IDENTIFICATION OF DOWN SYNDROME USING FACE RECOGNITION AND RANDOM FOREST CLASSIFICATION METHOD

[1] **Ms.Shweta shirpurkar** , [2] **Dr.(Mrs).R.A.Ingolikar,**
[1] Research Scholor ,IICC,RTM University Nagpur India, [2] Head Computer Science, S.F.S College , Nagpur.

Abstract : ***Down syndrome is a genetic disorder occurs due to human birth defects, which produces alterations in physical growth and mental retardation. It is chromosomal disorder, people affected by this disease having very specific facial characteristics. Children with Down syndrome generally have distinctive facial characteristics, which leads towards an avenue for developing a computer-aided diagnosis of Down syndrome using images of patients. In this paper, we propose face recognition methods such as Local Binary Patterns and Eigenfaces and test their ability to distinguish between a Down syndrome face and a normal one in digital images. For classification we have used random forest algorithm. Accuracy, precision, recall and F-measure are computed in order to evaluate the classification results.***

IndexTerms - Down syndrome, Eigenfaces , Local Binary Patterns, Face Recognition, Random Forest algorithm.

I. INTRODUCTION

Down syndrome may be diagnosed either during pregnancy or shortly after birth. Diagnostic and screening testing can be done during pregnancy. At birth, Down syndrome may be diagnosed by the presence of some typical facial appearances and physical characteristics. Some of the features include a small and flattened nose, small ears and mouth, upward slanting eyes, and protruding tongue. To confirm a diagnosis, a chromosome test called a karyotype can be performed. However, these tests are expensive and time-consuming and many remote healthcare centres do not have ready access to these technologies[1].

Down syndrome is a chromosomal condition caused by the presence of a third copy of chromosome 21. It is the most common chromosomal abnormality and it affects one out of every 300 to 1,000 infants worldwide depending on factors such as prenatal testing and maternal age [1, 2]. Patients with Down syndrome have an increased risk for developmental disabilities, heart defects, respiratory and hearing problems and the early detection of the syndrome is fundamental for managing the disease[2].

2. Proposed Work

In this paper, we propose face recognition methods such as Local Binary Patterns and Eigenfaces and test their ability to distinguish between a Down syndrome face and a normal one in digital images. For classification we have used random forest algorithm. The entire process is illustrated in Figure 1.

