they are concatenated into an enhanced feature vector that can be used as a face descriptor in the algorithm.

Despite of the excellent performance by Local Binary Pattern (LBP) in the texture classification as well as in face detection, its performance parameter in human detection has been limited. Local Binary Pattern differentiates a bright human that considers as object from a dark background and vice-versa. Due to this there is increase in the intra-class variation of humans.. Non-Redundant Local Binary Pattern (NRLBP) was proposed in order to solve the first issue of Local Binary Pattern. The Local binary pattern texture method is considered as the most successful method for face recognition. Due to the success of Local Binary Pattern, recently many models, which are variants of Local Binary Pattern are been proposed for texture analysis.

3. Proposed system

We have proposed a novel edge-texture feature for recognition that provides discrimination which is Discriminative Robust Local Binary Pattern and Local Ternary Pattern. Discriminative Robust Local Binary Pattern and Local Ternary Pattern help in discrimination of the local structures that Robust Local Binary Pattern seems to misrepresent. Also, the proposed features tend to retain the contrast information of the image patterns. They comprises of both edge and texture information which seem desirable for object recognition. K Nearest Neighborhood classifier is been used to provide image classification.

An object has 2 distinct states for differentiation from other objects - the object surface texture and the object shape formed by its boundary. The boundary often shows much higher contrast between the object and the background than the surface texture. Differentiating the boundary from the surface texture brings additional discriminatory information because the boundary contains the shape information. Local Binary Pattern does not provide differentiation between a weak contrast local pattern and a strong contrast pattern. It mainly captures the object texture information. The histogramming of LBP codes only considers the frequencies of the codes i.e. the weight for each code is the same. This makes it difficult to provide differentiation between a weak contrast and a strong contrast local pattern. To mitigate this, we propose to fuse edge and texture information together in a single representation by further modifying the way the codes can be histogrammed. Figure 1 shows Block Diagram representation.

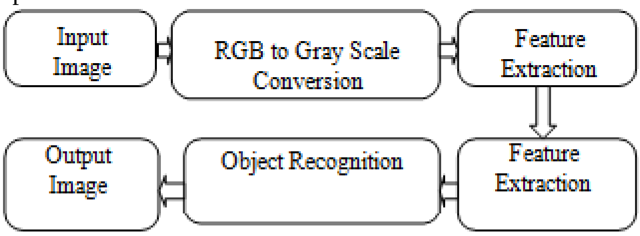

Figure 1: Block Diagram

For the Input, the image is selected from the database and edge texture features are extracted. Object from the image is cropped for recognition provided with its features. KNN classifier is used for Image Classification. In k-NN classification, the output seems to be a class membership. An object classification is done by a majority vote of its own neighbors, with the object to be assigned to the class which is most common among its k nearest neighbors. Figure 2 shows the Flow of the proposed system.

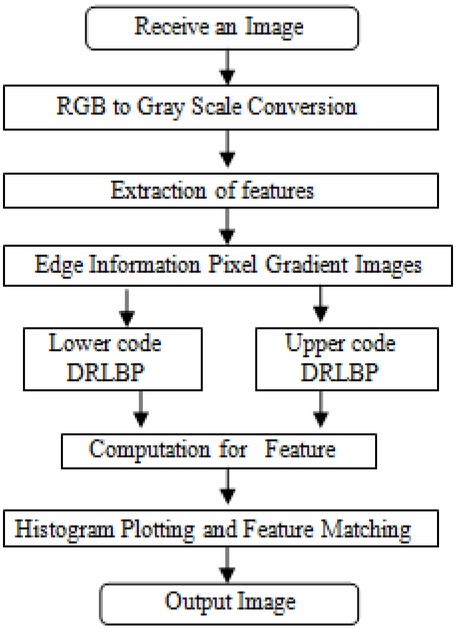

Figure 2: Flowchart

4. Evaluation

Figure 3 shows the basic Graphical User Interface of the proposed system. It uses MATLAB software for simulation. It provides a comprehensive set of reference standard algorithms, functions, and apps for image processing, analysis, visualization, and algorithm development.

