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Support vector machine based feature extraction for gender recognition from objects using lasso classifier

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Abstract

Object detection and gender recognition were two different categories to be classified in a single section is a complicated task and this approach helps in supporting the blind people for an artificial vision. In this paper, our method to the betters vision sensation of blind persons by conversion of visualized data to audio data. Therefore this artificial intelligence model helps in detecting the objects as well as human face recognition with gender classification based on face recognition approach. This model processed with feature extraction and classification models. The feature extraction was comprised with multi scale-invariant feature transform (MSIFT), with feature optimization with support vector machine algorithm then classified using LASSO classifier. For better performance identification, three different classification models were implemented and tested too. Feature selection helps in making tests early to detect the objects and recognizing human actions using image processing approach. This approach can be applied for both offline and online modes. But in this scenario, an offline mode was implemented and was tested with a combination of different databases. For this process of classification ridge regression (RR), elastic net (EN), lasso regression (LR) and LASSO regression were implemented. The final classification results with accuracy are as follows for RR-89.6%, EN-93.5%, LR-93.2% and proposed approach (LRGS) with 98.4% accurate detection rate with prediction name of classes.

Keywords: Support vector machine, Ridge regression, Eleastinet, Logistic regression, LRGS, Gender classification
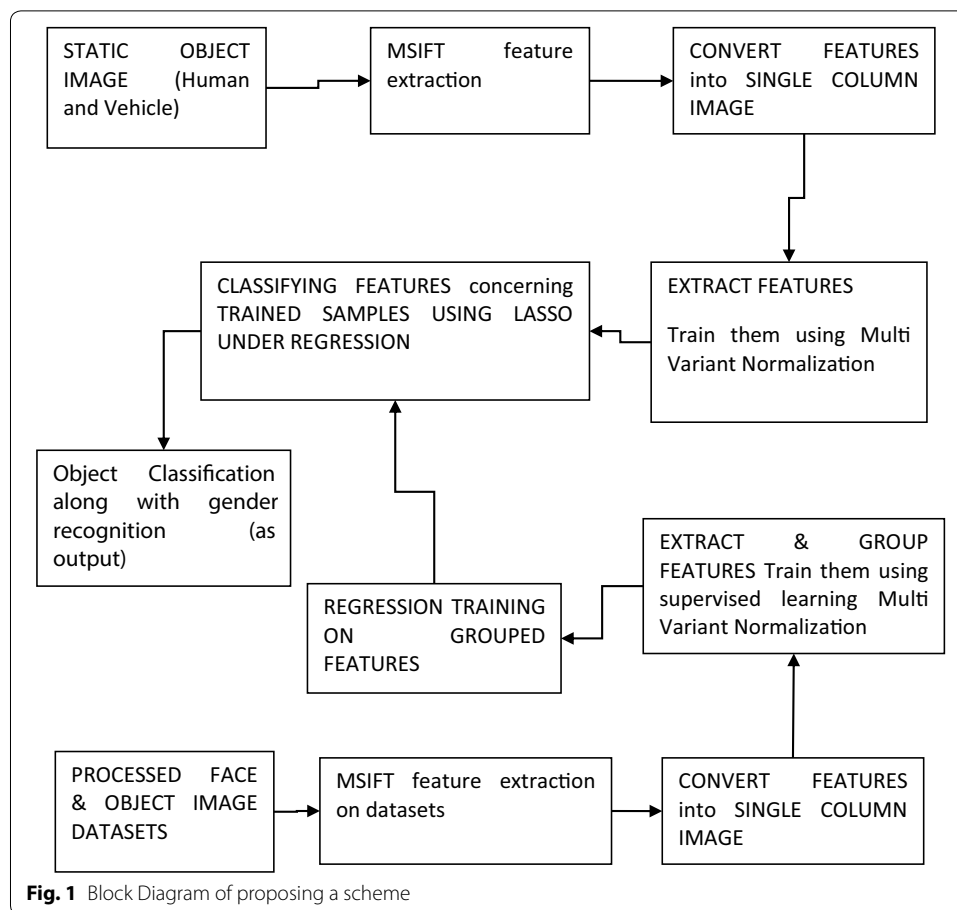
Introduction

Sex or gender is a feature that helps to identify a person initially. Gender-based separation among humans is classified into two: male and female. Specific gender groups might also show off diverse propensities. For instance, younger guys and young girls may like toys; human beings may incline a variety of clothes varying in colours and styles. In enterprise understanding, to know the gender (and age) of the customers may also assist business chiefs to publicize their objects as indicated by using numerous purchaser groups and accumulate sizeable statistic facts about the clients, for instance, the number of women entering during a retail region or a shopping centre inside a given period. In picture healing, gender (or age) can be a treasured semantic

concept for photo association and search, as coming across men or women in specific scenes. In social collaborations or exercises, guys and ladies can also perform contrastingly and have numerous jobs. In this manner perceiving the gender of a person has extensive variations. People can see the gender of each other. It has been dynamic research in brain science to reflect on consideration on the effect of gender on people [1–3]. In brain technology about, the development is usually the face photographs for gender popularity. The visible computational investigation for gender characterization or acknowledgement, a large portion of the current works applied face pictures. For example, see [4–8].

