Human Gender and Age Detection Based on Attributes of Face

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Abstract—The main target of the work in this paper is to detect the gender and oldness of a person with an accurate decision and efficient time based on the number of facial outward attributes extracted using Linear-Discriminate Analysis to classify a person within a certain category according to his(her) gender and age. This work was deal with color facial images via the Iterative Dichotomiser3 algorithm as a classifier to detect the oldness of a person after gender detected. This paper used the Face-Gesture-Recognition-Research-Network aging dataset. All facial images in the dataset were categorizing into binary categories using k-means. This is followed by the process of dividing all samples according to age classes that belonging to each specific sex category. Thus, this division process enabled us to reach a quick and accurate decision. The results showed that the accuracy of the proposal was 90.93%, and F-measure was 89.4.

Keywords—facial image, features extraction, human age and gender, k-mean, LDA, ID3

1 Introduction

Gender and age are human's identification that plays the main role in social communication [1]. A detection system is combined of two phases: gender detection and age detection which is a structure of three parts: face detection, gender estimate, and age guesstimate. Face detection is used to localize the faces in an image, there is quite challenging due to several reasons like environment, lighting, movement, orientation, and facial expressions, these factors lead to variations in color, shadows, luminance, and contours of images [2, 3]. In the real world, some males/females may lookthe same gender and this an error, some of the people may look youthful or more adult than the real age that leads to the differences between apparent age and real age [4–6]. The various attributes can be identified from the color-image of a human face such as hair on the upper lip, male/female, hair on the chin, age, scars, hair, height, skin color, weight, glasses, tattoo marks, facial attributes, etc [7–10]. Required information can be extracted from these attributes and compared with the patterns stored in the database to determine an identity [11, 12]. There are some difficulties in computer-based facial gender and age estimation [13].

A. Speed of aging is a result of different health conditions and the environment
B. Different forms of aging will emerge at different age levels.
C. Search and collect historic images which had been taken ago.
D. Some females have a propensity to exhibit their faces are younger.

To distinguish the face from the image there are keypoints in human faces must be detected and extracted [14, 15], these key points are called landmarks which included the eye, nose, and mouth, as shown in Figure 1 [16]. Texture descriptors. MuhammadSajid, *et al*. [17], in 2019, proved the importance of exact similarity aging inefficient age estimation. The findings of that work depended on two large datasets. Fatma S. Abousaleh, *et al*. [18], in 2016, proposed a proportional deep learning framework, named CCRCNN, the proposal first compares the input image of a face with known face ages that considered as a reference to produce a set of hints the input face is either younger or older than a reference. later, the estimation stage combines the hints to approximate the person's age. SudipMandal, *et al*. [19], in 2017, proposed an automatic age estimation system from facial images using wrinkle feature and Neural Network the system was implemented using MATLAB. Only three groups of age were taken into consideration child, young and old. Prajakta A. Mélange and G. S. Sable [8], in 2018, introduced a method to predicate sex and how older persons depend on some facial characteristics. Such that used Preprocessing phase then selected some geometric features for classification. Depended on the face angle, left the eye to right eye distance, and some other distance from eye to nose in addition eye to chin distance, with eye to lip distance. Bosea, S. Bandyopadhyay [20] in 2021 introduced a method of features extraction based on the size of the Face to the size of the Eye of a Face to identify the human. The main objective of this work is to find an automatic method to rapidly guesstimate human gender and oldness of the human using some information and attributes of the color face image accurately based on Iterative Dichotomiser3(ID3) algorithms. In addition to the introduction section, the paper structure is dealing with six other sections. Section two describes the features extracted from images while section three tells the details about the dataset that use. Section four with all subsections explain the required steps of the proposed method design, then discusses the results illustrated in section five. Section six expresses the conclusions and some ideas of future work.

2 Features of facial image detection

Classification of people depends on person faces images that contain signs and characteristics to classify those persons, so a face aging prediction is used in many applications in digital entertainment. Features of facial image detection **consist** of the facial features region of nose detection, Eyebrows, Lip detection, mustache, beard, Left/Right eye position, and skin wrinkle analysis i.e. eyebrows also help in gender recognition. Female eyebrows are longer, thinner, and curly at the ends. On the other hand, male eyebrows are mismanaged and thicker. Also, the male face has a more protuberant nose, brow, chin/jaw than the female face. Gender and age detection are estimated according to the number of these facial geometric features called the attributes [20–22].