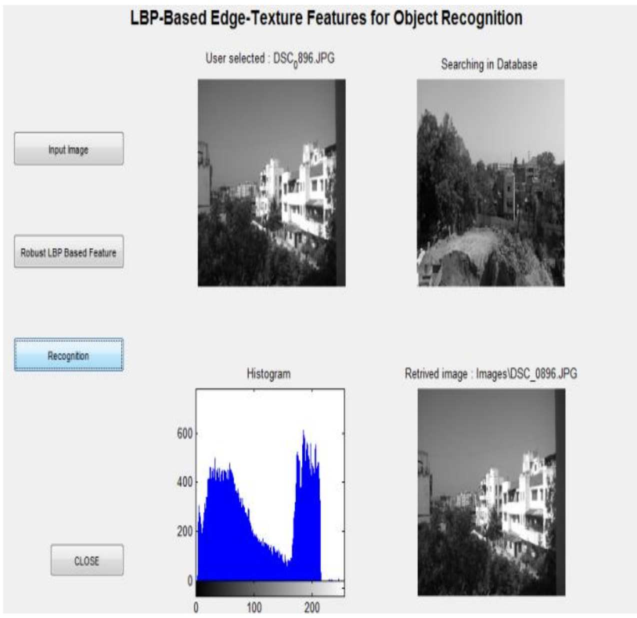

Figure 3: Basic GUI

The edge texture features are obtained using the DRLBP algorithm shown in Figure 4

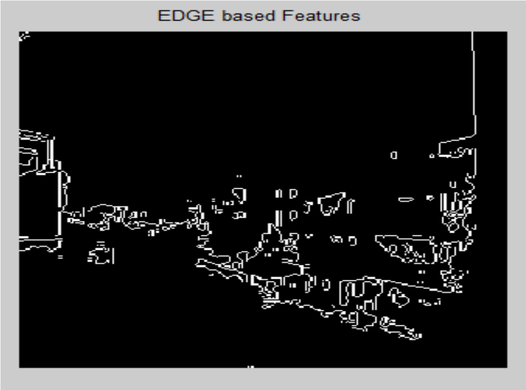

Figure 4: Edge based Features

The Local Binary Pattern Histogram along with the LBP values are obtained by simulation is as shown in figure 5 and figure 6

INPUTS <18x256 double>

	1	2	3	4	5	6	7	8	9	10	11	12
1	1168	141	901	361	154	30	333	447	419	201	112	581
2	924	142	214	256	175	58	197	516	382	258	45	520
3	1367	226	1038	415	209	43	398	617	619	317	161	592
4	1810	219	654	237	262	40	256	362	743	278	121	450
5	875	124	504	210	115	31	301	499	256	166	53	782
6	1666	274	549	225	265	57	218	427	546	220	86	390
7	574	89	345	72	81	7	73	139	222	52	23	96
8	1457	262	345	222	290	60	231	690	756	305	72	496
9	379	71	164	131	80	8	117	223	98	96	29	366
10	2177	242	787	352	248	56	371	366	453	304	94	453
11	2205	222	762	355	281	50	378	365	403	301	109	475
12	2199	259	723	363	268	36	394	367	396	346	84	478
13	2181	246	731	343	262	54	386	358	363	349	115	504
14	1157	199	818	428	201	24	358	764	457	405	84	896
15	1203	205	835	388	183	29	374	776	467	397	81	967
16	1147	199	854	413	161	35	388	802	461	370	92	936
17	1243	92	288	157	73	16	166	846	902	280	57	408
18	1276	87	247	138	69	27	190	857	905	261	70	399
19												

Figure 5: Local Binary Pattern Features

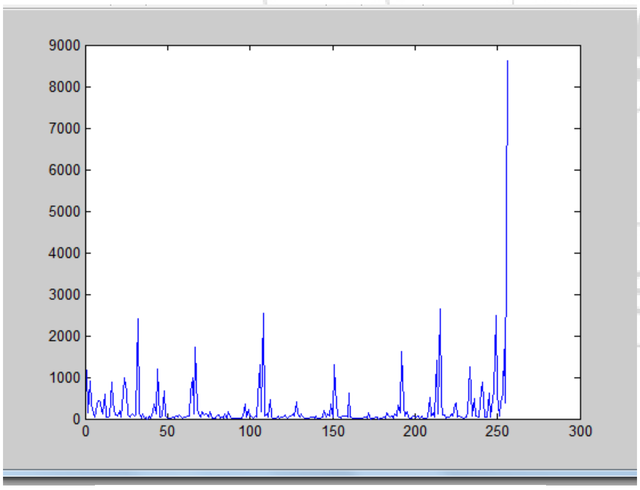

Figure 6: Local Binary Pattern Histogram

Speed up Robust Feature is a detector and a descriptor which provides points of interest in the images where the image is further transformed into coordinates by using the multi-resolution pyramid technique. This particular technique ensures that the points of interest tend to be scale invariant. Figure 7 Shows feature points using Surf.