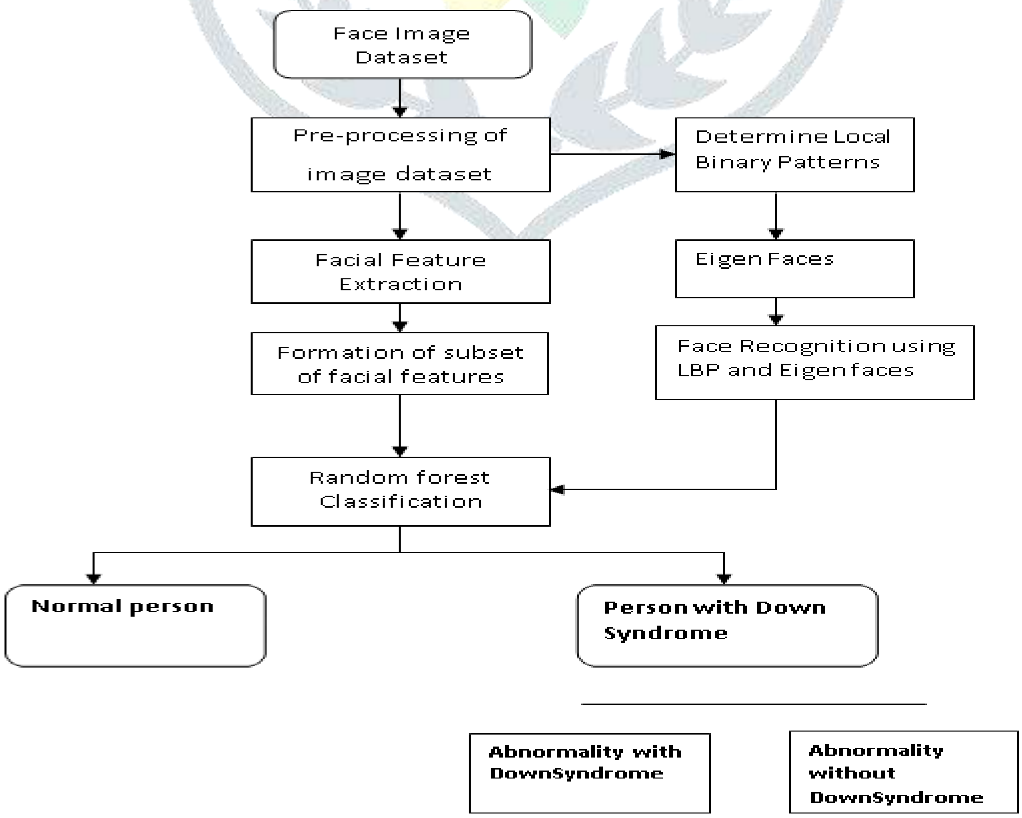


Figure 1 : Person identification using Face Recognition and Random Forest Classification technique.

As shown in Figure 1, the process starts with the image dataset of normal and abnormal faces comprising of 650 samples.

2.1 *Pre-processing of image dataset:*

The images in the image dataset are having varied resolutions and they are all colored images. The images are resized into a uniform resolution of 400 x 300 and are converted into gray level format. This process is called pre-processing

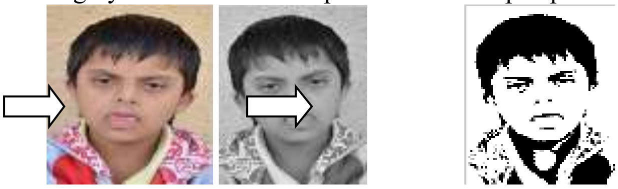


Figure 2 : a)Color image b) Gray image c)Binary image

2.2 Facial Features Extraction:

The face image is a 3-D matrix of intensity values or gray level values lying in the range 0 to 255. We have used RGB color model for this work. In RGB color model, each color space is a 2-D matrix of intensity values and it is represented as,

$$I=f(x,y) \quad \text{for } 0 \le x \le 255 \text{ and } 0 \le y \le 255 \qquad (1)$$

Facial features extraction deals with extraction of various facial features viz. distance between two eyes, length of nose, width of mouth etc.

Let $p[x_1, y_1] \rightarrow$ centre of left eye ball
$q[x_2, y_2,] \rightarrow$ centre of left eye ball
$r[x_3,y_3] \rightarrow$ mid-point of nose
$s[x_4,y_4] \rightarrow$ left end of mouth and
$t[x_5,y_5] \rightarrow$ right end of mouth

After doing pre-processing and feature extraction phase, we are getting feature point distribution of faces as shown in the figure 3 .The middle column shows the face feature pattern of normal person and remaining are of abnormal person .Here we can see the actual difference in both the types of faces.

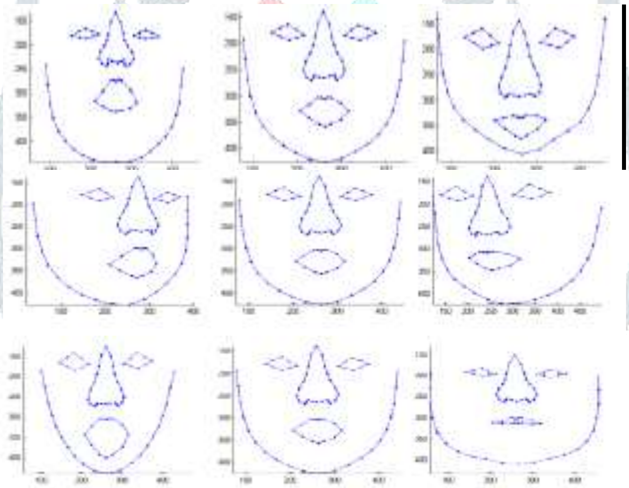


Figure 3 : Feature patterns of face image

A mathematical representation of an n -point shape in k dimensions could be to concatenate each dimension into a kn-vector. The vector representation for planar shapes (i.e. k = 2) would then be $x=[x_1, y_1,x_2,y_2,\ldots\ldots,x_n,y_n]^T$

2.3 Formation of subsets of facial features

Let the features of face images are:

$D_{eyes} \rightarrow$ distance between two eyes
$D_{LN} \rightarrow$distance between left eye and centre of nose,
$D_{RN} \rightarrow$ distance between right eye and centre of nose
$M_L \rightarrow$ mouth length
$D_{Lips} \rightarrow$ thickness of lips

$$D_{eyes} = |\, x1 - x2 \,| \qquad (2)$$
$$D_{LN} = |\, y1 - y3 \,| \qquad (3)$$
$$D_{RN} = |\, y2 - y3 \,| \qquad (4)$$
$$M_L = |\, x4 - x5 \,| \qquad (5)$$
$$D_{Lips} = |\, y6 - y7 \,| \qquad (6)$$

Let $X1=D_{eyes}$, $X2=D_{LN}$, $X3=D_{RN}$, $X4= M_L$ and $X5= D_{Lips}$. Figure 4 shows the extracted features of a child.

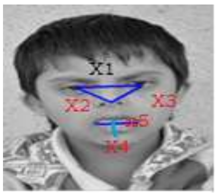


Figure 4 : Facial features of a child

Similarly, features of all the database images are extracted to form feature matrix. Some of features of normal and abnormal children are shown in Figure 5 and Figure 6 respectively.

Figure 5 : Features of abnormal children

Figure 6 : Features of Normal children

Numeric values of some of the extracted features of abnormal and normal objects are shown in Table 1 which is given below. The values given in the table helps us to determine the range of values of each parameter for abnormal and normal person.

Table I : Extracted Features of normal and abnormal faces

Face Image	Distance between the eyes	Distance between left eye and centre of nose	Distance between left eye and centre of nose	Width of mouth	Face Image	Distance between the eyes	Distance between left eye and centre of nose	Distance between left eye and centre of nose	Width of mouth
1	75	46	50	45	21	87	39	39	39
2	80	47	63	40	22	63	41	45	42
3	90	50	41	42	23	60	40	50	40
4	84	43	39	48	24	65	42	42	42
5	61	45	47	49	25	60	45	45	41
6	85	38	45	40	26	64	64	48	48
7	36	35	50	36	27	71	51	37	33
8	62	42	60	40	28	61	44	44	33
9	63	45	51	45	29	60	40	48	36
10	56	49	49	39	30	61	42	39	39
11	60	44	40	48	31	68	62	42	38
12	32	41	48	40	32	57	57	39	39
13	27	44	36	42	33	61	42	42	42
14	60	45	45	40	34	80	40	48	40
15	60	42	50	36	35	60	45	45	41
16	63	42	49	42	36	64	40	48	48
17	40	30	50	40	37	61	41	37	33
18	55	40	44	33	38	62	42	42	38
19	64	40	48	40	39	63	41	39	39
20	64	48	48	36	40	60	40	48	40

2.4 Random Forest Classification

As random forest classifier is ensemble algorithm, we start with construction of a decision tree. This is a standard machine learning technique. The decision tree, in ensemble terms, corresponds to our weak learner. In a decision tree, an input is entered at the top and as it traverses down the tree the data gets bucketed into smaller and smaller sets. In the proposed work, the random forest algorithm is used for classification of persons into normal and abnormal categories.

2.4.1 Formation of decision trees

The input of the decision tree consists of a training set which is given as : [X1, X2, X3, X4,X5] with corresponding labels as [L1, L2, L3, L4,L5], From the observation of values from Table I, it has been found that we can form four different combinations or subsets of feature values. The geometric facial features of normal and abnormal persons are tend to form specific pattern. To check the deformity in the face, these four patterns can be observed and examined.

Figure 6 : Subset formation for the facial features.

The Random forest may create three decision trees taking input of subset for example,

1. [X1, X2, X3]
2. [X1, X2, X4]
3. [X2, X3, X4]
4. [X3,X4,X5]

The split at each decision node will be decided on the basis some machine learning rules given as follows. Experimentation is carried out on different test images