3 FG-NET dataset

The FG-NET aging database is a publicly accessible aging database that has been broadly utilized for evaluation. The database is consisting of 1,002 color images of 82 different subjects. For males, there are 607 color images and 395 colorimages of females. Most subjects gossip from 10 to 13 images of themselves [23–26], Figure 2 shows some images of the FG-NET database. Split these images into a training setcontaining 720 images divided into 14 classes as shown in Table 1. Results demonstrate that some classes have the same number of features after extracting the features from these 14 classes. Then combined it into Multiclasses upon the Sum-attributes of features it contains as shown in Table 2 (explains in 4.1).

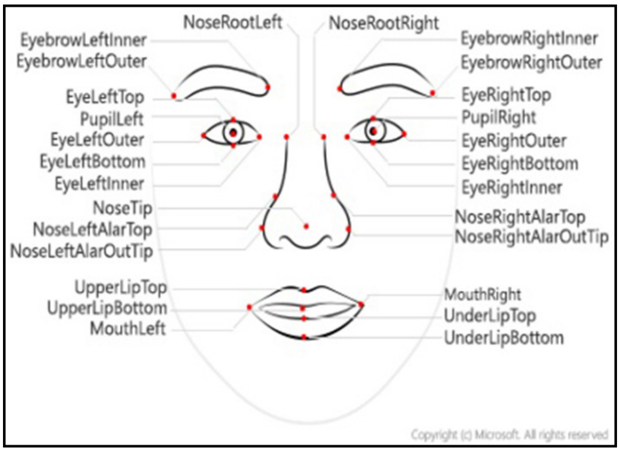

Fig. 1. Facial landmarks [6]

Fig. 2. Examples of some images from the FG-NET Aging database

Table 1. Aatalog of classes

Class#	Gender Type Male = 0, Female = 1	Rang of Age
One	0	3–7
Two	0	8–13
Three	0	14–19
Four	0	20–25
Five	0	26–30
Six	0	31–40
Seven	0	41–50
Eight	1	3–7
Nine	1	8–13
Ten	1	14–19
Eleven	1	20–25
Twelve	1	26–30
Thirteen	1	31–40
Fourteen	1	41–50

Table 2. The proposed multi class upon facial features

Class #	Range	Description
One	(3-7)(26-30)	Male
Two	(3-7)(26-30)	Female
Three	(8-13)(14-19)(20-25)	Male
Four	(8-13)(14-19)(20-25)	Female
Five	(31-40)(41-50)	Male
Six	(31-40)(41-50)	Female

4 Proposed method design

The proposed method applies decision tree mechanisms to intelligent gender and age estimation from facial images using the ID3 classifier on the FG-NET dataset after extracting the features by the LDA algorithm. The contents of the FG-NET dataset are categorized into two categories by k-means classifier, one for 607 male images and the other one is for 395 female images as a process to gender detection using the attributes extracted of each face-image in this dataset.The proposed method is shown in Figure 3.

4.1 Preprocessing phase

The first phase of the proposed system is preprocessing phase. This phase includes six steps which are image capturing, converting image into grayscale, removing noise from it using median filtering, detecting the face from the color image using a viola-joins algorithm which consists of 4 levels that are Haar-like features, integral image, Adaboost training, and cascade classifier as shown in Figure 3, normalization that can be done using contrast stretching and finally clipping it to delete undesirable outside parts of a color image such as white space in the background image around the face. In the proposal, the dataset was categorized into six categories as shown in Table 2, These categories were depended after manyexperiments, where it was found that thesechoices of age range mentioned for females or males within each category have the same number of attributes and does not constitute a distinction, so they were considered within the same category. To estimate the human-gender and human-age, there are two phases training set was 80% of dataset and the other 20% of it was the testing set.

4.2 Phasing of data mining-procedure

The second phase of this work is the data mining phase that includes the features extraction process and classification process.

Dimension reduction as features extraction process. Feature extraction is decreasing the dimension through excluded the most significant information from the entire data [27]. Using Fisher's face depends on the mechanism of Linear Discriminates Analysis LDA [28]. This is an important step that is used to decrease the dimension of the image in the dataset with good separable classes to avoid the problem of overfitting and to decrease the complexity of total cost-value. So the steps of LDA are as the following:

1st step: The image in 2D n×m was converted into a column vector that represents n×1.

