© MAR 2026 | IRE Journals | Volume 9 Issue 9 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I9-1715066

Face Recognition Using Diamond Sampling Structure-Based Local Adaptive Binary Pattern

DR. NALLA NEELIMA[1], SIDDHARDHA SHODA[2], PRATHIPATI AKASH CHOWDARY[3], SAHUKARI DILLESWARA RAO[4], VADRANAPU CHAITANYA VENKATA KRISHNA[5]
[1, 2, 3, 4, 5] *Information Technology, R.V.R & J.C College of Engineering*

Abstract- ***Local Binary Pattern (LBP) has been widely used in face recognition for its simplicity, but is very sensitive to noise and relies on bilinear interpolation for non-integer neighbor positions. The Binary Rotation Invariant and Noise Tolerant (BRINT) descriptor improved upon LBP through arc-segment averaging, yet still depends on circular sampling requiring interpolation. This paper proposes the Diamond Sampling Structure-Based Local Adaptive Binary Pattern (DLABP) for face recognition. DLABP introduces three contributions: (1) a diamond sampling structure placing all neighbors at integer grid positions, eliminating interpolation entirely; (2) an average method along the radial direction for noise robustness; and (3) a locally adaptive threshold that recovers noise-corrupted nonuniform patterns. DLABP produces a compact 200-dimensional feature and outperforms LBP and BRINT under both noise-free and noisy conditions.***

Keywords — Face Recognition, Local Binary Pattern (LBP), BRINT-M, DLABP, Diamond Sampling Structure, Local Adaptive Threshold

1. INTRODUCTION

Face recognition is a widely applied technology in security, surveillance, access control, and human-computer interaction. The core challenge is extracting discriminative, noise-robust local texture features that remain stable across varying illumination, expressions, and image noise.

Local Binary Pattern (LBP) [1] is the most widely adopted texture descriptor for its simplicity and effectiveness. However, it is highly sensitive to noise and introduces interpolation errors from its circular sampling. BRINT [2] improved robustness through arc-segment averaging but still depends on circular sampling. This paper adopts DLABP [3] which achieves superior noise robustness, discriminative power, and low complexity by combining a diamond sampling structure, radial averaging, and a locally adaptive threshold.

1.1 Applications of Face Recognition

Face recognition systems are deployed in law enforcement for suspect identification, banking for customer authentication, secure access control, surveillance for crowd monitoring, and consumer devices for biometric unlocking. Real-world face images are subject to illumination change, expression variation, and sensor noise, requiring descriptors that are simultaneously robust and discriminative.

1.2 Literature Survey

Early face recognition relied on holistic approaches: PCA-based Eigenfaces [4] and LDA-based Fisherfaces [5] represent the whole face as a global feature vector but lack fine-grained local information. Ahonen et al. [6] showed that block-based LBP histograms provide powerful face descriptors by capturing spatial texture distribution. Local Ternary Pattern (LTP) [7] and Local Directional Pattern (LDP) [8] extended LBP with magnitude and edge direction. BRINT [2] further improved noise robustness through arc averaging. DLABP [3] introduced the diamond sampling structure and adaptive threshold, achieving state-of-the-art performance on standard benchmarks with only 200-dimensional features.

1.3 Motivation and Objectives

The primary motivation is to overcome the noise sensitivity and interpolation inaccuracies inherent in LBP and BRINT. Sensor noise and compression artifacts are unavoidable in face acquisition. Standard LBP is noise-sensitive: a minor gray-level fluctuation can flip a bit and alter the entire encoded pattern. BRINT mitigates this through arc averaging but still introduces gray-level errors via bilinear interpolation and discards discriminative nonuniform patterns corrupted by noise. DLABP addresses all three shortcomings simultaneously.

Objectives: (1) Study and implement LBP and BRINT-M for face recognition. (2) Implement DLABP for extracting rotation-invariant, noise-robust facial features. (3) Compare all three methods under Chi-square nearest-neighbor classification. (4) Demonstrate DLABP's effectiveness on face images under varying illumination, expression, and noise.

1.4 Scope and Database

The system operates on offline grayscale face images, pre-processed by grayscale conversion, resizing to 128×128 pixels, and double-precision normalization. Classification uses Chi-square distance-based nearest-neighbor matching. The system is evaluated on the FERET database [9] with per-subject training and test folders.