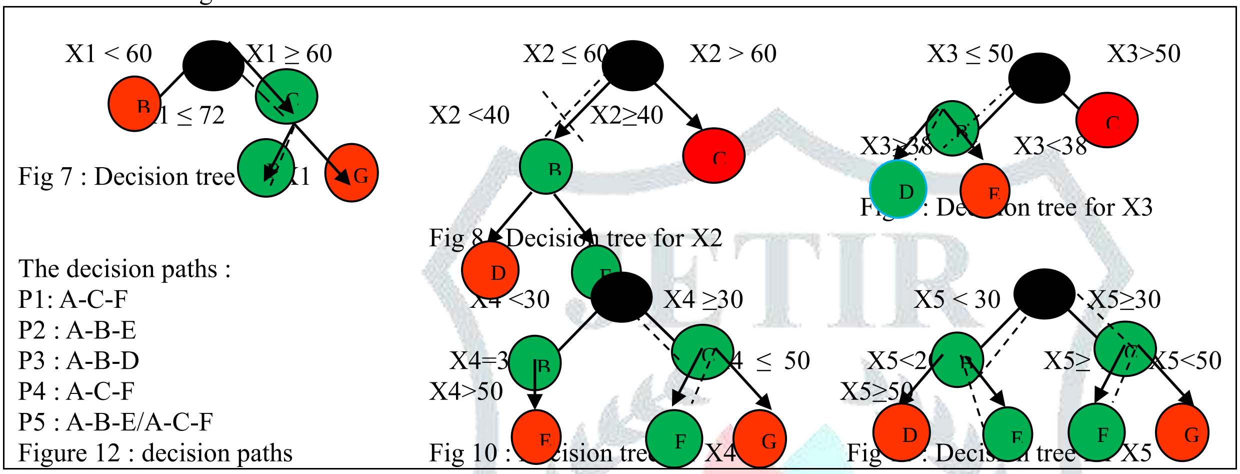


Fig 7 : Decision tree ... X1

Fig 8 : Decision tree for X2

Fig ... : Decision tree for X3

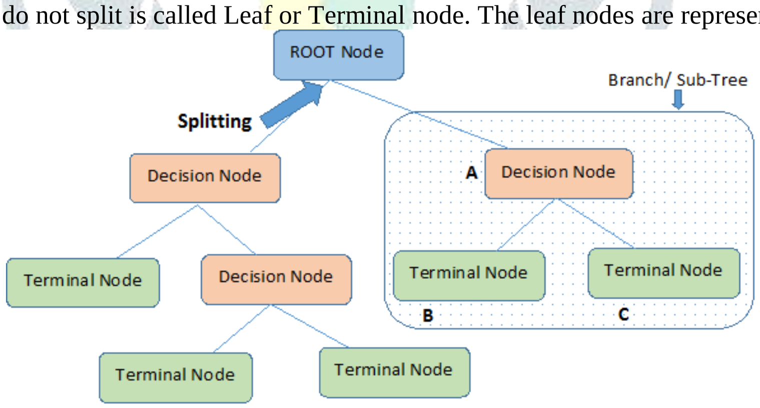
Fig 10 : ...ision tree ... X4

Fig ... : Decision tree ... X5

The decision paths :
P1: A-C-F
P2 : A-B-E
P3 : A-B-D
P4 : A-C-F
P5 : A-B-E/A-C-F
Figure 12 : decision paths

The types of nodes used in Decision trees is given below:

1. **Root Node:** It represents entire population or sample and this further gets divided into two or more homogeneous sets. We have represented the root node by black color.
2. **Splitting:** It is a process of dividing a node into two or more sub-nodes.
3. **Decision Node:** When a sub-node splits into further sub-nodes, then it is called decision node. We have represented the decision nodes with green color
4. **Leaf/ Terminal Node:** Nodes do not split is called Leaf or Terminal node. The leaf nodes are represented in red color.



Note:- A is parent node of B and C.

5. **Pruning:** When we remove sub-nodes of a decision node, this process is called pruning. You can say opposite process of splitting.
6. **Branch / Sub-Tree:** A sub section of entire tree is called branch or sub-tree.
7. **Parent and Child Node:** A node, which is divided into sub-nodes is called parent node of sub-nodes where as sub-nodes are the child of parent node.

2.5 Classification of Abnormal person into Down syndrome and Non-Down syndrome using decision trees

The set of images of abnormal persons are further classified into person with Down syndrome and person without Down syndrome using decision trees and random forest algorithms. The facial features such as geometric features include various points of the extracted features. The Point Distribution Variation (PDV) for each face image is calculated. The decision function for classification in decision tree is formed and used for splitting. The Point Distribution (PDV) and Mean shape Comparison (MSC) is shown in figure 13

