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Semantic annotation for gender identification using support vector machine

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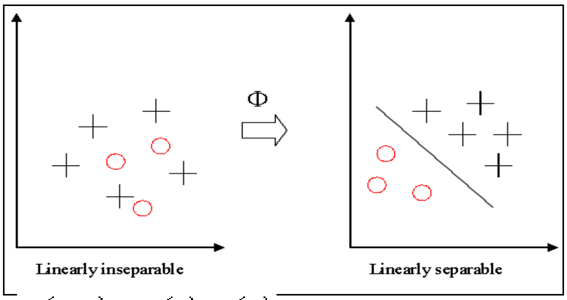
Abstract
Gender classification is a binary classification problem, which can be stated as inferring female or male from a collection of facial images. Although there exist different methods for gender classification, such as gait, iris, hand shape and hair, yet the prominent methods to achieve the goal is based on facial features.
Support Vector Machines (SVMs) are investigated for visual gender classification with low resolutions thumbnail faces (21-by-12 pixels) processed from 1,755 images from the FERET face database. The performance of SVMs (3.4% error) is shown to be superior to traditional pattern classifiers (Linear, Quadratic, Fisher Linear Discriminant, Nearest-Neighbor) as well as more modern techniques such as Radial Basis Function (RBF) classifiers and large ensemble-RBF networks.
In this paper SVM basic kernel function has been employed firstly to detect and classify the human gender Image into two labels i.e. (1) male and (2) female. These functions read as input the feature(s) of the human facial image. It uses two modes as 'Training Mode' and 'Classification Mode' and gender identification are made for semantic annotation of videos. The algorithm has been executed on elementary features of human facial image i.e. eyes, nose, lips and their all possible combinations. Finally based on the accuracy percentage of the computed result the admissible result of the Kernel Functions has been realized. The gender classifier achieves over 96% accuracy.

Keywords: SVM; Machine Learning; Gender Classification; Face Tracking; Face annotation

1. Introduction
In Artificial Intelligence, Machine Learning inculcates in every computer the ability to learn without being programmed categorically. Like Data Mining, Machine Learning too emphasizes on pattern analysis, yet unlike the former it does not necessarily extract data, instead utilizes the patterns to improve a program's own understanding. Machine Learning can be both (1) Supervised Learning in which case the target output is explicitly specified and (2) Unsupervised Learning where the training data comprises of a set of input vectors with no corresponding target values.
Support Vector Machine is one such Supervised Learning Model which has its own learning algorithms to analyses data to perform data classification and regression. The Support Vector Machine Classifier has its own variety of Kernel Functions which play a pivotal role in data classification. These are the similarity functions which read inputs and predict the similarity between them.
Support vector machine can be defined as a binary classifier which utilizes the concept of machine learning to predict the accuracy of data classification and regression while avoiding the over fitting of data. Alternatively, SVM can be employed to train a familiar set of data points (train set) whose results are utilized to classify the non-familiar data points (test set). [1] This technique of Data Classification can therefore be referred to as Supervised Learning where the target output is predefined as class labels. The defined class labels will then be compared with the actual output which will lead to the prediction of the accuracy percentage of the obtained result. However, to elucidate a Classification Problem, the dominant factor is the selection of the appropriate kernel relevant to the given classification problem. A Support Vector Machine alternatively viewed as a kernel machine, whose behavioral aspect can be ascertained with varying kernel functions. A kernel function enables operations to be performed in the input space over high dimensional feature space.

A linearly separable problem can be effortlessly classified into distinct groups by a separating hyper plane. Nevertheless, the role of a Kernel Function is realized evidently when the SVM classifier is implemented on inseparable data. For non- linear data, the kernel functions are used to non- linearly map the input data to a high-dimensional space. The new mapping can then be separated linearly. [2] The mapping has been depicted in figure 1.



Here $K(x,y) = \Phi(x) \cdot \Phi(y)$

K(x, y) is a kernel function

Fig 1: Mapping Function to depict the linearity measure of data

In this paper the principle idea is to appraise the performance of SVM basic kernel functions which has been employed to detect and classify the human gender. Image(s) classification into two labels i.e. (1) male and (2) female has been accomplished by utilizing the kernel functions of the specified classifier. These functions read as input the feature(s) of the human facial image. The purposed algorithm has been executed on elementary features of human facial image i.e. eyes, nose, lips and their all possible combinations. The aim of image annotation is to automatically assign keywords to images, so image retrieval users are able to query images by Keywords and automatically detect human faces from a photo image. Finally based on the accuracy percentage of the computed result the admissible result of the Kernel Functions has been realized for detecting gender.

2. Kernel Overview

The variety of Kernel functions in Support Vector Machine Classifier to perform similarity measure are (1) Linear Kernel. (2) Gaussian Kernel- RBF Kernel. (3) Polynomial Kernel. (4) Sigmoid Kernel.

The above stated SVM Kernel Functions performance is evaluated based on the parameter choice for each kernel and the values to be associated with each parameter. The Support Vector Machine requires appropriate tuning of these parameters which will consequently determine the accuracy percentage of the test results. Additionally, on careful selection of kernel parameters leads to the generation of a hyper plane which maximizes the margin and better generalization can be achieved. Consequently, the points nearest to the hyper plane will be assigned positive weight, resulting in sparsely weighted features within the higher-dimensional feature space. These points will be referred to as support vectors. Table 1 shows parameters and their default values.

Table 1: Tabulated version of the parameters and their default values

Parameter	Default Value
C	1
ϒ	1/Number of Features
Degree ‘d’(Polynomial Kernel only)	3
Coef r (Polynomial and Sigmoid kernel only)	0

A concise overview of the instances where SVM classifier kernel functions can be used to perform its intended function has been illustrated in the below mentioned cases.

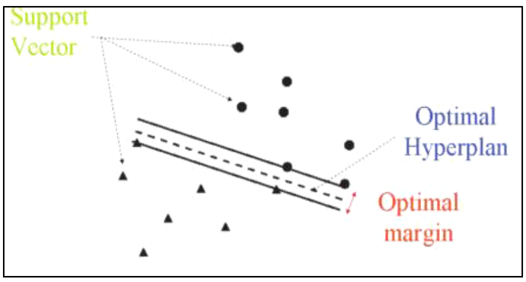
Case I: *Linear Problem*

This class deals with 1/0 problems with ‘N’ training samples. A support vector Xi describes each sample composed of disparate “band” with n dimensions. Each sample is assigned a class label which in this case is either +1 or -1. The linear function can be defined as

$f(x) = \text{sign}(\langle \omega, X\rangle + b)$

Here, ω is normal to the hyper plane, and |b| is the perpendicular distance from hyper plane to

‖ω‖ the origin. The class label of each sample is denoted by the sign of f(x) [3]. The hyper plane separation is shown below.



Kernel Type

The Linear Kernel- This type of kernel is best suited for(1) Solving problems which are inherently linearly separable and (2) The feature count of each sample is larger than number of instances. It operates faster than the other kernels. However its performance degrades with ‘noisy data’.