2nd step: To calculate d-dimension mean vectors for classes from the dataset use eq (1):

$$Ii = \frac{1}{n_i}\sum\nolimits_{i=1}^{\mathrm{n}} X_i \tag{1}$$

3rd step: Using **scatter matrix** to calculate the scatter matrix which comprises of three classes such that eq (2) to calculate within-class scatter matrix, eq (3) to calculate class-covariance matrices, **and eq (4) to calculate between-class:**

$$S_w = \sum\nolimits_{j=1}^{c}\sum\nolimits_{i=1}^{N_j}(I_i^j - \hat{I}_j) \tag{2}$$

Where I_i^j is the ith sample of class j, $\hat{I}_j$ is the mean-value of class j, c is the real number of classes and N_j is the number-value of samples in class j.

$$\Sigma\, j = \frac{1}{N}\sum\nolimits_{i=1}^{n}(X_i - \widehat{I}_j)(X_i - \hat{I}_j)^T \tag{3}$$

$$S_b = \sum\nolimits_{j=1}^{c}\widehat{I}_j - \hat{I}\widehat{I}_j - \hat{I}^T \tag{4}$$

Where $\hat{I}$ represent the mean of all classes and $\widehat{I}_j$ is the mean-value of class j.

4th step: Calculate the eigenvectors and eigenvalues for the scatter matrices using eq (5)

$$AV = \lambda V \tag{5}$$

Where $A = S_w^{-1} S_b$, V is an eigenvector and λ is an eigenvalue.

5th step: Sorting the eigenvectors by decreasing eigenvalues using eq (6) and selecting n eigenvectors from the biggest eigenvalues.

6th step: Use the matrix of 4 * 2D called W that is used to convert the samples into the modern sub-space by using eq (6).

$$\arg\max w = \frac{w^T * S_b * w}{w^T w * S_w * w} \tag{6}$$

Classification process. The other part of data mining is classification. The proposal uses a decision tree classification approach to build a tree as a model to predict the value of the image face.ID3 classifier read features of face which extracted by LDA algorithm and used it for classification. To construct a decision tree, ID3 was formed depending on the use of *Entropy* that calculated depends on eq (7), and *Information Gain* that calculated depends on eq 8.

$$EntropyS = \sum_{i=1}^{c} -P_i \log_2 P_i \tag{7}$$

Where c takes different values and P_i is the probability of S belonging to class i.

$$Gain(S, A) = Entropy(S) - \sum_{v \in ValueA} \frac{|S_v|}{|S|} EntropyS_v \tag{8}$$

Where A is an attribute that is a set of all possible values v and S_v is the subset of S. To implement the decision tree algorithm, the entropy of each target was calculated and the dataset was divided into distinct attributes the entropy-value of each division-tree was computed then accumulated together to get the overall total number of entropies. The Gain-value of information is computed from the differences between of entropy-value as a result and the entropy-value before the divide. The gain of the largest information called attribute was chosen as a decision node and the dataset was split up by its branches, this procedure was repeated on every branch. A leaf node was generated when the value of entropy is zero while it was a non-leaf node when it holds a value greater than zero and split furthermore. All non-leaf branches are considered by ID3-algorithm which executes recursively pending all data is classified. To detect human gender age, the image is classified into one of six classes, as shown in Table 2. The number of selected features from the image was checked with the feature number of class one, if it is matched then match tested image features with the rules of class one, the same procedure was done for all six classes, if true match the gender and age are estimated. Figure 4 summarizes this procedure, where Ti represents the test image and nf represents the number of features.