As of past due, some methodologies, for example, [9, 10], established that human bodies must use be for gender grouping. Victories display on available dataset images wherein a bodily drawn box containing someone walking utilized all round for frame records extraction. The upsides of using body over face pictures for gender acknowledgement include the accompanying list.

(1) Image Resolution. When the face locale has a shared dream or is motion obscured, the face highlights in all likelihood won't be usable for gender order. Be that as it can, the self-belief may also at gift help isolate guys from ladies.

(2) Viewpoint Change. At the factor when the head present is altogether one of a kind from frontal perspectives, the face-primarily based on gender acknowledgement may additionally have poor execution or even can not be appropriate. Notwithstanding, self-perception can at gift use. Indeed, even the returned angle on the frame can be used for gender acknowledgement [9, 10].

(3) Acquisition Distance. At the factor when the camera is some distance away from the person, the face photograph won't supply good enough records to gender segregation. Be that as it could, self-belief may additionally even now be usable.

(4) Occlusion. At the point, when the facial part is blocked, the face image probable might not be applied to do away with gender statistics. Be that as it can, the self-notion is as but useful, in any event, while a person features are impeded. Be that as it could, in the ones spearheading ways to deal with sex acknowledgement from the body, as an instance, [9, 10], merely the upstanding self-perceptions with the complete frame look explored. The information customarily applied are individual strolling images, as an instance, the MIT passer-by database [11], can be named, which is an interactive database for walker identity. One pressing necessity is that the whole body in upstanding shows up in each picture, as regarded in Fig. 1, and in this way, there is no compelling motive to pressure over to adjust the self-perceptions in coordination. Highlights can be extricated from the entire self-perceptions and used to put together a classifier.

The organization of the paper is as follows, in Literature survey section gives various machine learning schemes applied for object detection and face-based gender recognition were identified. In "Proposed methods" section, SVM based feature extraction in combination with MSIFT (Multi-Scale Invariant Feature Transform) demonstrated along with LASSO based regression classification analysis, in "Results and discussion" section various dataset based results were plotted along with simulation setup.

Fig. 1 Block Diagram of proposing a scheme

"Conclusion" section concludes the paper with a brief note on how our research paper finds a solution with performance metrics.

Literature survey

One of the simple issues with any photo making prepared or PC vision undertaking is the clear up of a becoming language for addressing the realities. Face association carries the extraction of a collection of parameters or estimations that permit portraying of the variations between human beings, instead of the sorts amongst snapshots of individuals.

This method is authentic notably after the photographs have been coded with the component of the dismissal of non-facial variations as the internal man or woman, regardless need to be banned. A regularly carried out method for characterization is Support Vector Machine (SVM) [1, 12]; those tune into the ideal hyper-flying system for keeping apart several getting ready by way of the method for confining the peril of mis-association. Recognition method is regularization or subject-based strategy. SVMs have in recent times been used for face grouping [10, 13], displaying dependably better. These compositions grew to become out to be maximum of the way maintained through the Ministry of Education, Culture, Sports, Science and Technology Grant-in-Aid for Scientific Research (B) 15300076. The makers are thankful to the Softopia Japan Foundation for the HOIP dataset. Prevalence execution than famous

nearest neighbour strategies. Facial sex plan has, also, been taken into consideration [3, 6, 9, 11]. Likewise, a non-instantly SVM based honestly classifier has appeared to make through and via higher outcomes than particular frameworks [14].

The sizeable separation between sexual orientations changed into approval to be strikingly twisted, and this comes to be the pinnacle gone to utilize the help of vector attitude. Regardless, none of those structures chooses to become, robust estimations at which point to organize the countenances. In this paper, a machine for showing up highlight the determination-making use of SVMs delineated wherein the improvement occurs in the parameter location.

Using the board model throughout the work, a pitiful combination of features made with a considerable scope of the classifier's parameter is assessed to be 0. The capabilities are greater vigorous than SVM estimations and are efficaciously among the considered. This tool has been named Lasso regression [15], or dynamic [1] or purpose intrigue [4] characterization.

When acting characteristic devotion, it's miles simple to realize the trustworthiness of the element choice method. This approach can do with the aid of discovering the most elements with bunches of complicated insufficient classifiers. In this paper, a different approach for finding the entire relationship of small SVMs is portrayed, which produces internationally perfect classifiers for the development of linear programming sub-problems.

It is then suggested to ap-contract Automatic Relevance Detection (ARD) [16] and choose alone rendition it is enhancing the probability of the practice statistics explained over the various stages of scantiness. At the same time, it is the far some distance average that numerous portrayals and an ever-growing number of versatile amounts supply the advanced arrangement exactness.

The simple thought system in this paper is to depict how the individual who wants, and between congruity of confirmation to bring about talented highlights works of art and smash down their duties in a prime dimension between containing a choice problem. All these research papers suggested object classification or gender recognition statements. But on a combination, these were not made especially object (Vehicle) detection and human face based gender recognition combination wasn't made enough and had no perfect pretrained dataset available. For this purpose then this made us clear to develop a dataset with combination of both objects and human face recognition system under single classification approach which will help the blind one to identify the surroundings effectively, but this wasn't found in any of the systems early developed.