Unlike other kernels, linear kernel has only one tunable parameter i.e. ‘c’. It is shown in figure 2.

A Linear Kernel can be written as the function of x_i, x_j.

$$K(xi; xj) = xiTxj$$

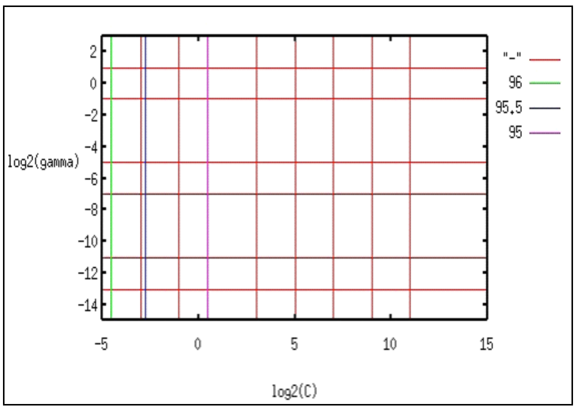


Fig 2: Linear Kernel Parameter Tuning [5]

Case II: *Non Linear Problem*

A problem with his nature has two possible solutions. (1) Create a soft margin adaptable for noisy data. (2) Use of an appropriate kernel. The kernel simulates the projection of non-classified data into a high dimensional feature space Φ: $Kn \rightarrow H$. The graphical representation is shown in figure 3.

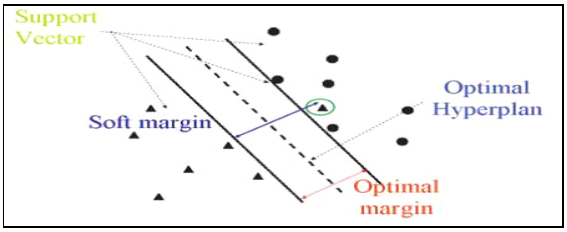


Fig 3: Diagrammatic Representation of Non- Linear Data [3]

Kernel Type

- **The RBF kernel:** This type of kernel is practically applicable for non- linear data set i.e. data which non-linearly separable and is to be mapped to the high dimensional space. This Gaussian kernel is delineated as

$K(x_i; x_j) = e^{(-\Upsilon\|x_i ? x_j\|^2)}$, $\Upsilon>0$ [5]

RBF Kernel is considered to be the default kernel of the SVM Library. Unlike Linear Kernel, this particular kernel has two tunable parameter i.e 'c' and 'γ' and the refined tuning of these parameters determines the efficacy of the kernel. It is shown in figure 4.

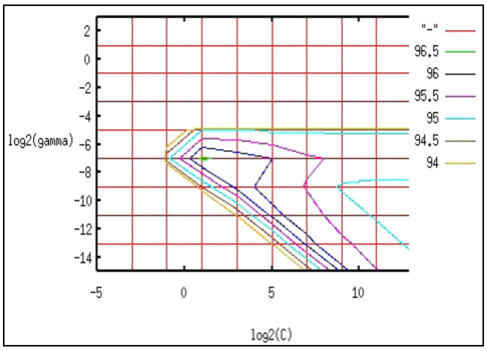


Fig 4: Parameter Tuning of Radial Basis Function [5].

- **The Polynomial kernel:** It is a non- linear kernel suited for similar characteristic of data. Implementation of the polynomial kernel is achieved by the decomposition method which consume considerable amount of time for a larger data set, hence it is less widely used than the RBF (Gaussian) kernel, since under similar training and testing cost, a polynomial kernel yield a less accurate result.

Polynomial Kernel has four tunable parameters i.e. 'c','ϒ, polynomial degree'd' and degree coefficient 'r'.It describes in figure 5.

$K(x_i,x_j)=(\Upsilon x_i x_j + r)^d$, $\Upsilon>0$

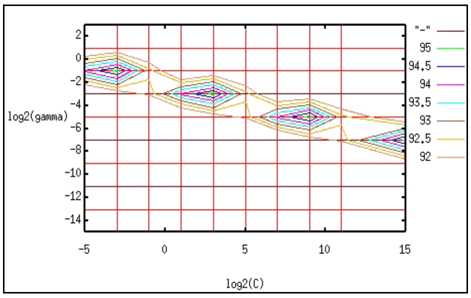


Fig 5: Polynomial Kernel Parameter tuning [5]

- **The Sigmoid kernel**

This kernel is best suitable for neural network though it is also applicable for Support Vector Machine. The characteristic feature of this kernel is that it is a positive semi-definite function [6] which makes this an unsuitable for certain parameter values. The kernel can be represented by the following function as shown in figure 6.

$$(x_{i,j}) = \tanh(\Upsilon x_i^T x_j + r)$$

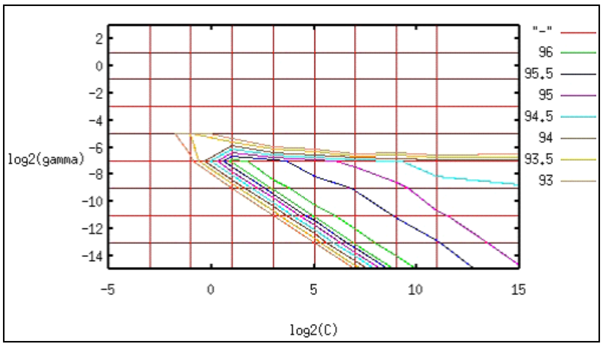


Fig 6: Sigmoid Kernel Parameter Tuning [5]

Case III: *Multiclass Problem*

The Support Vector Machine Classifier offers a satisfactory solution for a binary classification. However for multiclass problem, algorithms like "One against All" (OAA), "One Against One" (OAO) offer favorable solutions. For instance consider a k class problem, the OAA algorithm performs the construction of 'k' hyper planes which separates one class and the (k-1) other classes respectively. Alternatively the OAO algorithm when implemented to obtain the solution of similar problem performs the construction of $(k-1)2$ hyper plane which separate each pair of classes. [3]

3. Literature Review

In the year 1992, Boser, Guyon, and Vapnik in COLT-92 first acquainted Support Vector Machine as a set of interrelated supervised learning techniques which can be applied to a data set for classification and regression [7] incorporated into a family of generalized linear classifiers. The classifier can be applied on variety of data set including text, image, audio, video to achieve a degree of classification. One such renowned application of SVM Classifier is in the field of Human Gender Detection and its Classification. The connotation of Gender Recognition and its Classification was first identified in the field of research and development at the inception of 1990s. Initially Golomb *et al.* [8] used multi -layer neural network to recreate a solution to the gender classification issue. Approximately 900 manually aligned facial images were compressed into 40 images on which the classification was performed. An 8.1 % of error rate was identified and reported. In this field of research work, human facial features were the primary components on which the gender classification algorithm was implemented. Hence facial feature extraction was a crucial criterion. Shobeirinejad and Gao [8] proposed an Interlaced Derivative Pattern (IDP) to extract facial features. The IDP image is a four-channel derivative image representing images in different angles that are0°, 45°, 90°, and 135°. This method contains more important information about gender face recognition as it is based on extraction of distinct facial features. Similar task was accomplished by LU *et al.* [10]. In the experiment CAS-PEAL database was used. 480 × 360 Grey scale images were transformed to a normalized whole face image and a normalized internal face image. Experiments were performed based on a technique on seven facial regions of varying resolution. In order to improve the overall performance this method performed fusion of multiple facial regions. In the year 2015, an allied task of Human Gender Classification was attained by Mrs Sayantani Ghosh &Prof. Samir Kumar Bandyopadhyay. They used the 'lip' as the primary feature of the human facial image based on which the gender was detected and classified. [11] In addition, utilizing the aforesaid extracted feature, a similar experiment was percolated using multi class SVM to consummate the task of Age Detection and its classification into predefined class labels i.e 'child', 'adult' and 'old'. [11]

