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# Human emotion recognition based on block patterns of image and wavelet transform

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## Abstract
***In this manuscript, Human Emotion Recognition based on Block Patterns of Image and Discrete Wavelet Transform (HER-BP-DWT) is proposed. The different facial parts, such as eyebrows, eye, lips, mouth, and muscle movements play an important role in emotion recognition. But according to change in age, the movements of facial parts and muscles become weaker, so recognizing emotions can be a little more tedious and complicated. Therefore, in this manuscript, a new approach that is different from the conventional one using block patterns and discrete wavelet transform is proposed. Here, first of all, the test image is divided horizontally and vertically into different block patterns. Then, each block is separated as sub blocks. The particular area block is decomposed into different frequency sub bands with the help of discrete wavelet transform. The energy of these sub bands of each block is calculated. The energy of sub bands of the test image and the reference image is compared. The main aim of this proposed method is to recognize emotional expressions using a simple parameter, like energy of sub bands that is obtained from discrete wavelet transform and it is easy to use. The main objective is to increase the accuracy during face image recognition. The proposed HER-BP-DWT method can be efficiently and accurately recognized different emotions, such as happiness, sadness, anger, etc. The proposed method is very convenient to use due to the use of block patterns. The proposed approach is activated in MATLAB platform, then the performance is compared with other existing approaches, such as Human Emotion Recognition using Convolutional Neural Networks (HER-CNN) and Human Emotion Recognition using Bimodal Fusion Algorithm (HER-BFA). Finally, the experimental results show that the HER-BP-DWT method is superior to the existing methods. From the experimental analysis, the HER-BP-DWT method shows the accuracy of 99.55%, sensitivity of 85.93%, precision of 92.43% and 90.74% of specificity, which is prominent than the existing methods.***

## Keywords
***Energy component, Discrete wavelet transform, Image blocks, Pattern, Coefficients of frequency sub bands, Facial emotion expression.***

## 1.Introduction
Nowadays, the facial images, such as facial expression, gestures, and other factors are making them hard to recognize accurately. The main issue of facial recognition is "how to remove such harmful factors?" To extract the facial feature, the facial features need some robustness for the beyond factors [1]. Human being normally communicated, either verbally or non-verbally with the world. In both ways of communication, the expression of the face varies with the state of situation [2].

Expression of people is considered as a non-verbal communication. While expressing themselves, words and gestures are not enough to exhibit, but emotion plays a vital role to understand the person's desires or expectations. Through emotions, human can fully express themselves [3]. Therefore, this is a significant way of nonverbal communication between the human. In various application fields, such as robotics, surveillance, information security, human machine interaction, and video editing, the different emotion recognition techniques and its analysis carry enormous significance to run that particular application smoothly [4]. The development of an effective emotional recognition system is still a major

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challenge due to the moment of the muscles under the face skin and the micro expression that is present in the face for a few milliseconds [5, 6]. The facial expression is always the main focus when interacting with each other [7]. These expressions provide a lot of details of social information [8–10]. Furthermore, these expressions may be voluntarily or involuntarily adopted by human, while these are utterly controlled by the nervous system of the human and it differs from person to person [11–13]. From these facial expressions of human, one can easily understand the mental, emotional, and physical state of communication. The emotion recognition system has a wide range of utilizations, viz emotional robot, performance forecasting user-friendly interface amid the man and machine [14–16]. Nevertheless, emotion recognition by untrained person is difficult. Hence, it is significant to know the mind status from expression, because mind status can be easily read from different parts of the face such as mouth, eyes, eyebrows, etc. Proper feature extraction is a noteworthy step of automatic recognition, emotion system [17, 18]. In many self-assessment applications, emotions are being utilized for the improvement of individual as well as company performance, but humans are very skilful in hiding and suppressing emotions. Hence, there is a need to develop a defective and easy emotion recognition technique that can be user friendly and it can be easily implemented in the hardware platform.

The dimension of the higher dimension image information should be minimized, as there is a higher dimension with unnecessary information present in the original facial image. Nevertheless, facial information contains only a smaller portion of full-face information and traditional Principal Component Analysis (PCA) exposure can lead to more information loss [19]. Lastly, classified work can be done through machine learning methods, like Support Vector Machine (SVM) classification, Neural Network (NN). The success of the facial recognition system is to deal with the problem that light, colour and background are exposed to many variations of the complex human face. Therefore, this manuscript proposes the recognition of automated face identification, face expression utilizing wavelet methods under complex backgrounds. This Discrete Wavelet Transform (DWT) method provides high accuracy, high speed with less computational complexity compared with the existing methods.