Most of the approaches mentioned in this section were focused on gender recognition with the help of various classifiers, and most of the approaches were applied on nominal databases.

The significant contributions of all other researchers were stopped with just detecting the gender with 2 class identification approach. However, here in this research article, a combination of 13 classes which supports in identifying the objects and human faces will separate in them, and the gender will be identified. This approach made other researchers think on blind vision people problem solution tracing.

Proposed methods

In this paper, proposing scheme comprised with Multi scale-invariant feature extraction and then these features converted into image frame then these get normalized by using multi-variant normalization. This the feature extraction process followed by the training process. Then these two gets classified by using MSVM, GSVM, LASSO, Logistic Regression based LASSO, ELASTIC NET, RIDGE and compared these results in the results section of the paper. The entire process was comprised and showcased in block diagram Fig. 1.

Over comparing with all existing approaches, i.e., object recognition or face recognition system deployment feature selection and grouping them with the same procedure isn't a part of existing approaches. But in our proposing scheme, the combinational feature combined and worked on various algorithms.

The database generation for objects and face recognition is a complicated term but in our approach with advanced MSIFT and clustering of the feature made this possible.

Feature extraction

Classification

Table 1 represents the different feature extraction process that was implemented along with our proposing approach to verify which feature extraction will result in the high accuracy rate for classification. In Table 1, the results column helps in.

Selecting the best approach for feature selection process applied by the support vector machine.

Logistic regression a modelling method for estimating the $\theta(X) = P(Y = 1|X)$, and hence $P(Y = 0|X) = 1 - P(Y = 1|X) = 1 - \theta(X)$ As well. Thus it can be used as a classification method for binary classification problems, i.e. the nominal response has two levels, generically "Yes/Success $(Y = 1)$" and "No/Failure $(Y = 0)$".

Our general classification rule based on these estimated probabilities is given by, If $\widehat{\theta}(X) = P(Y = 1|X) \geq p$ then classifies Y as being from class 1, i.e. "Yes" or "Success". If $\widehat{\theta}(X) = P(Y = 1|X) < p$ then classify Y as being from class 0, i.e. "No" or "Failure".

$p = 0.50$ Makes the most sense from a logical standpoint, but we could certainly use other values. Also, we can rank observations based on these estimated probabilities to find most likely observations/cases where $Y = 1$ (see the "Discussion" of Lift in Section 12).

The probabilities are estimated using a generalized linear model (GLM) for the natural log of the odds for "success", which is called the logistic (L). The logistic regression model is given by,

$$L = ln\left(\frac{\theta(X)}{1 - \theta(X)}\right) = \beta_o + \beta_1 U_1 + \beta_2 U_2 + \ldots + \beta_{k-1} U_{k-1} \tag{1}$$

As was the case with the general OLS model, the terms $\left(U_j's\right)$ are all functions of the predictors $(X_1, X_2, \ldots, X_p)$. Once we have obtained estimates of the model parameters $\left(\widehat{\widetilde{\beta_j}}s\right)$, and hence the estimated logit $\widehat{L}$, we can estimate the probability of "Yes/Success" as,

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Table 1 Different feature extraction algorithms on FERET data sets

S. No	Feature Extractor	Formula	Remark	Result analysis
1	Gabor PCA [19]	$GP = argmax(Real(I * \psi)^2 + Img(I * \psi)^2) * \lambda$	Extracted real and imaginary features of Gabor (G) were optimized by PCA (P)	Extracts edges from the edges by different frequency scaling components concerning PCA provides a recognition rate of 89.4%
2	Gabor MEAN PCA [19]	$GP = argmax(\sum(Real(I * \psi)^2 + Img(I * \psi)^2)) * \lambda$	Here mean of Gabor filter were subjected to PCA optimization	All the extracted edges applied by mean and provide a recognition rate of 92.7%
3	HOG [8]	$H = \frac{v}{\sqrt{v_2^2 + e^2}}$	This theory will perform local feature extraction and normalization.	All the block-wise extracted histogram features will result in an under-recognition rate of 83.9%
4	SIFT [12]	Scale $D(x,y,\sigma) = L(x,y,K_i\sigma) - L(x,y,K_j\sigma)$ Position: $D(x) = D + \frac{\partial D^T}{\partial x}x + \frac{1}{2}x^T \frac{\partial^2 D}{\partial x^2}x$ Orientation: $m(x,y) = \sqrt{(L(x+1) - L(x-1))^2 + (L(y+1) - L(y-1))^2}$ $\theta(x,y) = atan2(L(y+1) - L(y-1), L(x+1) - L(x-1))$	One descriptor base four features will be extracted from the SIFT algorithm, and point descriptor of the best form will help exact identification of objection. Even the scale of the object varied yet will recognize it.	As per remarks, it compares the object with point key descriptors and results with an accuracy of 92.7% for recognition
5	MSIFT-Proposing	Scale $D(x,y,\sigma) = \left(L(x,y,K_i\sigma) - L(x,y,K_j\sigma)\right) * \Psi$ Position: $D(x) = \left(D + \frac{\partial D^T}{\partial x}x + \frac{1}{2}x^T \frac{\partial^2 D}{\partial x^2}x\right) * \Psi$ Orientation: $m(x,y) = \sqrt{(L(x+1) - L(x-1))^2 + (L(y+1) - L(y-1))^2}$ $\theta(x,y) = atan2(L(y+1) - L(y-1), L(x+1) - L(x-1))$	The image is split into multiple frequencies components and extracted sift features from them will result in effective detection even in images of different sizes.	The modified SIFT results in most format and results in the best recognition rate of 98.3% in this proposing approach

$$\widehat{\theta}(X) = \frac{e^{\widehat{L}}}{1 + e^{\widehat{L}}} = \frac{1}{1 + e^{-\widehat{L}}} \tag{2}$$

