triangulation.

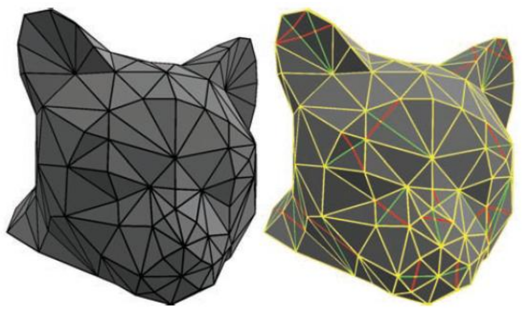

Figure 1: *Left: carrier of the (cat head) surface as defined by the original embedded mesh. Right: the intrinsic Delaunay triangulation* **2b** *edges are part of the original and intrinsic Delaunay triangulation; red edges resulted from flipping; and green edges denote original edges which are not part of the intrinsic Delaunay triangulation. Note that the red edges are geodesic lines on the original surface.*

One of the key properties of Delaunay triangulations is the empty circumscribing sphere condition. In R ~ there is a unique sphere with any given n + 1 points on its boundary. Delaunay Triangulation method has shown remarkably exceptional results. The distances calculated are then loaded into the database, from where they were fetched and analyzed. Delaunay Triangles calculated for input image has been shown in figure 2c (male) and figure 2d (female). As seen in figure, features detected from face have been labeled in yellow boxes. 1 refers to left eye, 2 refer to right eye, 3 refer to nose and 4 refer to lips.

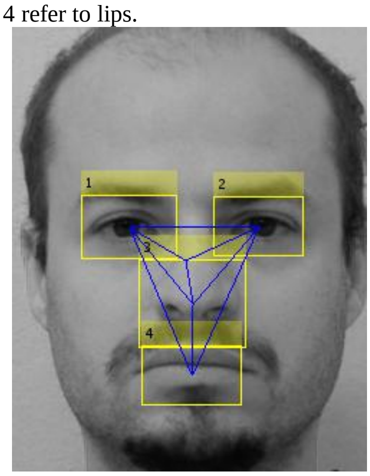

Figure 2c
Delaunay Triangles for male face

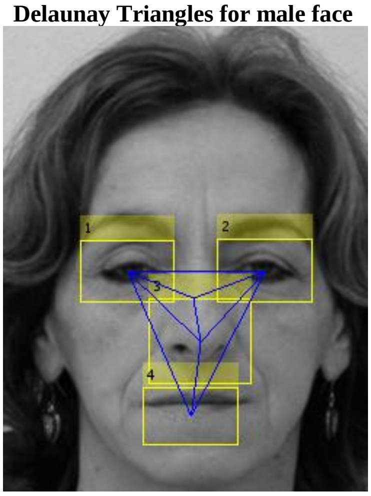

Figure 2d
Delaunay Triangles for Female face

3.4 Analysis and Classification

After extracting all the relevant features, Machine Learning algorithms were applied, that classifies the image as a Male or a Female face. The WEKA tool was used to apply various algorithms. Functional Trees algorithm outperformed the second best by **8.0848 %**, and showed highest accuracy level. The accuracy obtained in this research is more than that of [14, 24]. Several other algorithms were also deployed for the comparison purposes. These include, Random forest, Naïve Bayes, AdaBoost and J48. The results are formally represented in 4^{th} section of this article.

3.4.1 Functional Trees

In the context of machine learning, it is imperative to first classify the given problem as a regression problem, or a classification problem. If the target class variable takes a value ‘k’, where k Є S{0,1,…N} and S is a set consisting of finite number of values ‘N’, then, given problem is a classification problem. If the target class variable takes any continuous value, then the given problem is termed as “Regression” problem.Given a set of examples and an attribute constructor, the general algorithm [25] used to build a functional tree is described as:-

Function GrowTree(Dataset, Constructor)

1. If Stop_Criterion(Dataset)
   - Return a Leaf Node with a Constant Value
2. Construct a model ϕ using Constructor
3. For each example x є DataSet
   - Compute $\hat{y} = \phi(x)$
   - Extend x with new attributes $\hat{y}$
4. Select the attribute of original as well as of newly constructed attributes that maximizes some merit-function.
5. For each partition *i*of the DataSet using the selected attribute
   - $Tree_i$= GrowTree($DataSet_i$, Constructor)
6. Return a *Tree*, as a decision node based on the selected attribute, containing the ϕ model, and descendants $Tree_i$.