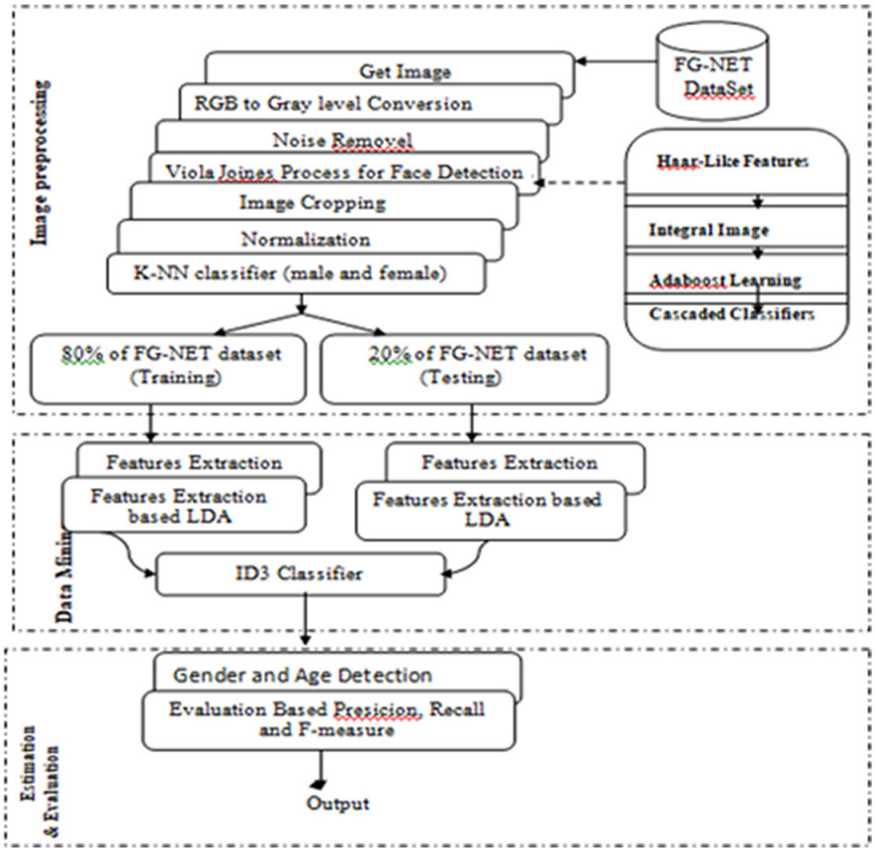

Fig. 3. Steps of the proposed method

5 Results and discussion

The proposed system has three-phase which were face image detection, data mining model, and Gender and age detection model. Implement the normalization step using contrast streaking on images after face detection steps on these preprocessing input images. The next step is feature extraction of the face's image using the LDA algorithm. The final step is the classification based on ID3 deals with the attributes of the face's image that is found from the previous step. It is worth mentioning that 120 of the additional images of human faces that the classifier trained on were added to the test dataset, to get a test dataset containing both known and unknown images of faces. Table 3 describes the correctly and incorrectly percentage of six class categories and the total correct rate of gender detection. First-class has 7 attributes with correctly classified of 195 images while incorrectly classified of 20 images. Class no. three describes with 5 attributes with correctly classified of 377 images while incorrectly classified of 32 images. So class five has 9 attributes with correctly classified of 68 images while incorrectly classified of 28. See class two has 8 attributes with correctly classified of

192 images while incorrectly classified of 23 images. Class four has 6 attributes with correctly classified 371 images while incorrectly classified of 38 images. The last one is class no. six which has 11 attributes with correctly classified 66 images while incorrectly classified of 30. So, the total correctly classified percentage is 85.9, 85.6 for males and females respectively while the total missed classified percentage is 14.28, 14.29 for males and females respectively. Table 4 reviews the accuracy of performance evaluation measures of the ID3 classification step on the items which are used as training set where the total number of these items is 720. The criterion Mean-Absolute-Error M.A.E. and Root-Mean-Square-Error R.M.S.E. are measures of error rate in prediction [29, 30]. Nevertheless, R.M.S.E. is more robust since it is less sensitive to extreme values than mean-absolute-error [31], A small value for these criteria means that the estimated model is close to the real value, thus 0.7628 of M.A.E. and 14.2814 of R.M.S.E. are mean the error rate is very low. In Table 5, based on LDA and ID3 human age of class1 and class2 of 450 sample size has a total correct rate equal to 93.3%, while the 210 males and 330 females of class3 and 4 has a total correct rate equal to 93.5% and the human age of class5 and class6 of 100 sample size has total correct rate equal to 86%. That means the total correct rate for all 1090 sample sizes is 90.93%. Figure 5 states the diagram of the age detection-based samples of the Table 6. When comparing the results of the proposed method to classify the human gender as male and female with other existing methods like PNN and SVM1.The results of the gender test on 20% of items are used for testing of data set that is used, so the proposed method introduces an acceptable rate of correctly classified corresponding to the PNN and SVM1 [32] methods as shown in Table 6. So the proposal achieve is too close to the other existing methods. Table 7, the number of all instances was 1090 images. For the male gender, the highest precision is for class2 because FP is the biggest one according to the number of attributes of this class, and the class sample size is bigger than others. class1 has the highest recall because FN is big although class3 has the same FN as class1 the number of attributes is bigger than one of class1 also a sample size of class3 is less than the sample size of class1. Also, notice that the highest F-measure is for class2 because it provides a single score that balances both the concerns of precision and recall in one number. For the female gender, the highest precision is class4 because of the balance of attributes number and FP is the large enough relative to sample size while the class5 has the highest recall although class6 has FN that bigger than it but attributes the number of this class is bigger than class5. So the highest F-measure is for class4 because of balancing between the number of facial attributes and sample size. Figure 6 shows the accuracy of the proposed detection method depending on the number of attributes. Table 8 displays the results of the LDA and ID3 classifier of accuracy. The six classes have calculated the precision, recall, and F-measure. The average of accuracy in the three classes of male gender gave precision of 83.066, recall 93.8.569, and f-measure 88.49. While the average accuracy in the three classes of female gender gave precision of 87.8, recall 93.33.569, and F-measure 90.4. The obtained results of the proposal were compared with another classifier.