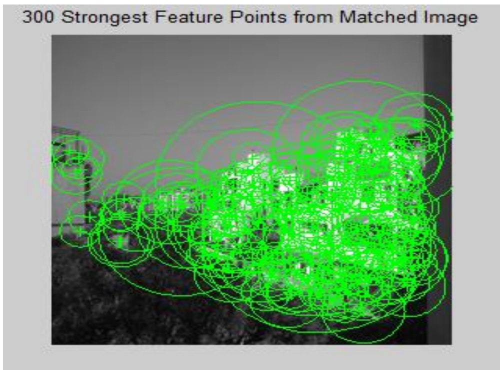

Figure 7: Strongest Feature points

Figure 8: Matched points

5. Conclusion

The features extracted are found robust to image variations that are caused due to the intensity inversion and they also provide discrimination to the image structures which are within the histogram block. The Interclass variations are also reduced. The Proposed system provides efficient recognition and helps to alleviate the issues of Local Binary Pattern, Robust Local Binary pattern and local ternary pattern.

References

[1] J. Ren, X. Jiang, and J. Yuan, “Noise-resistant local binary pattern with an embedded error-correction mechanism,” IEEE Transaction. Image Process. vol. 22, no. 10, pp. 4049–4060, Oct. 2013.

[2] A. Satpathy, X. Jiang, and H.-L. Eng, “Human detection using discriminative and robust local binary pattern,” in Proc. IEEE Int. Conf. Acoust. Speech. Signal Process. May 2013, pp. 2376–2380.

[3] J. Stottinger, A. Hanbury, N. Sebe, and T. Gevers, “Sparse color interest points for image retrieval and object categorization,” IEEE Transaction. Image Process, vol. 21, no. 5, pp. 2681–2692, May 2012.

[4] A. Fernández, M. Álvarez, and F. Bianconi, “Texture description through histograms of equivalent patterns,” J. Math. Images. Vis., vol. 45, no. 1, pp. 1–27, 2012.

[5] A. Suruliandi. K. Meena. R. Reena Rose “Local binary pattern and its derivatives for face recognition”. Published in IET Computer Vision Received on 1st November 2011 Revised on 4th April 2012.

[6] Z. Guo, L. Zhang, and D. Zhang, “A completed modeling of local binary pattern operator for texture classification,” IEEE Transaction. Image Process, vol. 19, no. 6, pp. 1657–1663, Jun. 2010.

[7] D.T. Nguyen, Z. Zong, P. Ogunbona, and W. Li, "Object detection using non-redundant local binary patterns," in Proc. IEEE Int. Conf. Image. Process. Sep. 2010, pp. 4609–4612.

[8] J. Mutch and D. Lowe, "Multiclass object recognition with sparse, localized features," in Proc. IEEE Int. Conf. Computer. Vision. Pattern Recognition. vol. 1. Jun. 2006, pp. 11–18.

[9] T. Ahonen, A. Hadid, and M. Pietikainen, "Face description with local binary patterns: Application to face recognition," IEEE Transaction. Pattern Anal. Mach. Intell., vol. 28, no. 12, pp. 2037–2041, Dec. 2006.

[10] S. Agarwal, A. Awan, and D. Roth, "Learning to detect objects in images via a sparse, part-based representation," IEEE Transaction. Pattern Anal. Mach. Intell., vol. 26, no. 11, pp. 1475–1490, Nov. 2004.

[11] A. Suruliandi. K. Meena. R. Reena Rose "Local binary pattern and its derivatives for face recognition". Published in IET Computer Vision Received on 1st November 2011 Revised on 4th April 2012.

Author Profile

Rasika Raikar has received the B.E. Degree in Electronics and Telecommunication Engineering from All India Shri Shivaji Memorial Society Institute of Information Technology in 2013 from Pune University. Presently pursuing post graduation in Dhole Patil College of engineering.