End Function

3.4.2 AdaBoost

The AdaBoost algorithm proposed by Yoav Freund and Robert Schapire is one of the most important ensemble methods, since it has solid theoretical foundation, very accurate prediction, great simplicity (Schapire said it needs only “just 10 lines of code”), and wide and successful applications [26]. **XindongWu et al.** in paper [26] has described AdaBoost algorithm as follows:-

Let *X* denote the instance space and *Y* the set of class labels. Assume *Y* = {−1, +1}. Given a *weak* or *base learning algorithm* and a training set $\{(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)\}$ where $x_i \in X$ and $y_i \in Y$ (*i*= 1, . . . ,*m*), the AdaBoost algorithm works as follows. First, it assigns equal weights to all the training examples (x_i, y_i)($i \in \{1, \ldots, m\}$). Denote the distribution of the weights at the *t*-th learning round as *Dt*. From the training set and *Dt* the algorithm generates a *weak* or *base learner ht:X → Y* by calling the base learning algorithm. Then, it uses the training examples to test *ht* , and the weights of the incorrectly classified examples will be increased. Thus, an updated weight distribution *Dt*+1 is obtained. From the training set and *Dt*+1 AdaBoost generates another weak learner by calling the base learning algorithm again. Such a process is repeated for *T* rounds, and the final model is derived by weighted majority voting of the *T* weak learners, where the weights of the learners are determined during the training process. The pseudo code for the algorithm is presented in [26] as:-

Input: Data set D = $\{(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)\}$;

Base learning algorithm ***L***;

Number of learning rounds ***T***.

Process:

$D_1(i) = 1/m$ % Initialize the weight Distribution

For t = 1,…,T:

$h_t = L(D, D_t)$; % Train a weak learner h_t from D using distribution D_t

$\varepsilon_t = \Pr_{i \sim D_i}[h_t(x_i \neq y_i)]$; % Measure the error of h_t

$\alpha_t = \frac{1}{2} \ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right)$; % Determine the weight of h_t

$$D_{t+1}(i) = \frac{D_{t(i)}}{Z_t} \times \begin{cases} \exp(-\alpha_t) & \text{if } h_t(x_i) = y_i \\ \exp(\alpha_t) & \text{if } h_t(x_i) \neq y_i \end{cases}$$

$$D_{t+1}(i) = \frac{D_t(i)\exp(-\alpha_t y_i h_t(x_i))}{Z_t}$$

End

Output: $H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$

4. RESULTS

Several Classification algorithms were used to monitor the accuracy levels. The results are summarized in table 2.

Table: 2
Summarized results

S.no.	Classifier	Accuracy
1	Functional Trees	**93.8283%**
2	Random Forest	**85.7475%**
3	Naïve Bayes	**84.7475%**
4	AdaBoost	**83.7374%**
5	J48	**80.6970%**

Figure 3 provides a performance comparison of various algorithms

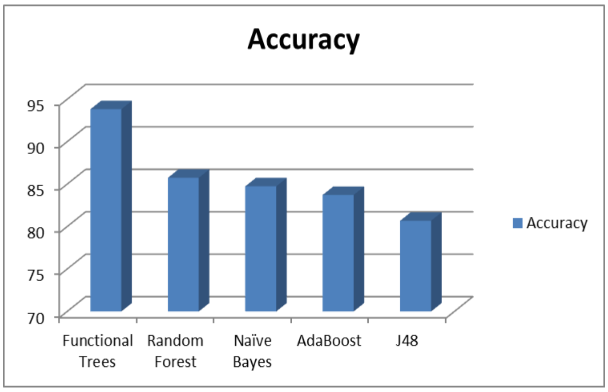

Figure 3
Performance Comparison

5. CONCLUSION

The results show that Delaunay Triangulation indeed can be used for gender prediction. From the table 2, it can be seen that Functional Trees algorithm performed best, and accuracy of **93.8283%** is observed, which shows improvement in results as compared to [14] and [24]. Gender prediction finds importance in diverse areas such as HCI, AI, and other related fields, hence; there is a need to constantly upgrade existing methods to a new level of perfection and higher accuracy levels.

6. FUTURE WORK

The possibility of gender detection through Euclidean distance and Delaunay Triangulation has been demonstrated in this article. The accuracy levels are satisfactory, but the question arises: Whether the accuracy can be improved any further? The next steps in the research would be to address the solution to better accuracy levels with improved algorithms. Another initiative would be to detect the age of the subject through the same frontal facial image, as used in gender detection. Age prediction can prove to be a very useful technique in order to improve the HCI interaction and make it more realistic. Age prediction can also be exploited in surveillance systems where there prevails the need to detect the subject's age. Machine Learning has the capability to address most of the real world problems by virtue of robust algorithms and thus, age prediction can also be solved through the techniques of Machine learning, which will be addressed in the next phases of this research.

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