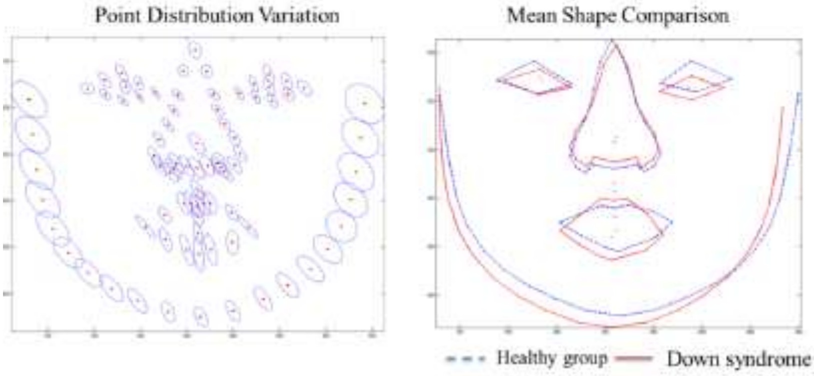


Figure 13 : Shape model (a) Point Distribution Variation (b) Mean shape comparison for healthy group and down syndrome group

The fig 13 and 14 illustrates the decision functions f1 for left eye, f2 for right eye,f3 for nose,f4 for mouth that is used for classifying abnormal faces into down syndrome and non-down syndrome faces .Range for the decision function is calculated and shown in the following table 11.

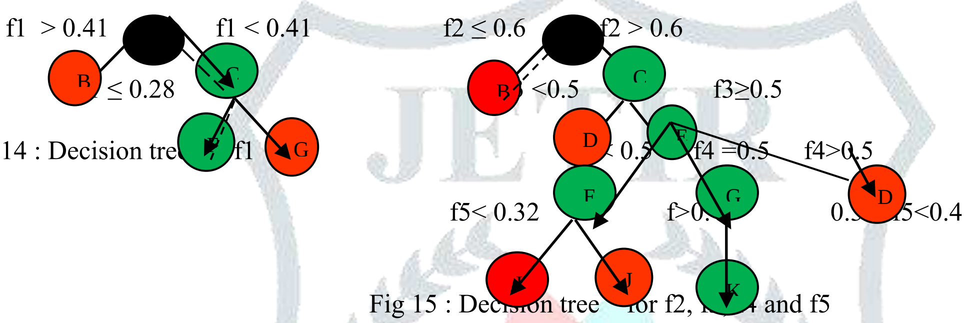


Fig 14 : Decision tree for f1

Fig 15 : Decision tree for f2, f3, f4 and f5

The decision paths :
P1: A-C-F
P2 : A-C-E-G-K
P3 : A-C-E-F-I
Figure 16 : decision paths

We have determined the range of values for these decision functions by rigorous experimentation and these values are shown in following table.

Table II : Decision function values

Decision function	Down syndrome	Non-down syndrome
f1	< 0.28	>=0.28
f2	>0.6	<=0.6
f3	>=0.5	<0.5
f4	<=0.4	<0.4
f5	0.33 to 0.39	<0.4 & >0.39

We have done experimentation on the present face image database for identifying the person as normal and Down syndrome or without Down syndrome with the help of above classification technique. The sample result is demonstrated as follows. Let us take a face image shown in Figure 17 as an input for identification.

Figure 17 : Input image

Figure 18 : Features Extracted

First of all its geometric feature are extracted as per the method discussed above. The results are shown in Figure 18. The random forest classifier is employed for classification and following decision function are computed. {f1= 0.179, f2=0.89, f3=0.61,f4=0.48 f5=0.38} and two trees in random forest are traversed and the paths are : [T1 → A-C-F and T2→ A-C-E-G-K]. Therefore, the person is identified as Abnormal with Down syndrome disease.

2.5 Traversing the random forest for classification

The algorithm selection is also based on type of target variables. Let's look at the four most commonly used algorithms in decision tree:

Gini Index

Gini index says, if we select two items from a population at random then they must be of same class and probability for this is 1 if population is pure.

1. It works with categorical target variable "Success" or "Failure".
2. It performs only Binary splits
3. Higher the value of Gini higher the homogeneity.
4. CART (Classification and Regression Tree) uses Gini method to create binary splits.

Steps to Calculate Gini for a split

1. Calculate Gini for sub-nodes, using formula sum of square of probability for success and failure (p^2+q^2).
2. Calculate Gini for split using weighted Gini score of each node of that split

The five decisions tree are traversed by using Gini index for split. The solution paths are P1,P2,P3,P4 and P5 as shown in figure in 12.