One on a challenging research topic is human face recognition method. The Facial Expression Recognition (FER) approaches contain Gabor Wavelet Transform (GWT), Active Appearance Model (AAM), Local Binary Pattern (LBP). The GWT technique extracted face imagery texture information in several scales with direction attains better outcomes [20]. But the cost of time and the complexity of space are high. The facial expression dynamics can capture through analyzing locations of signs from AAM, which is utilized for extracting shape feature. Even though AAM can effectively get facial feature points, the fitting approach has a non-linear optimized issue, which has increased the calculation process to a more complex as well as computational complexity.

In this manuscript, an emotion recognition algorithm is proposed based on specific block patterns and discrete wavelet transforms. Emotion recognition is carried out by the analysis of the movement of facial muscles, which is very critical for the micro expression and remains very short time on the face. Many researchers have identified the human emotion based on different psychological signals, such as heart rate, brain signal, and skin temperature but recently brain signal has captured a lot of popularity for the recognition of emotion. For the extraction of features either for processing and classification of emotions from the human face, many researchers have adopted different tools ranging from frequency transform into different kinds of wavelet transform along with advanced methods. Several works were presented in the literature to overcome the limitations, such as diminish the dimensionality of face image, loss of information due to lack of space, poor accuracy of the system, but the presented works are not much effective. These drawbacks have motivated to do this research work.

The objective of this proposed algorithm is to identify the emotional expressions with the help of a simple parameter, like energy of sub bands that is obtained from DWT and it is easy to use and it is to increase the accuracy during the face image recognition.

The choice of wavelet transform is driven through its insensitivity. Here, experiments utilized contact as well as start values to ensure greater consistency of the produced classified results. The encouraging test outcomes established the proposed approach utilizing frontal and side-view images are feasible, effective solution to identifying faces, which can lead to, well, practical use of forensic databases that exist in computerized human facial recognition requests.

The main contributions of this manuscript summarizing below,

1) In this manuscript, human emotion recognition depending on block patterns and DWT is proposed
2) Initially, the test image is divided horizontally and vertically into different block patterns [21].
3) Each block is separated as sub blocks. The particular area block is decomposed into different frequency sub bands with the help of DWT. The energy of these sub bands of each block is calculated [22].
4) The main aim of this proposed algorithm is to identify emotional expressions with the help of a simple parameter, like energy of sub bands that is obtained from DWT and it is easy to use.
5) The proposed algorithm can be able to identify the different emotions, such as happiness, sadness, anger, etc. efficiently and correctly
6) Due to the use of block patterns, the proposed algorithms become convenient to use.
7) The proposed Human Emotion Recognition based on Block Patterns of Image and Discrete Wavelet Transform (HER-BP-DWT) method shows better than the existing methods, such as Human Emotion Recognition using Convolutional Neural Networks (HER-CNN) and Human Emotion Recognition using Bimodal Fusion Algorithm (HER-BFA).

In this work, an explanation of the system description and methodology consists of three parts: block pattern of the image (text /reference image), the use of DWT, and extraction of features and its comparisons have been discussed thoroughly. The rest of this manuscript is structured as follows: section 2 presents the literature review. Section 3 illustrates about the proposed method. Section 4 demonstrates the experimental results and discussions. Section 5 concludes the manuscript.

## 2.Literature review

Xu et al. [23] have presented the emotional computing in the field of Internet of things (IoT). Here, emotions were identified and classified by feature extraction with the help of double tree complex wavelet transform. The presented algorithm was proved its effectiveness for the extraction of feature vector and it was improved the efficiency of emotion recognition system.

Acharya et al. [24] have presented the combined emotions and brain signal, which was obtained while stimulating the emotions of humans using different movie clips. Furthermore, these brain signals as electroencephalogram device were removed with fast Fourier transform and apply that genetic programming for the classification of emotions.

Zang et al. [25] have introduced bi-orthogonal wavelet entropy for the extraction of multiple scale characteristics with the fuzzy support vector machine was used for classifying emotions from the facial images.