Model selection (e.g. stepwise methods) and cross-validation (if the goal is accurate prediction) are essential elements of the model building process in logistic regression. Term creation, for example, power transformations and interactions, is less straight forward for these models but can be crucial in developing a "good" model for a given situation. On the next page, some guidelines for term creation in logistic regression given.

Our proposing approach comprised of three stages as earlier mentioned, namely features extraction, feature optimization and classification.

With the help of Table 1 feature extraction made possible, and feature optimization was done with the help SVM classifier and algorithm is given below in Algorithm 1.

ALGORITHM 1: Feature optimization and selection using GSVM

Input: Feature extracted using MSIFT

1. Initialization: $Ranked = []$; $Var = [1,...,N]$

2. repeat
   (a) Train a SVM classifier with all the training data and the variables Var
   (b) **for** all variables in Var, **do** evaluate the ranking criterion $R_C(i)$ of variable i **endfor**
   (c) $best = \arg\min_i R_C$
   (d) rank the variable that minimizes R_C: $Ranked = [best\ Ranked]$;
   (e) remove the variable that minimizes R_C from the selected variables set: $Var = [1,...,best-1, best+1,...,N]$

3. **until** Var is not empty

Output: Optimized reduced features.

The reduced features were subjected to lasso classification models. This feature optimization reduces the test time response and helps in obtaining pleasing experimental results for the datasets combination we considered. Then the classification procedure will be carried out with the help of the following Algorithm 2 with the help of Table 2.

Table 2 Univariate Considerations [15]

$f(x|y)$- conditional distribution x gave as y which is 0 or 1.	Suggested model terms
The standard, common variance i.e. $Var(x_j|y=0) = Var(x_j|y=1)$	X_j, i.e. the predictor itself These values imply that i X_j t is NOT customarily distributed we might consider transforming X_j to approx. Normality.
Normal, unequal variances i.e. $Var(x_j|y=0) \neq Var(x_j|y=1)$	X_j and X_j^2
Skewed right	X_j and $\log_2\left(X_j\right)$ Log base 2 is more comfortable to interpret
$x \in [0,1]$	$\log_2\left(X_j\right)$ and $\log_2\left(1-X_j\right)$
$X_j \sim$ Poisson i.e. X_j is a count	X_j, i.e. the predictor itself

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Algorithm 2: Proposed **uni-variant elastic net classification algorithm** and for object and gender identification

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Input: Features from training and test features which were selected by SVM classifier

1.   for p in 1:P:
2.   for k in 1:K:
3.   keep fold k as hold-out data
4.   use the remaining folds and λ = λ_p to estimate β
5.   predict hold-out data: ytest,k=Xtest,kβ
6.   compute a sum of squared residuals: $SSR_k = \|y - y_{test,k}\|^2$
7.   end for k
8.   average SSR over the folds: SSRp=1K∑Kk=1SSRk
9.   end for p
10. choose optimal value: $\lambda_{opt} = argmin_p SSR_p$

Output: Classified test class out 13 classes considered

Here p indicates the test samples, λ indicated the train samples, k is the size of total features, β is sample match count, y & y_{test} are labelling match condition with respect residuals.

As the residual identification for the optimized features made the classification rate to improve and results in obtaining the best performance metric values. These two algorithms implementation made the test results more effective in combination with different feature extraction algorithms were tested and mentioned the database based results in the results section. This approach made an error rate to suppressed and enhances the accuracy rate of the system, along with the minimization of testing time.

Multivariate considerations

When considering multiple continuous predictors simultaneously, we look at multivariate normality.

$$f(\underset{\sim}{x}|y) \sim MVN(\mu_{y=k}, \Sigma) \tag{3}$$
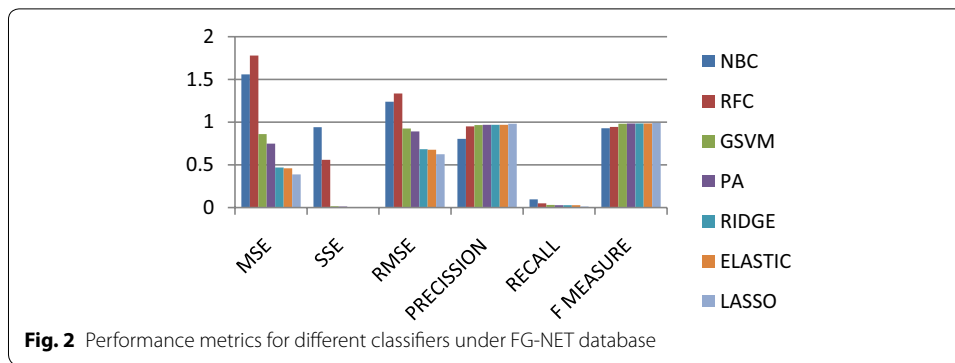
then use the x's themselves

$$f(\underset{\sim}{x}|y) \sim MVN(\mu_{y=k}, \Sigma_{y=k}) \tag{4}$$

then include X_j^2's and $X_i X_j$ terms

For example in the two predictor case $(p = 2)$ $x_1 x_2$ is needed if $E(x_1|x_2) = \beta_o + \beta_{1,y=k} x_2$

