**3 Proposed Methods**

In this paper, propsoing scheme comprised with Multi scale invariant feature extraction and then these features converted into image frame then these gets normalized by using mulit variant normalization. This the feature extraction process followed by training process. Then these 2 gets classified by using MSVM, GSVM, LASSO, Logistic Regression based LASSO, ELASTIC NET, RIDGE and compared these results in results section of the paper.

**3.1 Feature Extraction**

**Table 1** Different feature extraction algorithms on FERET data sets

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **S. No** | **Feature Extractor** | **Formula** | **Remark** | **Result Analysis** |
| 1 | Gabor PCA |  | Extracted real and imaginary features of gabor(G) were optimized by PCA(P) | Extracts edges from the edges by different frequency sacling components with respect to PCA provides a recognition rate of 89.4% |
| 2 | Gabor MEAN PCA |  | Here mean of gabor filter were subjected to PCA optimization | All the extracted edges applied by mean and provides a recognition rate of 92.7% |
| 3 | HOG |  | Local feature extraction and normalization will be performed by this theory. | All the block wise extracted histogram features will result under recognitio rate of 83.9% |
| 4 | SIFT | Scale  Position:  Orientation: | One descriptor base 4 features will be extracted from SIFT algorithm and point descriptor of best form will help exact identificaiton of objection. Even 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  Position:  Orientation: | The image is splitted 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 best recognition rate of 98.3% in this proposing approach |

**3.2 Classification**

Table 1 represents different feature extraction process that were implemented along with our proposing approach to verify which feature extraction will results the high accuracy rate for classification. In table 1 the results column helps in selecting the best approach for feature selection process applied by support vector machine.

Logistic regression a modelling method for estimating the ), and hence 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 ” and “No/Failure ”.

Our general classification rule based on these estimated probabilities is given by, If then classifies as being from class 1, i.e. “Yes” or “Success”.  
If then classify as being from class 0, i.e. “No” or “Failure”.

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 (see the discussion of Lift in Section 12.)

The probabilities are estimated using a generalised linear model (GLM) for the natural log of the odds for “success”, which is called the logit (). The logistic regression model is given by,

As was the case with the general OLS model, the terms are all functions of the predictors . Once we have obtained estimates of the model parameters, and hence the estimated logit , we can estimate the probability of “Yes/Success” as,

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.

**Table 2** Univariate Considerations

|  |  |
| --- | --- |
| **- conditional distribution x gave as y which is 0 or 1.** | **Suggested model terms** |
| Normal, common variance  i.e. | , i.e. the predictor itself  These values imply that if is NOT normally distributed we might consider transforming to approx. normality. |
| Normal, unequal variances  i.e. | and |
| Skewed right | and  Log base 2 is more comfortable to interpret |
|  | and |
| ~ Poisson, i.e. is a count | , i.e. the predictor itself |

**3.3 Multivariate Considerations**

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

 then use the x’s themselves

 then include ’s and  terms

For example in the two predictor case ()  is needed if 

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

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:**

**Lasso Logistic:**

**Elastic Net Logistic:**