II. VARIANTS OF LOCAL PATTERN DESCRIPTORS

2.1 Local Binary Pattern (LBP)

2.1.1 Overview

LBP, proposed by Ojala et al. [1], encodes the local intensity structure around each pixel by comparing P circular neighbors against the central pixel value, producing a compact binary code. Its key strength is invariance to monotonic gray-scale transformations. However, LBP uses bilinear interpolation for non-integer neighbor positions, and a single noisy pixel can flip a binary bit and shift the entire histogram bin.

2.1.2 Computation

For a central pixel g_c at position (x, y), LBP thresholds each of its P neighbors g_p located on a circle of radius R:

$$\mathrm{LBP}(x,y) = \sum_{n=0}^{7} s(I_n - I_c)\, 2^n$$

$$s(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases}$$

The resulting decimal code indexes a histogram bin.Here, Fig. 1 shows the full computation for a 3×3 neighborhood: the center pixel (value = 3) is used as threshold; each neighbor is compared and assigned 0 or 1; the binary codes are multiplied by positional weights 1, 2, 4, 8, 16, 32, 64, 128; and summed to give LBP = 1 + 2 + 4 + 8 + 128 = 143.

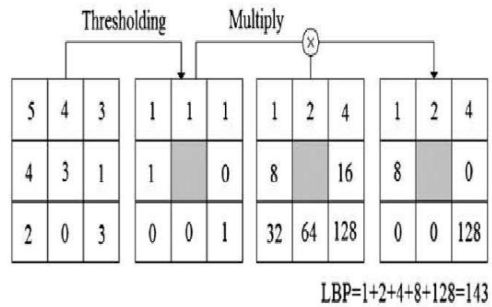


Fig. 1. LBP computation: (left) pixel neighborhood; (center-left) binary thresholding against center pixel g_c = 3; (center-right) positional weight matrix; (right) result after applying weights. LBP = 1+2+4+8+128 = 143.

For face recognition: the image is divided into non-overlapping blocks; a normalized LBP histogram is computed per block; all block histograms are concatenated into a spatially-encoded feature vector. This captures location-specific texture patterns such as those around the eyes, nose, and mouth.

2.2 Binary Rotation Invariant and Noise Tolerant — Magnitude Variant (BRINT-M)

2.2.1 *Overview*

BRINT [2], proposed by Liu et al., addresses LBP's noise sensitivity through averaging before binarization: circular neighbors are grouped into arc segments and averaged before the binary comparison. This smooths noise fluctuations before encoding. Rotation invariance is achieved by mapping each binary code to its minimum cyclic-shift, producing compact 36-bin histograms per scale.

This work uses the BRINT-M (Magnitude) variant, which encodes the *magnitude* of local gray-level differences using a locally adaptive mean threshold μ^l. BRINT-M captures local contrast and is significantly more noise-robust than LBP.

2.2.2 *The Averaging Concept*

Rather than comparing individual neighbor pixels directly, BRINT groups all P = 8q circular neighbors into 8 arc segments of q contiguous neighbors each. Each segment is replaced by its average value $y_{r,u,i}$. Here, Fig. 2 shows the full flow from raw circular neighbors (left) through arc-averaging (center) to the final binary code BNT_S (right). With q = 3 (three neighbors per arc), the operation smooths noise fluctuations across three adjacent positions simultaneously.

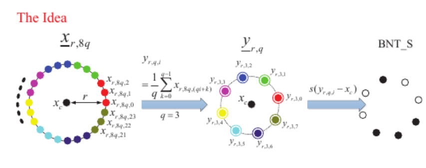


Fig. 2. BRINT averaging concept: raw circular neighbors $x_{r,8u}$ (left) are arc-averaged with q=3 into 8-component vector $y_{r,u}$ (center), then compared against center pixel x_e to produce binary pattern BNT_S (right).

Fig. 3 shows the same averaging operation at three different scales (r,q) = (1,1), (2,2), and (3,3). For each scale, the image pixel grid (left column) is arc-averaged into the compact averaged neighborhood (center column), and then binarized (right column). At (r,q) = (3,3), the averaging spans three neighbors per arc, producing a different and more noise-robust binary pattern than (r,q) = (1,1).