Moreover, if the variances are different for the x_i across levels of y then, we add x_i^2 terms as well. A scatterplot matrix with the colour of the points coded by the levels of the response Y is a useful tool for visualizing which situation is appropriate for our classification problem.

Fig. 2 Performance metrics for different classifiers under FG-NET database

In cases where this instability in the predicted probabilities happens (as in the previous example), ridge, LASSO, and Elastic Net logistic regression are good options. These are also good options when one has a "wide data" problem where $n < p$ or when p is large and also when you have some highly correlated predictors. For logistic regression, the regularised logistic models using the ridge and Lasso given below.

Ridge Logistic:

$$ln\left(\frac{\theta(\boldsymbol{x})}{1 - \theta(\boldsymbol{x})}\right) = \beta_o + \sum_{j=1}^{k} \beta_j u_j + \lambda \sum_{j=1}^{k} \beta_j^2 \tag{5}$$

Lasso Logistic:

$$ln\left(\frac{\theta(\boldsymbol{x})}{1 - \theta(\boldsymbol{x})}\right) = \eta_o + \sum_{j=1}^{k} \beta_j u_j + \lambda \sum_{j=1}^{k} |\beta_j| \tag{6}$$

Elastic Net Logistic:

$$ln\left(\frac{\theta(\boldsymbol{x})}{1 - \theta(\boldsymbol{x})}\right) = \eta_o + \sum_{j=1}^{k} \beta_j u_j + \lambda_1 \sum_{j=1}^{k} |\beta_j| + \lambda_2 \sum \beta_j^2 \tag{7}$$
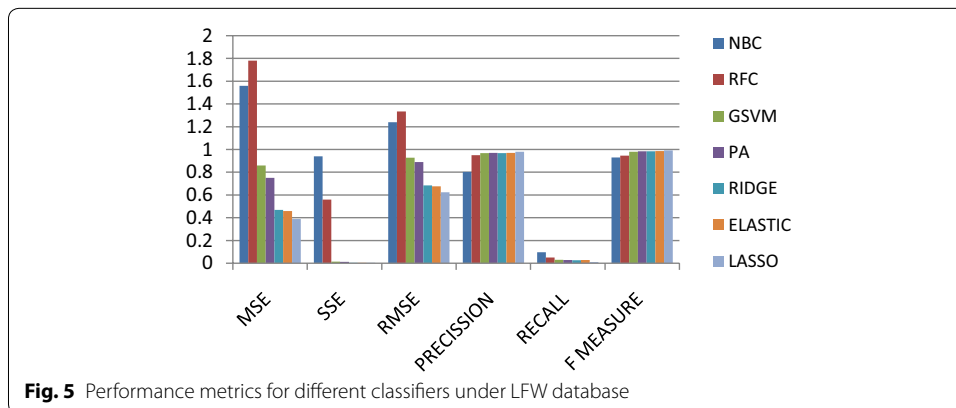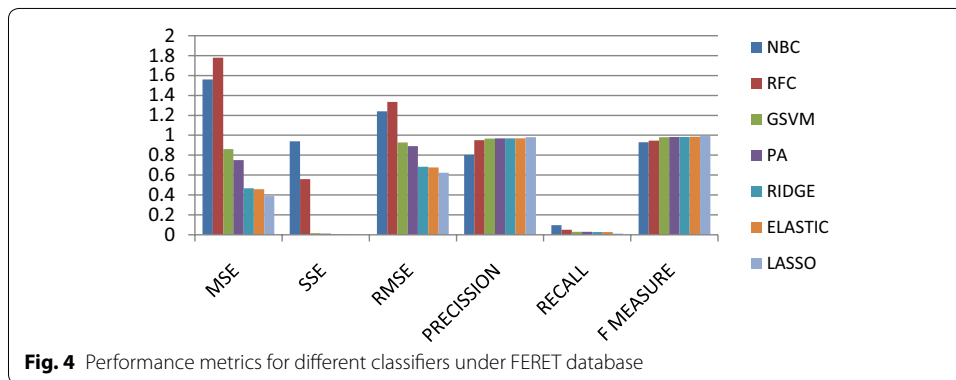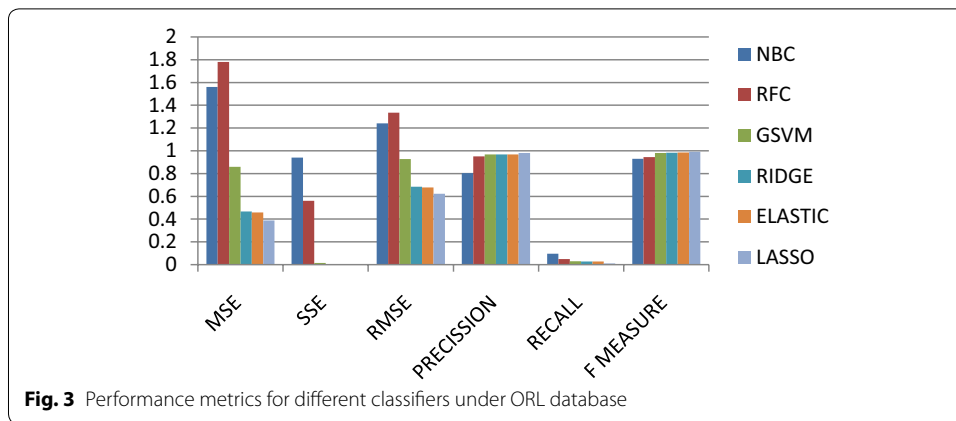
As mentioned in algorithm 2 Eqs. (3) & (4) of this section were helps in obtaining the result and minimizing the error rate and then different tests cases were subjected to Eqs. (5) (6) and (7) as kernel function of models for classification and compared using the tabular results in results section