In this paper, analogous to the preceding methodologies, a refined technique has been proffered. In this methodology, the specified algorithm has been implemented on extracted facial feature(s) and their variety of combinations i.e eye, nose lip, eyes nose, nose lip, eyes lip eyes, nose lip. An evaluation process computed the accuracy percentage of the resultant outcome for each input feature(s). The primitive objective of this procedure is to evaluate the performance of the primary kernel functions of SVM classifier i.e linear, Gaussian, and polynomial kernel. The coequal algorithm is actualized on each kernel, and the performance evaluation of each kernel function is determined on the basis of the predicted accuracy of the resultant outcome. The dataset chosen for the algorithm comprises of 100 JPEG frontal facial images which includes 50 male and 50 female images. Using Region of Interest (ROI) principle, the primary components of a face i.e eyes, nose, lip is detected and extracted. These extirpated features are passed as parameters.

Biometric-based technologies include identification based on Physiological characteristics and behavioral traits [9]. Face recognition appears to offer several advantages over other Biometric method, facial images can be easily obtained with a couple of inexpensive fixed cameras. Good face recognition algorithms and appropriate preprocessing of the images can compensate for noise and slight variations in orientation, scale and illumination. Since most people usually organize collection of photos on the basis of some particular persons of interest (e.g., photos including their friends) [13]. Each face is a node in the graph and a random field is solved either for each picture or for a group of pictures. To index and retrieve personal photos based on an understanding of „who? is in the photos, annotation (or tagging) of faces is essential. However, manual face annotation by users is a time-consuming and inconsistent task that often imposes significant restrictions on exact browsing through personal photos containing their interesting persons. As an alternative, automatic face annotation solutions have been proposed. So far, conventional FR (Face Recognition) technologies have been used as main part to index people appearing in personal photos [13]. FR techniques can take benefits to improve annotation accuracy by taking into account context information. In addition, in contrast to previous research in this field, method requires no training data labeled by hand from photos. From a practical point of view, it is highly desirable in most cases with a shortage of labeled data. Work considers retrieving faces of specific people from caption-based supervision [14].

4. Proposed Methodology

This section emphasizes on the analysis of the proposed technique being adapted to attain the task of Gender Detection and its Classification using variety of combinations of human facial features. In addition, a metamorphic reasoning on the performance of the Kernel Functions in predicting the accuracy percentage of activated result has been accomplished.

4.1 Algorithm

Step 1: Input JPEG Image Set.
Step 2: Metamorphose individual image to grey scale version.
Step 3: Extract the primary features from the facial image.
Step 3.1: for each extracted feature image accomplish the below specified steps
Step 3.1.1: Reshape the extracted image from 2 D -1D.
Step 3.1.2: Generate a feature vector for each extracted feature image(s).
Step 3.1.3: Associate with each image i.e. for each row vector a class label. Assign +1 to female image and -1 to male image.

End

Step 4: Shuffle each row of Feature Vector.
Step 5: Cross- Validation the updated matrix and generate the train set and the test set.
Step 6: Select appropriate kernel and the kernel parameters of the SVM classifier and train the appropriate known data set.
Step 7: Apply test method of SVM to test the unknown data set.
Step 8: Retrieve the final classified result.

4.2. Implementation

The implementation details of the above stated methodology are enlisted as follows:

- Software used- MATLAB routines [12].
- Input Set- An image set comprising 100 Jpeg frontal facial images (50 males and 50 females).Each image resized to dimension 128*115.
- Individual image pre-processed to remove unwanted components, enhance the image and improve the image contrast.
- The train set is executed to generate the train vector.
- The class labels of the unknown data set are determined by invoking the classify routine.

4.2.1 Preprocessing Phase

1) Select each Gray scale image from the Image Matrix.
2) Perform Histogram Equalization on individual image. This improves the contrast of the image by even distribution of intensities thereby assuring contrast stretching where regions with lower contrast achieve higher contrast.

4.2.2 Feature Extraction Phase

The extraction principle applied on facial images to extract its distinguishable features is the Region of Interest (ROI) principle. The steps followed in this principle are matriculated as follows.

- Select an appropriate window dimension based on the location of the facial feature of the human facial image.
- The feature is then identified and extracted from the selected location using the cropping function.

- Each extracted image is resized to a one dimensional vector.
- Feature Vectors of the extracted feature/ feature pair i.e ‘eyes’, ’nose’, ’lips’, ’eyes nose’, ‘nose lips’, ‘eyes lips’ are generated. With each row vector of the Feature Matrix class label of +1 is assigned for the female image and a class label -1 is assigned for the male image.

After processing method described above the following figures appears as Diagrammatic Representation of the Feature Extraction Phase.

Fig 7: Gray Scale Image

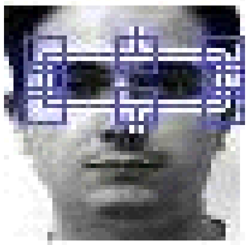


Fig 8: Identified Region of Interest 1

Fig 8.1: Extracted Eyes Region

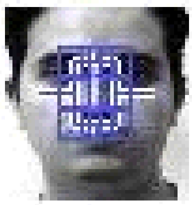


Fig 9: Detected Region of Interest 2

Fig 9.1: Extracted Nose Region

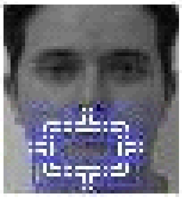


Fig 10: Identified Region of Interest2

Fig 10.1: Extracted Feature

4.2.3 Shuffling Phase

At this stage, the individual row of the feature vector is shuffled. The shuffled matrix is then subjected to the next level of processing i.e. cross validation. The main objective of shuffling is to obtain a cross validated result with improved precision as shown Table 2. The shuffled matrix is shown in Table 3.

Table 2 : Tabulated version of the class labels of the original feature vector consisting of 100 chosen images where ‘1’ represent the female gender and ‘0’ represent the male gender.

1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0				

Table 3: Tabulated Version of the Shuffled Matrix.