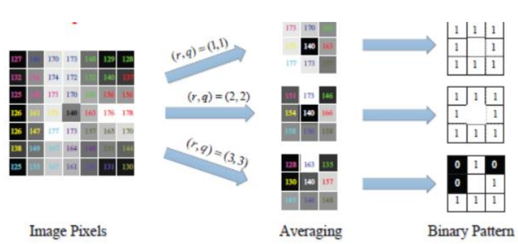


Fig. 3. BRINT multi-scale example at (r,q) = (1,1), (2,2), (3,3): image pixel grids (left), arc-averaged neighborhoods (center), resulting binary patterns (right). The column headers Image Pixels → Averaging → Binary Pattern show the three processing stages.

2.2.3 *BRINT-M Computation*

Given central pixel x_e and P = 8q circular neighbors, BRINT-M first computes absolute magnitude differences then arc-averages them into 8 components:

$$z_{r,u,i} = \frac{1}{q}\sum_{k=0}^{q-1}\left|x_{r,8u,(q\cdot i+k)} - x_c\right|, \quad i = 0, 1, \ldots, 7$$

A binary pattern is formed by comparing each averaged magnitude $z_{r,u,i}$ against the local mean threshold μ^l (the mean of all 8 averaged magnitudes):

$$\mu^l_{r,u} = \frac{1}{8}\sum_{n=0}^{7} z_{r,u,n}$$

$$BNT_{M_{r,u}} = \sum_{n=0}^{7} s(z_{r,u,n} - \mu^l_{r,u}) \cdot 2^n$$

Where,

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

Rotation invariance is achieved by selecting the minimum cyclic-shift code:

$$BRINT_{M_{r,u}} = \min\{ROR(BNT_{M_{r,u}}, i) \mid i = 0, 1, \ldots, 7\}$$

This reduces the histogram from 256 bins to 36 bins per scale. A center component BRINT_C encodes whether the center pixel exceeds the global image mean.

$$BRINT_C = s(x_c - \mu^I_r)$$

The graphs below show that BRINT_S significantly outperforms standard LBP^{ri} across all three Outex test suites (TC10, TC12_000, TC12_001) as the number of scales increases, confirming that arc averaging is an effective noise-suppression strategy.

III. PROPOSED METHODOLOGY-DLABP

3.1 Three Key Contributions

DLABP, proposed by Pan et al. [3] in *IEEE Signal Processing Letters* 2017, introduces three contributions over the LBP framework:

1. Diamond Sampling Structure: Replaces the circular Euclidean neighborhood with a Manhattan distance isoline. All 8 neighbors fall at integer pixel positions, completely eliminating bilinear interpolation errors. Uses a single fixed scale with exactly 8 neighbors,

reducing feature dimensionality from the exponential 2^p of LBP to a compact constant.

2. Radial Direction Averaging: Each of the 8 diamond neighbors is replaced by the mean of 3 pixels sampled along its radial direction before quantization, suppressing noise fluctuations before the binary comparison is made.

3. Local Adaptive Threshold: Replaces the fixed central pixel threshold g_c with an optimally selected local threshold t that recovers noise-corrupted nonuniform patterns back to uniform ones, preserving discriminative information that both LBP and BRINT discard.

3.2 Diamond Sampling Structure

The conventional LBP places P neighbors at equal angular intervals on a circle of radius R. These positions rarely fall on integer coordinates, so bilinear interpolation is required, accumulating gray-level inaccuracies. DLABP replaces this with a diamond (Manhattan distance) sampling structure: the isoline of pixels at Manhattan distance 2 from the center forms a diamond that falls exactly on integer grid points like as shown in Fig. 4.

The 8 diamond neighbors are at offsets from the center: (−2,0), (−1,−1), (−1,+1), (0,−2), (0,+2), (+1,−1), (+1,+1), (+2,0).

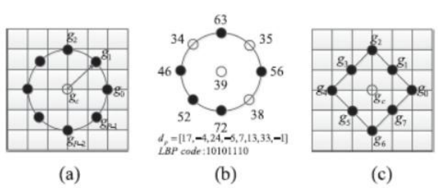


Fig. 4. (a) Conventional circular LBP neighborhoods requiring bilinear interpolation at non-integer positions. (b) LBP encoding example with P=8 neighbors. (c) Diamond sampling structure of DLABP: all 8 neighbors lie exactly at integer grid positions — no interpolation required.