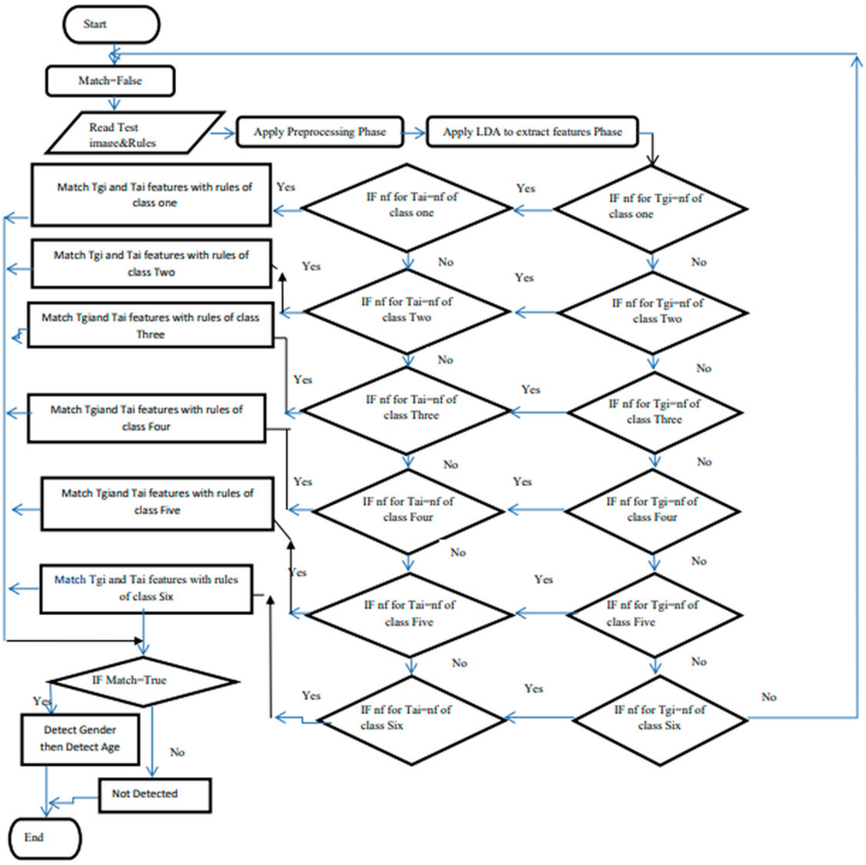

Fig. 4. Flow chart gender and age estimation

Table 3. Age and gender results of LDA and ID3 classifier

Class No	Gender	Class-Range	Instance	Attribute	Correctly Classified	Correctly Percentage	Incorrectly Classified	Incorrectly Percentage
One	Male	(3–7) (26–30)	215	7	195	90.6977%	20	09.3023%
Three	Male	(8–13) (14–19) (20–25)	409	5	377	92.1760%	32	07.8240%
Five	Male	(31–40) (41–50)	96	9	72	75.0000%	24	00.2570%
Two	Female	(3–7) (26–30)	215	8	192	89.3023%	23	10.6900%
Four	Female	(8–13) (14–19) (20–25)	409	6	371	90.7090%	38	09.2900%
Six	Female	(31–40) (41–50)	96	11	74	77.0835%	22	22.9160%
			720/M	–	644M	85.9570%M	78/M	14.2800%/M
			720/F		637/F	85.6000%F	83F	14.2960%/F

Table 4. Accuracy of the proposed method

Accuracy measures	Result
MAE = $\frac{1}{n}\sum_{i=1}^{n}\left\|y_i - \widehat{y_i}\right\|$ where n = 1442	0.0198
RMSE = $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}$ where n = 1442	0.7525