Results and discussion

For simulation MATLAB (2018b) GUI was used with I3 processor based composition and 8 GB ram. Initially the GUI was set face recognition system then the system upgraded with MIOTCD vehicle and object database. Then training and classification was performed using the GUI.

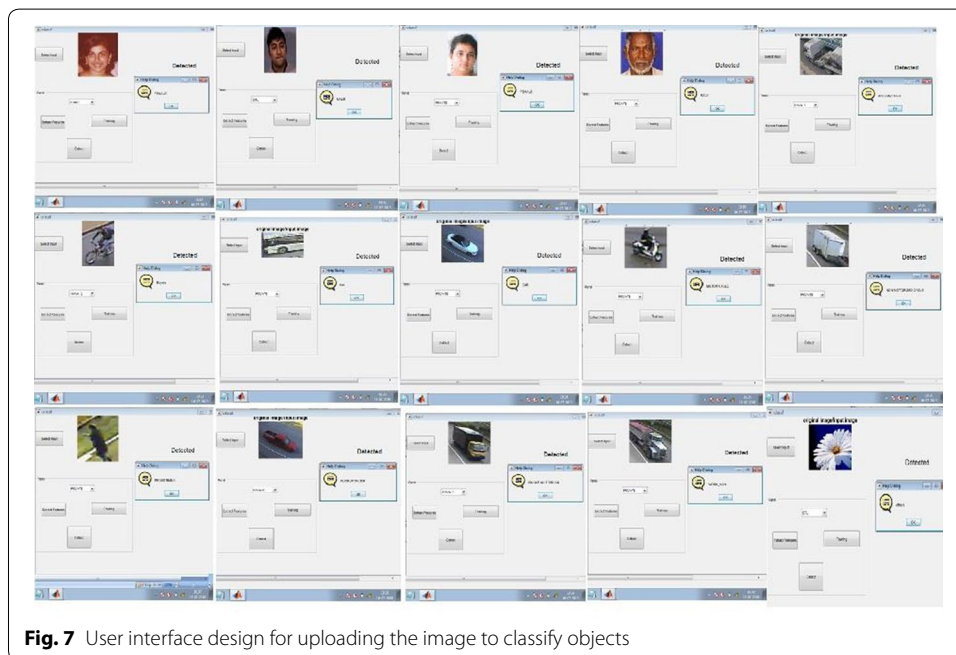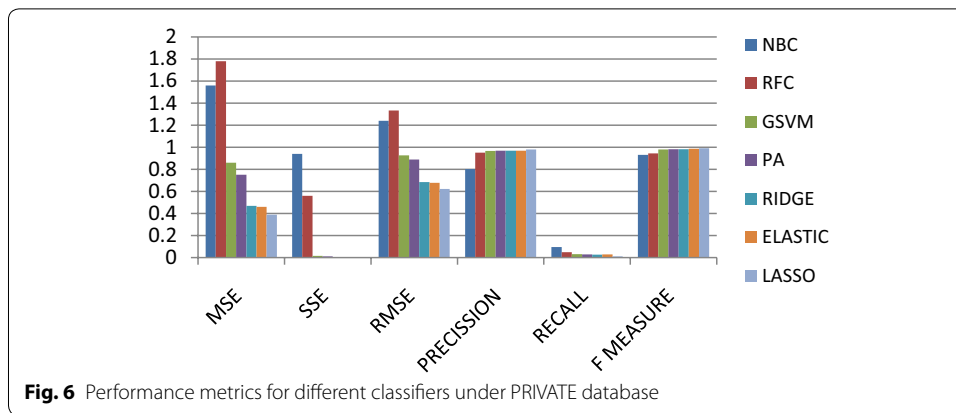### Datasets performance metrics with description

All the graphs from Figs. 2, 3, 4, 5, 6, and 7 were generated with the help of MS word with the values obtained during the simulation in matlab. Here x-axis indicates the

Fig. 3 Performance metrics for different classifiers under ORL database

Fig. 4 Performance metrics for different classifiers under FERET database

Fig. 5 Performance metrics for different classifiers under LFW database

performance metrics and y-axis provides error rate for different datasetes, as the accuracy was high and nearly 98.3% for all the datasets the performance were so closer and approximately equal to all the datasets.