0	0	0	1	1	0	1	0	0	0	1	0	1
1	0	0	1	1	1	0	0	1	1	1	0	1
0	1	0	0	1	0	1	1	1	1	1	0	0
1	1	1	1	1	0	1	1	0	1	1	1	0
1	0	0	0	0	1	0	0	1	1	1	0	1
1	1	0	0	0	0	0	1	1	0	1	1	0
1	0	0	1	0	0	0	0	0	1	1	1	0
1	0	0	0	0	0	0	1	1				

4.2.4 Cross Validation Phase

Cross Validation of the Shuffled Matrix is one of the key steps in Gender Recognition Algorithm. It resolves the issues like over fitting of images. Besides if the original data set is appropriately cross validated, it can be effortlessly divided into the train set and the test set. The size of the train set and the test set however depends on the degree of the cross validation technique. Like the 'hold out technique divides the original set into two equal sized sets, while the other techniques like '10 fold' cross validation and '5 fold 'cross validation dissociates the primitive data into 10 segments and 5 segments respectively. Each time one segment is tested to predict the class labels of the undetermined set after acquiring the result of the training of the remaining (n-1) segments.

Table 4: Tabulated version of '10 fold 'Cross Validated Data Set. Here the train set comprises of the data with class label '1'which includes 90 instances while the test set comprises of the data with class labels '0'which includes 10 instances of the 100 prime data set.

1	1	0	1	1	1	1	1	1	1	1	1	1
1	1	1	0	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	0	0
1	1	1	0	1	1	1	1	1	1	0	1	1
0	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	0	1	1	0
1	0	1	1	1	1	1	1	1				

4.2.5 Train / Test Phase

The cross validated data are then trained and the trained result classifies the test set and predicts the class labels of the unknown set in Table 5 and Table 6.

Table 5: Tabulated version of the output class labels of the Tested Result

0	1	1	0	0	1	1	1	0	0

Table 6: Tabulated version of the actual class labels of the original Feature Vector

0	1	1	0	0	1	1	1	0	0

5. Experimental Result

In this segment, the result of the implementation of the proposed algorithm has been manifested. The program code of the above stated algorithm has been written using MATLAB version R2013a. On proper using of the key kernels available in SVM i.e (1) Linear (2) RBF and (3) Polynomial, the proposed algorithm is executed to accomplish the following computations.

Accuracy= (TP+TN)/ (TP+TN+FP+FN).

Sensitivity= (TP)/ (TP+FN).

Specificity = (TN)/ (TN+FP).

The experimental results are shown in Table 7, Table 8 and Table 9.

Table 7: Tabulated Version of Tested Result using Linear Kernel

Serial No	Cross Validation Technique	Identified Features	Train Set	Test Set	Output Class Labels	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)	Accuracy %	Sensitivity %	Specificity %
1	10 Fold	Eyes	90	10	0,1,1,1,0,1,0,0,0,1	5	5	0	0	100	100	100
1.1			90	10	1,1,1,0,0,0,1,0,0,0	4	5	1	0	90	100	83.33
2	5 Fold	Eyes	80	20	0,0,0,1,0,1,1,0,1,0,0,0,0,1,0,1,1,1,0,0	8	10	2	0	90	100	83.333
2.1			80	20	0,0,1,1,0,0,0,1,1,0,1,1,1,0,0,1,0,1,0,0	9	10	1	0	95	100	90.9091
3	Hold Out	Eyes	50	50	1,1,1,1,1,0,0,0,1,0,1,1,0,1,0,1,0,0,0,0,0,1,0,0,0,0,1,1,1,1,1,1,1,1 ,0,1,1,1,1,0,0,0,0,0,1,1,0,0,0,0	23	23	2	2	92	92	92
3.1			50	50	0,1,0,0,1,1,1,1,1,0,0,1,0,0,0,0,1,0,0,1,1,0,0,0,1,0,1,1,1,1,0,0,1,0 ,1,1,0,0,0,1,1,1,1,0,0,0,0,0,1,1	22	23	3	2	90	91.6667	88.4615
4	10 Fold	Nose	90	10	1,0,0,1,1,1,0,0,0,1	5	5	0	0	100	100	100
4.1			90	10	1,0,0,1,1,1,0,1,0,1	5	4	0	1	90	83.33	100
5	5 Fold	Nose	80	20	1,1,1,0,0,0,1,1,1,0,0,1,1,1,0,0,0,0,1,0	10	10	0	0	100	100	100
5.1			80	20	1,0,0,1,0,1,1,1,1,1,1,1,1,0,0,0,0,1,0,0	10	9	0	1	95	90.9091	100
6	Hold Out	Nose	50	50	0,1,1,0,1,0,1,1,1,0,0,0,1,0,0,0,1,0,1,0,1,0,1,0,0,1,1,0,0,0,1,0,1,0 ,0,1,1,0,0,1,0,0,1	19	22	6	3	82	86.3636	78.5714
6.1			50	50	1,1,0,1,0,0,0,0,1,0,1,0,0,1,1,0,0,1,0,1,0,0,1,0,1,1,0,1,0,1,1,0,0,0 ,1,0,1,1,1,0,0,0,0,1,0,0,1,0,1,1	20	22	5	3	84	84.9565	81.4815
7	10 Fold	Lips	90	10	1,0,0,1,0,1,1,0,1,1	5	4	0	1	90	83.333	100
7.1			90	10	0,1,0,1,1,0,1,0,1,0	5	5	0	0	100	100	100
8		Lips	80	20	0,0,0,0,1,1,0,1,0,0,0,1,0,0,1,1,0,1,1,1	8	9	2	1	85	88.8889	81.8182
8.1			80	20	0,1,1,1,0,0,1,0,0,1,0,0,1,0,1,0,0,1,1,1	9	9	1	1	90	90	90
9		Lips	50	50	0,0,0,0,0,0,1,1,0,0,0,1,0,1,1,1,0,1,0,0,1,1,1,1,0,1,1,0,1,0,1,1,1,1 ,1,0,1,1,1,0,0,0,0,0,1,0,1,1,0,1	25	24	0	1	98	96.1538	100
9.1			50	50	0,1,0,0,1,0,0,1,0,1,0,1,0,1,0,1,1,0,1,0,1,1,1,1,0,0,1,1,0,0,1,0,1,0 ,1,0,1,0,1,1,0,0,0,0,0,0,1,0,0,1	22	24	3	1	92	95.6522	88.8889
10	10 Fold	Eyes Nose	90	10	0,1,0,1,0,0,1,1,0,0	4	5	1	0	90	100	83.3333
10.1			90	10	1,1,1,0,0,1,0,0,0,1	5	5	0	0	100	100	100
11	5 Fold	Eyes Nose	80	20	0,0,0,1,0,1,1,0,0,1,1,1,0,1,1,1,1,0,1,0	9	8	1	2	85	81.8182	88.8889
11.1			80	20	1,1,0,0,0,0,0,0,0,1,1,1,1,1,0,0,1,1,1,1	10	9	0	1	95	90.9091	100