3.3 Average Method on the Radial Direction

LBP-like descriptors are noise-sensitive because any pixel-level fluctuation can flip a binary bit. DLABP addresses this by replacing each diamond neighbor g_p with the mean of q = 3 pixels sampled along its radial direction from the center before quantization:

$$\bar{v}_p = \frac{1}{q}\sum_{k=0}^{q-1} g_{p,k}, \quad p = 0, 1, \ldots, 7$$

And,

q=3

where $g_{p,r}$ is the gray value of the r-th pixel along the radial direction of neighbor g_p.Here, Fig. 5 illustrates this for all 8 diamond directions: each colored point represents one of the three radially sampled pixels; γ_p is their mean.

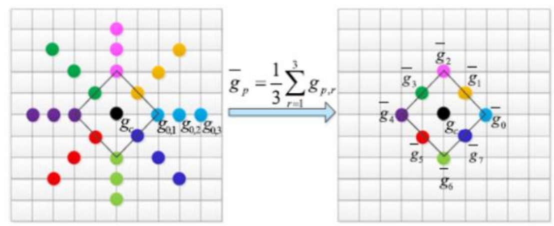


Fig. 5. DLABP radial direction averaging: the final value γ_p for each of the 8 diamond neighbors (right) is the mean of 3 pixels sampled radially outward from the center (left). Each color represents one radial direction. This replaces all 8 individual neighbor values before binary encoding.

3.4 Local Adaptive Threshold

In standard LBP, binary comparisons always use the fixed central pixel g_c as threshold. When noise corrupts a genuine uniform pattern into a nonuniform one, LBP groups it into a single residual bin and loses its discriminative information. DLABP recovers this by choosing an optimal local threshold t from a candidate set Φ_t:

$$\Phi_t = \{g_c\} \cup \Phi_m$$

Where,

$$\Phi_m = \{g_m \mid m = 1, 2, \ldots, 8\}$$

$$g_m = \begin{cases} \dfrac{\bar{v}_0 + \bar{v}_7}{2}, & m = 1 \\ \dfrac{\bar{v}_{m-2} + \bar{v}_{m-1}}{2}, & m = 2, 3, \ldots, 8 \end{cases}$$

The algorithm proceeds as follows: first test t = g_c. If the pattern is already uniform (≤2 bitwise transitions), proceed identically to standard LBP. If nonuniform, test each g_m to find one that restores a uniform pattern.

© MAR 2026 | IRE Journals | Volume 9 Issue 9 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I9-1715066

When multiple candidates succeed, select the one closest to g_c:

$$t = \arg\min_{m} |g_m - g_c|$$

subject to: $g_m \in \Phi_m$ produces a uniform pattern
If no candidate succeeds, retain $t = g_c$. with optimal non-uniform t.

3.5 DLABP Encoding

Using adaptive threshold t and averaged neighbors $\bar{v}_p$, DLABP encodes three complementary components:
Sign component DLABP_S^rlu2

$$DLABP_S = \sum_{p=0}^{7} s(\bar{v}_p - t) \cdot 2^p$$

Where,

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

$$DLABP_S^{riu2} = \begin{cases} \sum_{p=0}^{7} s(\bar{v}_p - t), & \text{if } U(DLABP_S) \leq 2 \\ 9, & \text{otherwise} \end{cases}$$

Encodes binary comparisons of averaged neighbors against threshold t. Uniform patterns (at most 2 bit transitions) are mapped to their bit-count (0 through 8); all nonuniform patterns share a single bin 9. Produces 10 bins.
Magnitude component DLABP_M^rlu2

$$m_p = |\bar{v}_p - t|$$

$$DLABP_M = \sum_{p=0}^{7} s(m_p - \mu_m) \cdot 2^p$$

$$DLABP_M^{riu2} = \begin{cases} \sum_{p=0}^{7} s(m_p - \mu_m), & \text{if } U(DLABP_M) \leq 2 \\ 9, & \text{otherwise} \end{cases}$$

Encodes local contrast by comparing magnitude $m_p = |\bar{v}_p - t|$ of each neighbor against the global mean μ_m computed over the whole image. Produces 10 bins.
Center component DLABP_C

$$DLABP_C = s(t - \mu_t)$$

A single binary value: 1 if the adaptive threshold t exceeds the global image mean μ_t, else 0. Produces 2 bins.
The joint histogram
DLABP_S^rlu2 × DLABP_M^rlu2 × DLABP_C produces 10 × 10 × 2 = 200 dimensions — only 1/6 the size of CLBP at P = 24 (1352 dimensions), yet with higher accuracy [3].