FG-NET database
The face and gesture recognition network (FG-NET) database discharged in 2004. The FG-NET database is a freely accessible picture database containing face pictures of

Fig. 6 Performance metrics for different classifiers under PRIVATE database

Fig. 7 User interface design for uploading the image to classify objects

several subjects at various ages not just for age estimation for gender based extraction at various ages. The database contains 1002 pictures from 82 distinct subjects with ages extending between infants to 69 years of ages. Be that as it may, ages between zero to 40 years are the most populated in the database.

ORL database

ORL (Olivetti Research Laboratory) database [17] contains many face images taken between April 1992 and April 1994 at the lab. The database utilized with regards to a face based gender extraction task did in a joint effort with the Speech, Vision and Robotics Group of the Cambridge University Engineering Department. There are ten unique images of every one of 40 particular subjects. For certain subjects, the images were taken on various occasions, differing the lighting, outward appearances and facial subtleties. Every one of the images taken against a dim homogeneous foundation with the subjects

in an upright, frontal position. Ten various images of every one of 40 particular subjects. For certain subjects, the images were taken on various occasions, fluctuating the lighting, outward appearances.

FERET database

The FERET database gathered in 15 sessions between August 1993 and July 1996. The database contains 1564 arrangements of pictures for a sum of 14,126 pictures that incorporates 1199 people and 365 copy sets of pictures. A copy set is a moment set of pictures of an individual as of now in the database and typically taken on an alternate day. The Facial Recognition Technology (FERET) database is a dataset utilized for facial based gender extraction framework assessment as a significant aspect of the Face Recognition Technology (FERET) program. The FERET database fills in as a standard database of facial pictures for specialists to use to create different calculations and report results.

LFW database

(LFW) Labeled Faces in the Wild, a database of face photos intended for examining the issue of the unconstrained face-based gender extraction. The informational collection contains more than 13,000 pictures of appearances gathered from the web. Each face has marked with the name of the individual imagined. One thousand six hundred eighty of the general population imagined having at least two unmistakable photographs in the informational collection.

Private database

Private database contains various gender orientations and also had various ages of coloured facial images with proper resolution. Human images are accumulated through the camera with quality facial images with 275*314 dimensional measurements and also 254 dpi resolutions. The data base comprised with different age group ones, but These images are in JPEG format with reasonable contrast and white balance. The database provided 259 images gathered for face recognition.

Simulation setup

In this section, the paper describes the experimental setup for different objects based on feature extractions concerning facial and other related images. For simulation MATLAB latest version with minimum 4 GB RAM and 250 HD for processing multi-label images. Implementation of design for uploading data sets shown in Fig. 7.

Matched and mis-matched class detection is carried out by various algorithms and compared with performance metrics like MSE, RMSE, SSE, PRECISION, RECALL, FMEASURE, ACCURACY and TIME for various datasets. In Fig. 4, to show case the performance of different classification algorithms naive bayes (NBC), Random Forest (RFC), Gaussian SVM (GSVM), Fuzzy C Means Gaussian SVM (FGSVM) [18],

Multi-variant ridge logistic regression (RIDGE), Multi-variant elastic net logistic regression (ELASTIC), Multivariant Lasso logistic regression (LASSO)Here data set size varied based results are tabulated for accuracy and time for various datasets mentioned in the initial stages of results section.

Performance metrics

The Metrics used to compare the performance of various algorithms for feature extraction, selection and classification are Mean Square Error, Accuracy, Precision, Recall, Sum of Squared Error, Root Mean Square Error, F measure.

Their formulation is dependent on true positive, true negative, false positive and false negative conditions. These were selected during the classification of the images and were mathematically represented using the below equations.

$$Accuracy = \frac{TP + FN}{TS} \tag{8}$$

$$F - Measure = 2 * \left(\frac{1}{\frac{1}{Precision} + \frac{1}{Recall}} \right) \tag{9}$$

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

$$Recall = \frac{TP}{TP + FN} \tag{11}$$

$$MSE = \frac{1}{N} \sum_{j=1}^{1} \left(y_j - \widetilde{y}_j \right)^2 \tag{12}$$

$$SSE = \sum_{j=1}^{1} \left(y_j - \widetilde{y}_j \right)^2 \tag{13}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{j=1}^{1} \left(y_j - \widetilde{y}_j \right)^2} \tag{14}$$

Figures 3, 4, 5, and 6 resembles the performance metrics for different datasets with effective minimization of error. In all the figures mentioned above 6% to 8% effective in F-measure for the proposing scheme similarly RMSE has 3% change, MSE has 6% similar to SSE.

In Table 3 classification algorithms based accuracy on FGNET was observed, from Tables 4, 5, 6, 7, and 8 Accuracies were compared with different databases under different classifiers was presented. Outratedly our proposing approach delivers the best accuracy out of all algorithms with a minimum of 3% best rate.

In Table 9 the above face databases were combined with object databases named MIO-TCD and formed a total of 13 classes each section of training images considered 130 samples. For testing of each class 50 samples were considered.

The accuracies were not effective in case of combination for existing and proposing algorithms. In future direction the combination accuracy can be updated.