Table 5. The total correct rate of human age using LDA and ID3

Age	Gender	Sample Size	Correctly Detect	Correct Rate	Total Correct Rate
(3–7) (26–30)	Male	200	186	93.00%	93.30%
	Female	250	234	93.60%	
(8–13) (14–19)(20–25)	Male	210	189	90.00%	93.50%
	Female	330	322	97.00%	
(31–40)(41–50)	Male	59	52	82.00%	86.00%
	Female	41	37	90.00%	
Total	M+F	1090	1020	90.93%	90.93%

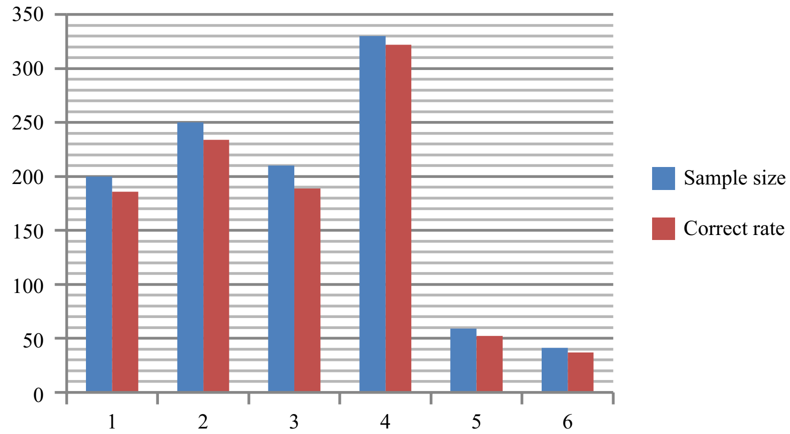

Fig. 5. The correct rate of human age

Table 6. Result of gender test on 20% of items are used for testing of Dataset

Gender Type	PNN		SVM1		Proposed Method	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
Male	89.75	10.25	95.08	4.29	89.73	10.7
Female	11.88	88.12	4.41	95.59	12.77	87.23
Correctly classified %	88.935		95.335		88.48	

Table 7. Accuracy Using ID3 Classifier

Class No.	Gender	Class-Age Range	Confusion Matrix		#Attribute	Precision	Recall	F-Measure
			TP	**TN**				
			FP	**FN**				
1	Male	(0–7) (26–30)	122	73	7	0.890	0.960	0.9200
			15	5				
2	Male	(8–13) (14–19) (20–25)	244	143	5	0.897	0.938	0.9380
			28	4				
3	Male	(31–40)(41–50)	55	13	9	0.705	0.916	0.7967
			23	5				
4	Female	(0–7) (26–30)	173	19	8	0.905	0.971	0.9368
			18	5				
5	Female	(8–13) (14–19) (20–25)	283	88	6	0.901	0.975	0.9365
			31	7				
6	Female	(31–40)(41–50)	53	13	11	0.828	0.854	0.8407
			7	9				

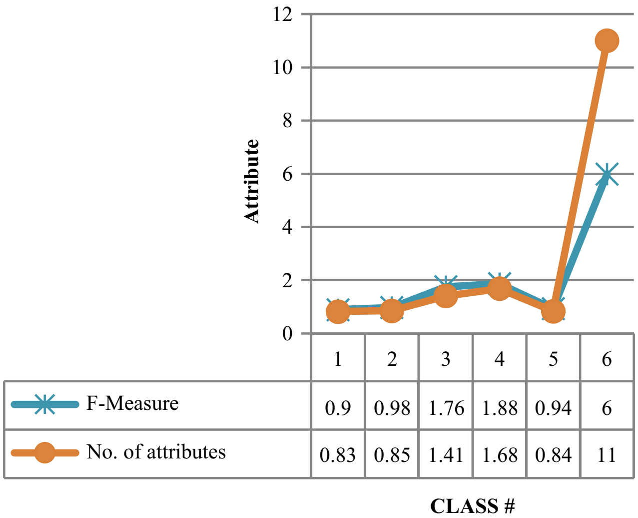

Fig. 6. The relation of detection and no.of attributes

Table 8. Results of various classifiers

Algorithms Accuracy	ID3 Classifier	LDA+ID3	J-48	SMO	Multilayer Perceptron	Hoeffding Tree
Precision	85.0794	85.62	89.3113	73.9333	91.0000	92.8667
Recall	86569	93.56	87.6004	78.0000	90.9000	92.8333
F-measure	80	89.445	87.7374	73.1667	90.2333	92.4333

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