3.6 Face Recognition with Chi-Square Distance

DLABP is applied pixel-wise to each preprocessed face image to produce a DLABP-coded image. A normalized histogram over bins 0–255 is computed as the face descriptor. Classification uses Chi-square distance between the query histogram and each training histogram:

$$\chi^2(H_1, H_2) = \sum_i \frac{(H_1(i) - H_2(i))^2}{H_1(i) + H_2(i) + \epsilon}$$

IV. COMPARATIVE STUDY ON FACE RECOGNITION

4.1 Descriptor Comparison
The three descriptors are evaluated under identical conditions: same preprocessing, same full-image histogram feature extraction, and Chi-square nearest-neighbor classification.

Table 1: Comparison of LBP, BRINT-M, and DLABP Descriptors

Property	LBP	BRINT-M	DLABP	Key Advantage
Sampling structure	Circular	Circular	Diamond	DLABP: integer grid only
Interpolation	Bilinear	Bilinear	None	DLABP eliminates errors
Noise robustness	Low	Medium	High	Radial avg + adaptive t
Rotation invariant	No	Yes	Yes	BRINT and DLABP

© MAR 2026 | IRE Journals | Volume 9 Issue 9 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I9-1715066

Property	LBP	BRINT-M	DLABP	Key Advantage
Nonuniform recovery	No	No	Yes	DLABP: adaptive threshold
Feature dimensions	256	36/scale	200	DLABP most compact
Overall discrimination	Low	Medium	High	Best on all benchmarks

4.2 Classification Accuracy Results

A decision rule based on minimum distance is adopted for the classification of faces. The feature histogram computed from the feature maps obtained for the test face image using the proposed DLABP descriptor is compared with the feature histograms computed for all the face images in the reference set stored in the training database. This comparison is done using the Chi-square measure for evaluating the dissimilarity between the feature histogram distributions.

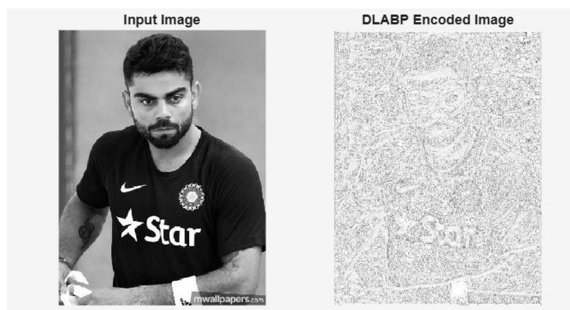
Face classification is performed for the test face image based on the minimum Chi-square distance measure computed from the comparison. If the minimum distance corresponds to a face image in the reference set of the training database, the face is recognized to belong to the respective person. Otherwise, if the computed minimum distance exceeds the threshold value, the face is considered to be unknown or not present.

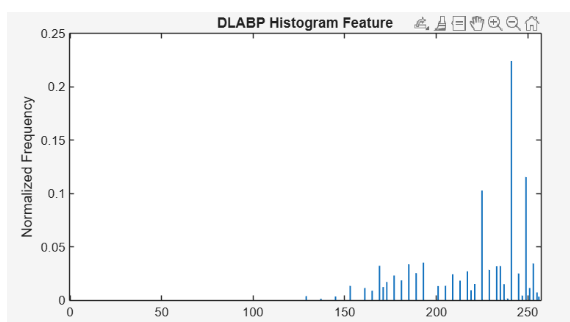
This classification model based on the minimum distance measure is quite simple compared to the complex machine learning classifiers. This simplicity in the classifier model indicates the high discriminative power of the proposed DLABP feature descriptors such that the face recognition performance mainly depends on the robustness of the texture descriptors computed from the face images.