Table 3 Accuracy and Time comparison of 3proposing classification algorithms with MSIFT features training based on Multi-variant principle for FERET database comparing

Dataset size	Training images	Testing images	RIDGE		LASSO		Proposed	
			Accuracy	Time (s)	Accuracy	Time (s)	Accuracy	Time (s)
170	130	40	92.4	0.59	94.6	0.6	99.7	0.48
280	130	190	91.7	0.59	94.6	0.6	98.9	0.48
350	130	220	91.7	0.59	92.7	0.6	98.6	0.48
500	130	370	90.6	0.59	91.5	0.6	97.6	0.48
750	130	620	90.3	0.59	89.4	0.6	96.7	0.48

Table 4 Accuracy for different classifiers worked on FERET database

Technique	Dictionary [11]	SVM-MSIFT	GSVM-MSIFT	LASSO	RIDGE	Proposed
Accuracy	93.86	92.45	94.86	94.23	92.46	**97.1**

Table 5 Accuracy for different classifiers worked on FGNET database

Technique	Dictionary [11]	SVM-MSIFT	GSVM-MSIFT	LASSO	RIDGE	Proposed
Accuracy	–	86.45	91.69	93.4	92.46	**93.3**

Table 6 Accuracy for different classifiers worked on ORL database

Technique	Dictionary [11]	SVM-MSIFT	GSVM-MSIFT	LASSO	RIDGE	Proposed
Accuracy	–	92.76	92.86	91.23	94.46	**94.8**

Table 7 Accuracy for different classifiers worked on PRIVATE database

Technique	Dictionary [11]	SVM-MSIFT	GSVM-MSIFT	LASSO	RIDGE	Proposed
Accuracy	–	92.59	94.86	94.63	93.46	**98.2**

Table 8 Accuracy for different classifiers worked on FERET database

Technique	Dictionary [11]	SVM-MSIFT	GSVM-MSIFT	LASSO	RIDGE	Proposed
Accuracy	–	92.45	94.86	94.23	92.46	**97.4**

Table 9 Accuracy for different classifiers worked on different databases in combination with MIO-TCD DATABASE

Algorithms in combination with MIO-TCD database	FGNET	FERET	ORL	LFW	PRIVATE
SVM-GAUSSIAN	83.52	89.64	83.78	84.59	76.21
LASSO REGRESSION	88.67	91.55	87.49	83.98	84.64
ELASTIC NET LASSO	92.54	93.23	94.06	93.56	93.46
PROPOSSED (LRGS)	95.65	94.60	96.23	95.54	98.86

Fig. 8 Different mertics for Proposed (LRGS) classifiers worked on different databases in combination with MIO-TCD DATABASE
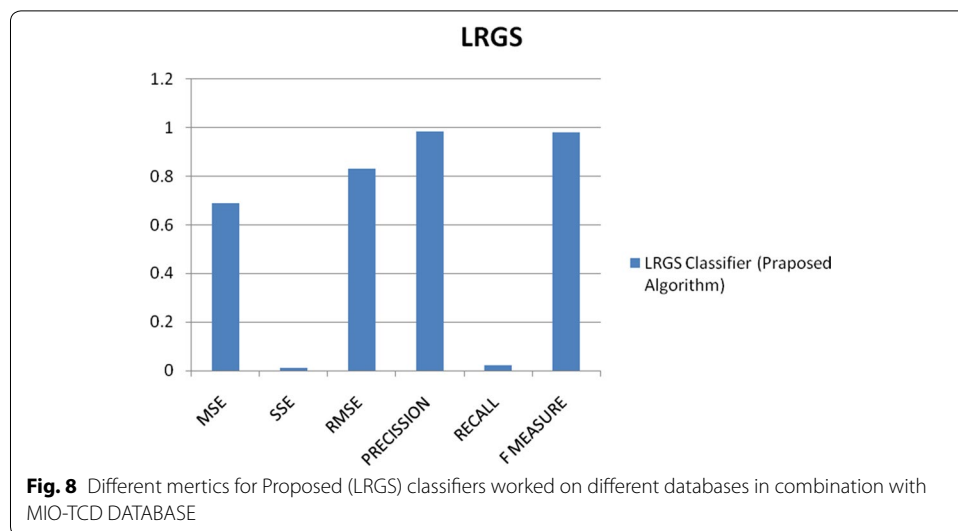
Figure 8 explains, the performance metrics of our proposed algorithm (LRGS) worked on different databases in combination with MIO-TCD DATABASE; precision is 98.3%, recall is 0.022%, MSE is 0.69, SSE is 0.011, RMSE is 0.83 and F-measure is 98.2.

Conclusion

In this paper, 5 different databases (combined with MIO-TCD vehicle Database) are tested with different algorithms and some techniques are compared with respect to references. In results section of this paper, 3 different approaches are compared with multivariant mode. At most of the references are authors implemented FERET databases, to show case the best outcome cited the comparison this dataset results are compared with other results are compared at dataset level. The proposed approach results in best accuracy with less time of execution. In future the enhanced process can be applied on video processing units for real time operations of detection in objects. All these accuracies obtained with respect to the number of test samples with subjective mean of all classified accuracies.

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