12	Hold Out	Eyes Nose	50	50	1,0,0,0,1,1,0,0,0,0,1,0,0,1,0,1,0,1,0,0,0,1,1,0,1,0,1,0,0,0,1,0,0,0 ,1,0,0,1,0,1,0,0,0,1,1,1,1,1,0,0	22	25	3	0	94	100	89.2857
12.1			50	50	0,0,1,0,0,0,1,0,0,1,0,0,0,1,0,0,1,0,0,0,1,1,1,1,1,1,0,0,0,0,1,0,1,0 ,0,0,0,1,1,0,1,1,0,1,1,1,0,1,0,1	22	25	3	0	94	100	89.2857
13	10 Fold	Nose Lip	90	10	0,1,1,1,1,0,0,1,0,0	5	5	0	0	100	100	100
13.1			90	10	0,1,1,1,1,0,0,1,0,0	5	5	0	0	100	100	100
14	5 Fold	Nose Lip	80	20	1,0,0,0,0,1,1,0,0,0,0,1,0,1,1,0,1,1,0,1	9	10	1	0	95	100	90.9091
14.1			80	20	0,0,0,1,1,1,1,1,0,1,1,0,0,1,0,1,0,1,0,1	10	9	0	1	95	90.9091	100
15	Hold Out	Nose Lip	50	50	0,0,1,0,0,0,0,1,1,1,1,0,0,0,0,0,0,0,0,0,1,0,1,0,1,0,1,0,1,0,0,0,1 ,1,0,1,0,0,0,0,0,1,0,1,1,0,0,1,0	16	24	9	1	80	94.1176	72.7273
15.1			50	50	1,0,0,1,1,0,0,0,1,1,0,1,0,1,1,0,0,0,0,1,1,1,0,0,1,0,0,0,0,0,0,0,0,0 ,1,0,1,0,1,0,0,1,1,0,1,0,0,1,1,1	19	23	6	2	84	90.4762	79.3103
16	10 Fold	Eyes Lip	90	10	1,0,0,0,1,0,1,1,0,0	4	5	1	0	90	100	83.3333
16.1			90	10	1,1,0,0,0,0,1,1,0,1	5	5	0	0	100	100	100
17	5 Fold	Eyes Lip	80	20	1,1,1,1,0,0,0,1,0,0,0,1,1,1,0,1,0,1,1,0	10	9	0	1	95	90.9091	100
17.1			80	20	1,0,1,1,0,0,1,1,0,0,0,0,0,1,1,0,0,1,0,1	8	9	2	1	85	88.88889	100
18	Hold out	Eyes Lip	50	50	0,1,0,0,0,1,0,0,0,1,1,0,1,1,1,1,1,1,0,0,0,0,1,0,1,0,0,0,0,1,1,1,1,0 ,0,0,0,1,0,0,0,0,1,0,1,1,1,0,1,0	19	22	6	3	82	86.3636	78.5714
			50	50	1,0,1,1,0,0,0,0,1,0,1,0,0,1,1,0,1,1,1,1,0,0,1,1,1,0,0,0,0,0,1,0,0,0 ,1,0,1,1,1,0,0,1,0,1,0,0,1,0,1,1	23	24	2	1	94	95.8333	92.3077
19	Eyes Nose Lip	10 Fold	90	10	1,0,0,1,0,1,0,0,1,1	5	5	0	0	100	100	100
19.1			90	10	0,0,0,1,0,1,0,1,1,1	5	5	0	0	100	100	100
20		5 Fold	80	20	1,0,1,1,0,1,1,0,0,0,0,1,0,0,0,1,0,1,0,1	9	10	1	0	95	100	90.9091
20.1			80	20	0,1,0,1,1,1,1,1,1,0,0,0,1,1,0,1,0,0,0,0	10	10	0	0	100	100	100
21		Hold Out	50	50	0,0,1,0,1,1,0,0,0,0,1,1,0,1,1,1,0,1,0,1,1,0,0,0,1,0,1,0,0,0,0,1,1,1 ,0,0,1,0,1,0,0,1,0,0,1,1,1,1,0,1	22	23	3	2	90	91.6667	88.4615
21.1			50	50	1,0,1,1,0,0,1,0,1,0,1,1,0,0,0,0,0,1,0,0,1,0,0,1,1,0,1,0,0,1,0,1,0,0 ,1,1,1,1,1,1,1,1,0,0,1,0,1,0,1,1,1,1	25	24	0	1	98	96.1538	100

Table 8: Tabulated Version of Tested Result using RBF (Gaussian) Kernel

Serial No	Cross Validation Technique	Identified Features	Train Set	Test Set	Output Class Labels	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)	Accuracy %	Sensitivity %	Specificity %
1	10 Fold	Eyes	90	10	1,1,0,0,0,1,1,1,0,0	5	5	0	0	100	100	100
1.1			90	10	0,0,1,0,0,0,1,1,1,1	5	5	0	0	100	100	100
2	5 Fold	Eyes	80	20	1,1,0,0,0,0,0,0,1,0,1,0,1,1,0,0,0,0,1,1	8	10	2	0	90	100	83.3333
2.1			80	20	1,0,0,0,0,1,1,0,1,0,0,0,0,0,1,0,0,0,0,1	6	10	4	0	80	100	71.4286
3	Hold Out	Eyes	50	50	0,1,0,0,0,0,0,1,0,0,0,1,1,0,0,1,0,0,1,0,1,0,0,0,1,0,0,0,0,1,0,0,0 ,0,0,0,1,1,0,0,0,0,0,0,0,0,0,0,0,0	11	25	14	0	72	100	64.1026
3.1			50	50	0,1,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,1,0,0 ,0,1,0,1,0,0,1,1,0,0,1,1,0,0,1,0,1	12	25	13	0	74	100	65.7895
4	10 Fold	Nose	90	10	1,0,1,0,1,0,1,1,0,1	5	4	0	1	90	83.33	100
4.1			90	10	1,0,0,1,0,0,1,1,0,1	5	5	0	0	100	100	100
5	5 Fold	Nose	80	20	1,0,1,0,1,1,0,0,1,0,1,1,0,1,0,1,1,1,1,1	10	7	0	3	85	76.9231	100
5.1			80	20	1,1,1,0,0,1,1,1,0,1,1,1,0,0,1,1,0,0,0,1	10	8	0	2	90	83.3333	100
6	2 Fold	Nose	50	50	0,1,1,1,0,1,0,0,0,0,1,1,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0 ,0,1,0,0,1,1,0,0,0,0,1,0,1,1,0,0,0	13	25	12	0	76	100	67.5676
6.1			50	50	1,0,0,1,1,0,1,1,1,1,1,1,1,1,1,1,1,1,0,1,1,0,0,0,0,0,0,1,1,1,0,1,1 ,0,0,0,1,1,1,1,1,1,0,1,1,1,1,1,1,1	25	15	0	10	80	71.42	100
7	10 Fold	Lips	90	10	1,0,0,1,1,1,1,0,0,0	5	5	0	0	100	100	100
7.1			90	10	1,0,0,0,0,0,0,1,1,1	4	5	1	0	90	100	83.333
8	5 Fold	Lips	80	10	1,0,1,1,0,1,0,1,1,0,0,0,0,0,1,0,0,0,0,0	7	10	3	0	85	100	76.9231
8.1			80	10	1,0,0,0,0,1,0,0,0,1,0,0,0,0,1,1,0,1,0,0	6	10	4	0	80	100	71.4286
9	Hold Out	Lips	50	50	0,1,0,0,0,1,0,0,0,0,0,0,1,0,0,0,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0 ,0,1,0,0,1,0,1,0,0,1,1,0,0,0,0,0,1	12	25	13	0	74	100	65.7895
9.1			50	50	0,0,0,0,1,1,0,0,0,1,0,0,0,1,1,1,1,1,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0 ,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,0,0	11	25	14	0	72	100	64.1026
10	10 Fold	Eyes Nose	90	10	1,0,0,1,1,1,0,1,0,1	5	4	0	1	90	83.33	100
10.1			90	10	0,0,1,1,0,1,0,1,0,0	4	5	1	0	90	100	83.33
11	5 Fold	Eyes Nose	80	20	1,0,1,0,0,1,0,1,0,0,0,1,0,0,1,0,0,1,0,0	7	10	3	0	85	100	76.9231
11.1			80	20	0,0,1,0,0,0,0,1,1,0,0,1,0,1,0,1,0,0,0,0	6	10	4	0	80	100	71.4286
12	Hold Out	Eyes Nose	50	50	0,0,0,1,0,0,0,0,1,1,1,0,0,1,0,0,0,1,0,0,0,0,0,0,1,0,0,1,0,0,0,0,1 ,0,0,0,1,1,0,0,1,1,0,0,0,0,1,1,0,0	15	25	10	0	80	100	71.4286
12.1			50	50		13	25	12	0	76	100	67.5676