2.6 Local Binary Patterns

The original LBP method, shown in Figure 3, was first introduced by Ojala et al. [16]as a complementary measure for local image contrast. It operates with eight neighbouring pixels using the central pixel as a threshold. The LBP code is then computed by multiplying the threshold values by weights given by powers of two and adding the results in the way described in Figure 3. The LBP of a 3×3 neighbourhood produces up to 28=256 local texture patterns, and the 256-bin occurrence LBP histogram computed over a region is then employed for texture description.

Threshold

7	3	9
1	5	6
5	0	8

1	0	1
0		1
1	0	1

Multiply

1	2	4
8		16
32	64	128

1	0	4
0		16
32	0	128

LBP=1+4+16+32+128=181

Figure 7 : The original LBP operator

The original LBP was extended to a more general approach, the uniform LBP [16], in which the number of neighbouring sample points is not limited:

$$LBP^{riu2}_{P,R}(x,y)=\begin{cases}\sum_{p=0}^{P-1} s(g_p-g_c) & if U(LBP_{P,R})\le 2\\ P+1 & otherwise\end{cases}$$

$$S=\begin{cases}1 & x\ge 0\\ 0 & x<0\end{cases}$$

where p g corresponds to the grey values of P equally spaced pixels on a circle of radius R , c g is the grey value of the central pixel, and

$$U(LBP_{P,R})=|s(g_{P-1}-g_c)-s(g_0-g_c)|+\sum_{P-1}^{P}|s(g_p-g_c)-s(g_{p-1}-s_c)|s(g_{P-1}-s_c)|$$

The geometric and local texture features have 19 and 102 dimensions, respectively. The 121-dimensional combined features were generated by concatenating the geometric and local texture features. The features were ranked based on the area under the receiver operating characteristic (ROC) curve and the random classifier slope.

3. Results

For the mixed dataset, the optimal dimension is 3, 35, 5 for geometric, texture, and combined features, respectively. The results for the mixed dataset are shown in Table 2. The average accuracy for geometric features and local texture features are 77.1% and 75.0%, respectively. The combined features outperform them with 81.3% accuracy. The results show an improvement when combing the landmark spatial information and texture features. Similarly, the precision and recall of the combined features reached 84% and 82%, respectively.

Table 2 : Performance comparison

Features	Accuracy	Precision	Recall
Geometric	0.721	0.81	0.66
SVM	0.73	0.78	0.81
LBP+Eigenfaces	0.80	0.84	0.82

The result of various algorithms such as Geometric, SVM and LBP+EigenFaces (Combined) is compared and the graph of Receiver Operating Characteric (ROC) curve is plotted in following figure.

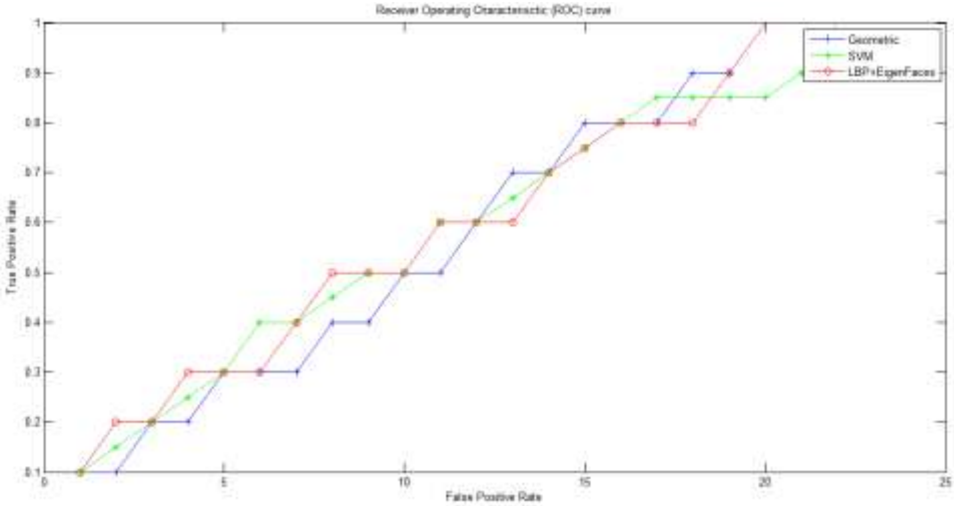


Figure 13 : Receiver Operating curve (ROC)