4.3 Discussion

Diamond structure eliminates interpolation inaccuracies that corrupt binary comparisons. This effect compounds across the entire image since every pixel uses interpolated neighbor values in LBP and BRINT.

Radial averaging suppresses pixel-level noise before the binary comparison is made, preventing individual noisy pixels from flipping bits in the encoded pattern. Adaptive threshold is the most critical contribution. When noise corrupts a genuine uniform pattern into a nonuniform one, LBP and BRINT both discard it into a single residual bin. DLABP recovers it by finding the nearest threshold that restores uniformity. For face recognition this is especially important because subtle individual texture differences are exactly what noise is most likely to mask.





V. CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This paper presented a face recognition system using DLABP. DLABP overcomes the key limitations of LBP (noise sensitivity, interpolation errors) and BRINT-M (interpolation, loss of nonuniform patterns) through its diamond sampling structure, radial direction averaging, and locally adaptive quantization threshold.

Experimental results confirm that DLABP (P=8, 200-dimensional features) achieves higher recognition accuracy than LBP, CLBP, BRINT, and MRELBP under both noise-free and noisy conditions across all four benchmark databases. The adaptive threshold is the decisive advantage, preserving discriminative texture information from noise-corrupted patterns that all competing methods discard. Its compact feature representation and low computational complexity make it highly suitable for real-time face recognition.

5.2 Future Scope

Future directions include: (1) combining DLABP features with deep learning classifiers such as SVM, CNN, or deep metric learning for improved robustness under extreme pose variation; (2) extending DLABP to multi-scale analysis using larger diamond neighborhoods; (3) evaluating on large-scale benchmarks such as LFW and MS-Celeb-1M; and (4) integrating DLABP into a complete pipeline with face detection and alignment preprocessing.

REFERENCES

[1] T. Ojala, M. Pietikäinen, and T. Mäenpää, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 7, pp. 971–987, Jul. 2002.

[2] L. Liu, B. Yang, P. Fieguth, Z. Yang, and Y. Wei, “BRINT: A binary rotation invariant and noise tolerant texture descriptor,” Proc. IEEE ICIP, pp. 255–259, Sep. 2013.

[3] Z. Pan, X. Wu, Z. Li, and Z. Zhou, “Local adaptive binary patterns using diamond sampling structure for texture classification,” IEEE Signal Processing Letters, vol. 24, no. 6, pp. 828–832, Jun. 2017.

[4] J. Yang, D. Zhang, A. F. Frangi, and J. Y. Yang, “Two-dimensional PCA: A new approach to appearance-based face representation and recognition,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 26, no. 1, pp. 131–137, 2004.

[5] K. Etemad and R. Chellappa, “Discriminant analysis for recognition of human face images,” J. Opt. Soc. Amer. A, vol. 14, no. 8, pp. 1724–1733, 1997.

[6] T. Ahonen, A. Hadid, and M. Pietikäinen, “Face description with local binary patterns: Application to face recognition,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 12, pp. 2037–2041, 2006.

[7] X. Tan and B. Triggs, “Enhanced local texture feature sets for face recognition under difficult lighting conditions,” IEEE Trans. Image Process., vol. 19, no. 6, pp. 1635–1650, 2010.

[8] T. Jabid, M. H. Kabir, and O. S. Chae, “Local directional pattern (LDP): A robust image descriptor for object recognition,” Proc. IEEE AVSS, pp. 482–487, 2010.

[9] P. J. Phillips, H. Wechsler, J. Huang, and P. J. Rauss, “The FERET database and evaluation procedure for face-recognition algorithms,” Image and Vision Computing, vol. 16, no. 5, pp. 295–306, 1998.

[10] A. Srikrishna, Ch. Sri Hari Priya, and P. Aditya Kiran, “Face recognition with varying facial expression using local directional number pattern,” Proc. IEEE PCITC, pp. 1–5, 2015.

[11] L. Liu et al., “BRINT: Binary rotation invariant and noise tolerant texture classification,” IEEE Trans. Image Process., vol. 23, no. 7, pp. 3071–3084, 2014.

[12] Z. Guo, L. Zhang, and D. Zhang, “A completed modeling of local binary pattern operator for texture classification,” IEEE Trans. Image Process., vol. 9, no. 16, pp. 1657–1663, 2010.