					0,0,0,0,1,0,0,0,1,0,0,1,0,1,0,1,0,0,1,0,1,0,1,0,0,0,0,1,1,0,0,0,0 ,0,1,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0							
13	10 Fold	Nose Lip	90	10	1,0,0,0,0,0,1,0,1,1	4	5	1	0	90	100	83.33
13.1			90	10	0,0,1,1,0,1,1,0,1,0	5	5	0	0	100	100	100
14	5 Fold	Nose Lip	80	20	1,1,1,1,1,0,0,1,0,1,1,0,1,0,1,1,0,0,0,1	10	8	0	2	90	83.33	100
14.1			80	20	0,0,0,1,0,1,0,1,1,1,0,0,1,0,1,1,0,1,1,1	10	9	0	1	95	90.9091	100
15	2 Fold	Nose Lip	50	50	1,1,0,0,0,1,1,0,0,0,0,1,0,0,1,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,0,0 ,0,1,1,0,0,1,0,0,1,1,1,0,0,0,0,0,0	14	25	11	0	78	100	69.4444
15.1			50	50	0,1,0,0,0,0,1,0,0,0,0,1,0,0,0,0,0,0,1,1,1,0,1,1,0,1,0,0,1,0,1,0,0 ,0,1,0,1,0,0,0,0,1,0,0,1,0,0,0,0,0	15	25	10	0	80	100	71.4286
16	10 Fold	Eyes Lip	90	10	1,0,1,1,1,1,0,0,0,1	5	4	0	1	90	83.33	100
16.1			90	10	0,0,0,1,0,1,1,1,1,0	5	5	0	0	100	100	100
17	5 Fold	Eyes Lip	80	20	0,1,0,1,1,0,0,1,0,0,0,0,1,0,0,1,1,0,0,1	8	10	2	0	90	100	83.3333
17.1			80	20	0,0,0,1,1,0,1,0,1,0,0,0,0,0,1,1,0,1,1,1	9	10	1	0	95	100	90.9091
18	2 Fold	Eyes Lip	50	50	1,0,1,0,1,0,1,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,1,0,1,0,0,0,1,0,0,1 ,1,0,0,0,1,0,0,0,0,0,1,1,0,0,0,0,1	14	25	11	0	78	100	69.4444
18.1			50	50	1,0,0,1,0,0,0,0,0,0,1,0,1,0,0,1,1,0,1,0,0,1,0,0,1,0,0,0,0,0,0,0,0 ,0,0,1,0,1,0,0,0,0,0,0,0,0,0,0,0,0	11	25	14	0	72	100	64.1026
19	10 Fold	Eyes Nose Lip	90	10	0,1,0,0,0,1,1,0,1,1	5	5	0	0	100	100	100
19.1			90	10	1,0,0,0,0,0,1,1,1,1	5	5	0	0	100	100	100
20	5 Fold	Eyes Nose Lip	80	20	1,0,1,1,1,1,0,1,0,0,0,1,1,1,1,1,1,1,0,1	10	6	0	4	80	71.4286	100
20.1			80	20	1,1,1,1,1,1,1,1,0,0,1,0,0,1,0,0,1,1,0,1	10	7	0	3	85	76.9231	100
21	2 Fold		50	50	1,1,1,1,1,1,1,1,1,1,0,1,1,1,1,1,1,1,0,1,1,0,0,1,1,0,0,1,0,1,1,1,1 ,1,1,0,1,0,1,0,0,1,1,1,0,1,0,0,1,1	25	14	0	11	78	69.4444	100
21.1			50	50	1,1,0,0,0,1,1,0,1,1,1,1,1,1,1,1,1,1,1,1,1,1,0,0,1,0,0,1,0,1,1,0,1,1 ,1,1,1,0,1,0,1,1,1,0,1,1,1,0,0,1,0	25	16	0	9	82	73.5294	100

Table 9: Tabulated Version of Tested Result using Polynomial Kernel

Serial No	Cross Validation Technique	Identified Features	Train Set	Test Set	Output Class Labels	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)	Accuracy %	Sensitivity %	Specificity %
1	10 Fold	Eyes	90	10	1,1,1,0,0,0,0,0,1,0	4	5	1	0	90	100	83.333
1.1			90	10	0,0,0,1,0,1,1,0,0,0	3	5	2	0	80	100	71.42
2	5 Fold		80	20	0,0,0,1,0,0,0,0,1,0,0,1,0,1,1,0,0,0,1,1	10	7	3	0	85	100	76.92