4. Conclusion

A method for the automated detection of Down syndrome using digital facial images was proposed. Geometric features based and local texture features based on Contourlet transform and local binary patterns were combined. After feature selection, a Random Forest algorithm classifier was employed to discriminate between the Down syndrome and normal cases. Comparisons among the geometric, LBP and LBP and Eigen faces combined features were performed. The experimental results showed that the performance of the method has improved when combined features of both LBP and Eigen faces texture were used; Down syndrome cases were detected with 97.9% accuracy. The encouraging results also demonstrated that our method has great potential to support the computer-aided diagnosis for Down syndrome from simple photographic data. Data collection is our on-going work for the more comprehensive validation of our method.

References

[1] Shweta Shirpurkar, R.A.Ingolikar, "Person Identification using Data Mining of Facial Features Extraction" Issue March 2018© 2016 IJSRCSEIT | Volume 1 | Issue 1 | ISSN : 2456-3307

[2] Shweta Shirpurkar, R.A.Ingolikar," Data Mining of Facial Features using Random Forest Algorithm forPerson Classification", IJPUB Vol 2, Issue March 2018

[3]G. de Graaf, M. Haveman, R. Hochstenbach *et al.*, "Changes in yearly birth prevalence rates of children with Down syndrome in the period 1986–2007 in the Netherlands," Journal of Intellectual Disability Research, 55(5), 462-473 (2011).

[4] F. K. Wiseman, K. A. Alford, V. L. J. Tybulewicz *et al.*, "Down syndrome—recent progress and future prospects,"Human Molecular Genetics, 18(R1), R75-R83 (2009).

[5] S. Boehringer, M. Guenther, S. Sinigerova *et al.*, "Automated syndrome detection in a set of clinical facial photographs," American Journal of Medical Genetics Part A, 155(9), 2161-2169 (2011).

[6] S. Boehringer, T. Vollmar, C. Tasse *et al.*, "Syndrome identification based on 2D analysis software," Eur J Hum Genet, 14(10), 1082-1089 (2006).

[7] H. S. Loos, D. Wieczorek, R. P. Wurtz *et al.*, "Computer-based recognition of dysmorphic faces," European Journal of Human Genetics, 11(8), 555-560 (2003).

[8] T. Vollmar, B. Maus, R. P. Wurtz *et al.*, "Impact of geometry and viewing angle on classification accuracy of 2D based analysis of dysmorphic faces," European Journal of Medical Genetics, 51(1), 44-53 (2008).

[9] Ş. Saraydemir, N. Taşpınar, O. Eroğul *et al.*, "Down Syndrome Diagnosis Based on Gabor Wavelet Transform,"Journal of Medical Systems, 36(5), 3205-3213 (2012).

[10] K. Burçin, and N. V. Vasif, "Down syndrome recognition using local binary patterns and statistical evaluation of the system," Expert Systems with Applications, 38(7), 8690-8695 (2011).

[11] T. S. Douglas, and T. E. M. Mutsvangwa, "A review of facial image analysis for delineation of the facial phenotype associated with fetal alcohol syndrome," American Journal of Medical Genetics Part A, 152A(2), 528-536 (2010).

[12] T. E. M. Mutsvangwa, E. M. Meintjes, D. L. Viljoen *et al.*, "Morphometric analysis and classification of the facial phenotype associated with fetal alcohol syndrome in 5- and 12-year-old children," American Journal of Medical Genetics Part A, 152A(1), 32-41 (2010).

[13] M. N. Do, and M. Vetterli, "Contourlets: a directional multiresolution image representation." 1, I-357-I-360 vol.1.

[14] M. N. Do, and M. Vetterli, "The contourlet transform: an efficient directional multiresolution image representation,"IEEE Transactions on Image Processing, 14(12), 2091-2106 (2005).

[15] M. N. Do, and M. Vetterli, "Contourlets: a new directional multiresolution image representation." 1, 497-501 vol.1.

[16] T. Ojala, M. Pietikäinen, and D. Harwood, "A comparative study of texture measures with classification based on featured distributions," Pattern Recognition, 29(1), 51-59 (1996).

[17] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," Pattern Analysis and Machine Intelligence, IEEE Transactions on, 24(7), 971-987 (2002).
[18] C. Cortes, and V. Vapnik, "Support-vector networks," Machine Learning, 20(3), 273-297 (1995).