2.1			80	20	1,1,0,1,0,0,1,1,0,0,0,1,0,1,0,0,0,1,1,1	9	9	1	1	90	90	90
3	Hold out	Eyes	50	50	0,0,1,0,0,1,1,0,0,0,0,1,0,0,0,0,1,0,0,1,0,0,0,0,1,0,0,0,0,1,1,0,1,1,0,1,0,1,1,1,0,1,1,0,0,0,0,1,0,1	17	23	8	2	80	89.4737	74.1935
3.1			50	50	1,1,0,0,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,1,0,0,0,0,1,0,1,0,0,0,1,1,0,0,0,0,0,0,0,0,1,1,0,1,0,0,0,1,1,0	12	23	13	2	70	85.7143	63.8889
4	10 Fold	Nose	90	10	0,1,0,0,1,0,0,0,0,0	2	5	3	0	70	100	62.5000
4.1			90	10	0,0,0,1,1,0,0,1,0,0	2	4	3	1	60	66.6667	57.1429
5	5 Fold	Nose	80	20	1,0,1,0,0,1,1,1,1,0,0,0,0,0,0,0,0,0,0,0	4	8	6	2	60	66.6667	57.1429
5.1			80	20	0,0,0,1,0,1,1,1,0,0,1,1,0,1,0,1,0,1,1,0	7	7	3	3	70	70	70
6	Hold Out	Nose	50	50	0,0,0,0,0,0,0,1,0,0,0,0,1,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,1,0,0,1,0,0,0,0,0,0,0,0,0,1	6	24	19	1	60	85.7143	55.8140
6.1			50	50	0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,0,0,0,1,0,1,1,0,0,0,0,0,0,0	6	25	19	0	62	100	56.8182
7	10 Fold	Lips	90	10	1,1,1,1,1,1,0,1,1,0	5	2	0	3	70	62.5000	100
7.1			90	10	1,1,1,1,0,0,0,0,0,0	3	4	2	1	70	75	66.6667
8	5 Fold	Lips	80	20	1,0,1,0,0,0,0,0,1,1,1,0,1,0,0,0,0,1,1,0	5	7	5	3	60	62.5000	58.3333
8.1			80	20	1,0,0,0,1,0,1,1,1,1,0,0,0,1,0,0,0,1,1,0	7	8	3	2	75	77.7778	72.7273
9	Hold Out	Lips	50	50	1,0,0,1,0,0,1,1,1,0,1,1,0,1,1,1,0,1,1,0,1,0,0,0,0,1,0,1,1,0,0,0,0,0,0,1,1,0,0,0,0,0,1,0,1,0,0,1,0,1	21	24	4	1	90	95.4545	85.7143
9.1			50	50	0,0,0,1,1,1,1,1,1,1,1,0,1,0,1,0,0,1,1,1,0,0,1,0,1,0,1,1,1,0,1,1,0,1,0,1,0,1,0,0,1,0,0,0,1,1,0,0,1,0	22	20	3	5	84	81.4815	86.9565
10	10 Fold	Eyes Nose	90	10	1,0,0,0,1,0,1,0,0,0	3	5	2	0	80	100	71.4286
10.1			90	10	0,1,1,1,0,1,0,0,0,0	3	4	2	1	70	75	66.6667
11	5 Fold	Eyes Nose	80	20	1,0,0,0,0,1,0,1,0,0,1,0,0,1,1,0,1,0,0,1	8	10	2	0	90	100	83.3333
11.1			80	20	0,1,1,1,0,1,0,0,0,0,1,1,0,1,1,1,0,0,0,0	9	10	1	0	95	100	90.9091
12	Hold Out	Eyes Nose	50	50	1,0,0,1,1,0,0,0,1,1,1,0,1,1,1,0,0,0,0,1,0,1,0,0,0,0,0,0,0,1,1,1,0,1,0,0,0,0,0,0,1,0,1,0,1,1,1,0,1,0	18	22	7	3	80	85.7143	75.8621
12.1			50	50	0,1,0,1,0,0,0,0,0,1,0,0,1,1,1,0,0,1,0,0,0,1,0,0,0,1,0,0,0,1,1,1,0,0,1,0,1,1,1,0,1,1,0,1,0,0,1,0,1,1	20	23	5	2	86	90.9091	82.1429
13	10 Fold	Nose Lip	90	10	1,1,0,0,0,0,1,1,1,1	5	4	0	1	90	83.3333	100
13.1			90	10	1,1,1,0,0,0,1,0,0,1	5	5	0	0	100	100	100
14	5 Fold	Nose Lip	80	20	1,1,1,0,0,0,0,0,0,1,0,1,1,0,1,1,1,1,1,1	9	7	1	3	80	75	87.5
14.1			80	20	0,0,0,0,1,0,0,1,0,0,1,1,1,1,1,0,0,1,0,1	8	9	2	1	85	88.8889	81.8182

15	Hold Out	Nose Lip	50	50	1,0,0,0,1,1,0,0,1,1,0,0,1,0,0,1,1,1,0,1,0,1,1,0,1,0,1,0, 0,1,0,0,1,0,0,0,0,1,1,0,1,1,0,0,1,1,0,0,0,0	20	23	5	2	86	90.9091	82.1429
15.1			50	50	0,0,0,0,1,0,1,1,1,1,0,0,1,1,1,0,1,0,0,1,1,0,1,0,1,1,1,1, 1,0,1,0,1,0,0,0,0,1,0,0,0,0,1,1,1,0,0,1,1,1	21	20	4	5	82	80.7692	83.3333
16	10 Fold	Eyes Lip	90	10	0,0,0,0,0,1,1,0,1,1	4	5	1	0	90	100	83.3333
16.1			90	10	1,1,1,1,0,0,1,0,0,0	5	5	0	0	100	100	100
17	5 Fold	Eyes Lip	80	20	0,0,1,1,1,0,1,0,0,0,1,0,1,0,1,0,0,0,0,1	8	10	2	0	90	100	83.3333
17.1			80	20	1,1,0,0,1,1,0,0,0,1,0,1,1,1,0,0,0,0,0,1	9	10	1	0	95	100	90.9091
18	Hold Out	Eyes Lip	50	50	1,1,0,0,0,0,0,1,0,0,0,1,0,0,1,1,1,0,0,0,0,0,1,1,1,0,0,0, 1,0,0,1,1,0,0,0,0,0,1,0,0,0,0,1,0,0,1,0,1,1	18	25	7	0	86	100	78.1250
18.1			50	50	1,0,0,0,1,0,0,0,0,0,1,1,1,0,0,0,1,0,0,0,0,1,0,1,0,0,0,0, 1,0,0,1,1,1,0,0,0,0,1,0,1,1,1,0,0,0,1,0,1,1	18	24	7	1	84	94.7368	77.4194
19	10 Fold	Eyes Nose Lip	90	10	0,0,0,1,0,0,1,1,1,0	4	5	1	0	90	100	83.3333
19.1			90	10	1,0,0,1,0,1,0,0,1,1	5	5	0	0	100	100	100
20	5 Fold	Eyes Nose Lip	80	20	0,1,0,0,0,1,0,1,0,1,0,1,0,0,0,0,1,0,1,0	7	10	3	0	85	100	76.9231
20.1			80	20	0,0,0,1,0,1,1,0,1,0,0,0,0,1,0,1,1,1,0,0	8	10	2	0	90	100	83.33
21	Hold Out	Eyes Nose Lip	50	50	1,1,0,1,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,0,1,1,0,1,1,0,1,1, 1,0,0,0,1,1,0,1,1,1,0,0,0,1,1,1,0,1,1,1,0,1	22	23	3	2	90	91.67	88.46
21.1			50	50	0,1,1,0,0,0,1,0,1,1,1,1,0,1,1,0,0,0,0,0,0,1,1,0,1,0,0,1, 0,0,1,1,0,1,0,0,0,0,0,0,1,0,0,1,0,0,0,0,0,0	17	24	8	1	82	94.4444	75

6. Inferences

The graphical analysis of different kernels is shown in Figure 10, Figure 11, Figure 12 and Figure 13. Graphical representation of comparative analysis of Kernels Functions is shown in Figure 14.

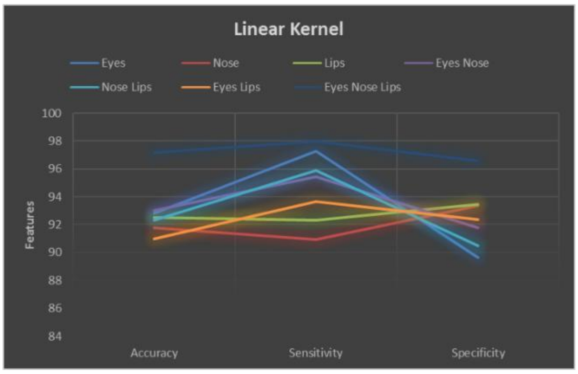


Fig 10: Graphical Analysis of the performance of Linear Kernel

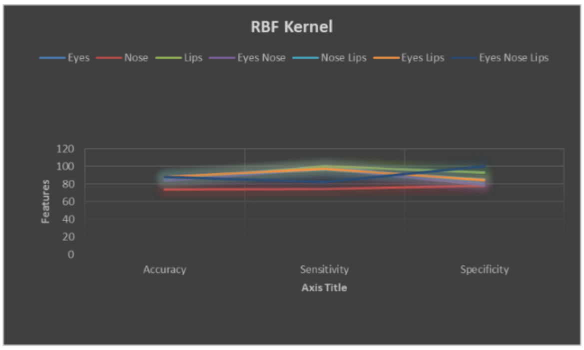


Fig 11: Graphical Analysis of the performance of RBF Kernel

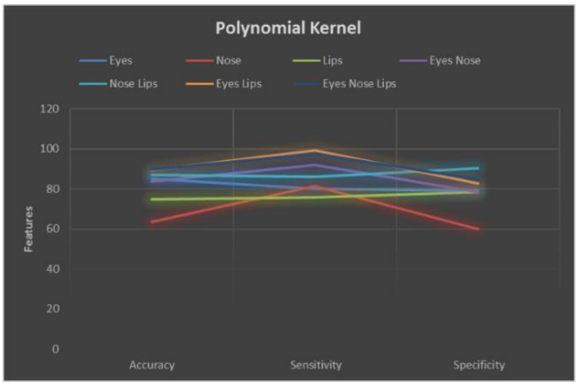


Fig 12: Graphical Analysis of the performance of Polynomial Kernel

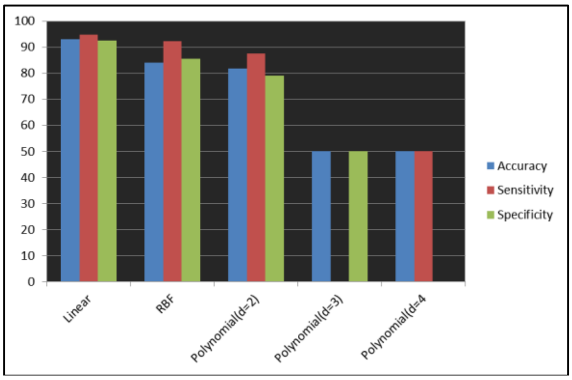


Fig 13: Graphical Representation of Comparative Analysis of Kernels Functions

Search-based face annotation plays a vital role. Specifically, given a user-uploaded facial image for annotation, the search-based face annotation scheme firstly retrieves a short list of top-K most similar facial images from a large scale web facial image database, and then annotates the query facial image by mining the labels associated with the top-K similar facial images. In general, the search-based face annotation system two challenges are:

a) There is a challenge in efficiently retrieving the top-K most similar facial images from a large facial image database given a query facial image.

b) There is a challenge in effectively exploit the shortlist of Candidate facial images and their weak labels for naming the Faces automatically.

In this section we shall emphasize on the implementation of the human gender detection and its classification from a group image which contains a set of male and female images. The technique that has been adapted in this model is similar to the one as discussed in the previous section. Except, that the individual image of male / female is first extracted from a group image which contain multiple facial images of male and female. Once the facial images are retrieved, the pre-processing of these images, the feature extraction and finally the classification of the gender is achieved by following the steps as discussed in the previous section.

A group image consisting of 30 facial images are read as input. The input image contain 15 male images and 15 female images. Each individual image is of dimension 300*250. After the individual images are extracted, each original facial image is resized to dimension 128*115. It is shown in the figure 14. This method performs a text-based query over the captions, returning the documents that have the queried name in the caption. The faces found in the corresponding images are then further visually analyzed. The proposed method performs annotation for finding particular face from the group and it is shown in figure 15.

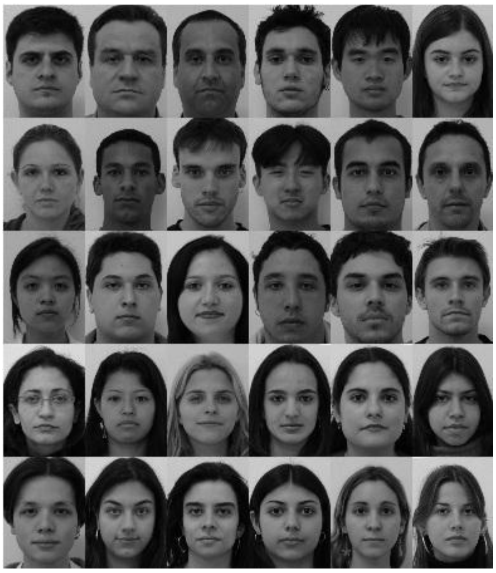


Fig 14: Original group Image

Fig 15: Extracted grey scale female image from group image

7. Conclusion

The test results as stated in the previous sections characterize the performance of the kernel functions in the evaluation of Gender Classification based on the combination of features of Human Facial Image. With this paper we have endeavored to prolongate our previous task of Human Gender Classification [11]. The evolutionary process involved the performance evaluation of Kernel Functions that includes 'Linear Kernel', 'RBF Kernel' and 'Polynomial Kernel'. In our experiment, the test results verified the behavior of a kernel on a given data set. The Linear Kernel yielded the best result when implemented on data set comprising of 100 Images linearly separated into 50 male and 50 Female images compared to RBF and Polynomial Kernel. The Polynomial Kernel which is best suited for non-linear data set generated poor result for degree's=3' or's=4'. Thus its degree was lowered to'd=2' that led to the generation of favorable yet no so high result. However the RBF kernel did not make a notable performance since firstly, the data set is inherently linearly separated and secondly the feature vector includes an increased feature count over input instances. Thus with an idea of achieving upgraded performance of the proposed methodology, the data set shall be increased with more instances. Manual face annotation by users is a time-consuming and inconsistent task that often imposes significant restrictions on exact browsing through personal photos containing their interesting persons. Here automatic face annotation solutions using SVM have been proposed.

8. References

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