Ayyavoo and Suseela [26] have suggested DWT to minimize the illumination effect of facial images before processing for emotion recognition.

Krishna et al. [27] have presented a tunable Q-wavelet transform by utilizing brain signals for the classification of emotions. Here, wavelet transforms decompose the brain signal that was obtained from the electroencephalogram and different features were extracted and processed for classification.

Meena et al. [28] have introduced the facial expression of the input image into local patterns and graph wavelet transform was applied to it to extract the features.

Ekman and Friesen [29] have introduced a legendarily FER named ‘Facial Action coding system (FACS)’ which was mostly referred by many upcoming researchers and scientists. Authors have discussed different facial emotions such as amazement, fright, anger, hatred, pleasure, sorrow; such emotions were typically utilized in the field of human recognition techniques [30]. The illumination conditions could play a vital role in determining the different emotions from facial images and videos as it affects more in those images.

Sown [31] have suggested the pioneer of the automatic FER method. The suggested system was deemed with the help of different twenty image structures. The suggested system was classified into three different parts: face identification with monitoring, feature extraction, emotion categorization. The features were extracted from the geometry or appearance of facial images or videos whose emotions need to be identified. Skin texture variations, via wrinkles, furrows were studied meticulously in the appearance-based feature extraction system or techniques for whole face including selected face areas.

Li et al. [32] have presented a texture descriptor-based Gabor wavelets were used in plane image transform. Most of the comprehensive literature surveys of facial emotion recognition techniques were adopted [33]. The most relevant part of this technique was to remove valid features in either spatial nor Frequency Domain (FD). The count of approaches depending on FD features was Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), DWT, Discrete Fourier Transform (DFT), GWT, Curve let transform. Presently, different facial elements such eyes, lips, eyebrows, etc., and movement of muscles which remain on a very short duration have not given enough attention on the FER systems field in the FD.

Huang et al. [34] have presented a strong face detected process depends on the skin color enhancement along with FER approach using block PCA. Here, the experimental outcomes show efficiency via 2.7% compared to the traditional process of LBPs.

Belhouchette et al. [35] have suggested a novel strategy to recognize fundamental emotions on image progression. The emotion of interest and generated their equivalent Action Units (AU) depending on psychology basics. Finally, the suggested method classified the outcomes with Kohonen Self Organizing Map (SOM)

Wei [36] have presented a new facial recognition algorithm on uncontrolled environment that combines Local Binary Pattern of Central Block Symmetry (CS-LBP) and the Deep Residual Network (DRN) form. The experimental results displayed the recognition rate and its superiority.

Zhang [37] have presented a dynamic face recognition approach based on block sample feature. According to the principal component feature decomposition approach, each block feature quantity was planned into foundation coordinates of test face sample set. The simulation outcomes portray that the algorithm had better feature matching and high recognition accuracy.

Putri et al. [38] have introduced a face recognition algorithm depending on block sample feature matching. According to principal component feature decomposition algorithm, each block feature quantity was planned into base coordinates of test face sample set. The simulation outcomes portray that the introduced algorithm had better feature matching and high recognition accuracy.

Li [39] have presented a gray relational analysis system. Here, the face image was considered a major investigation topic, an image recognition model depends on the gray relational analysis system was established and linked experimental outcomes were arriving. Compared with the traditional facial image recognition system, the presented system had greater recognition speed and good recognition efficiency.

Baker et al. [40] have presented an effectual system of facial recognition. Here, features were removed with PCA to diminish the dimensionality of facial images. FFBBL provides accuracy of (98.33, 98.80) with (40, 50) characteristics, while Elman provides (98.33, 95.14) with (40, 50) characteristics.

Shi and Tang [41] have presented a facial recognition approach depending on self-adaptable LBP, dual channel Convolutional Neural Network (CNN) using diverse convolutional nuclei. The outcomes portrayed that the presented system had a great respect rate as well as calculation performance.

Li and Cui [42] have presented 3D image reconstruction system of human maxillofacial defects based on lump model features matched. A human maxillofacial image features a matched pattern was built; 3-dimensional edge contour segmentation were executed for model images using blocking system. The simulation outcomes proved that the presented system contains better capability to detect and detect features and can provide high accuracy.

Nhat and Hoang [43] have presented a face recognition research topic on machine vision due to its highly secure demands. Here, the feature fusion was used with canonical association analysis to concatenate two dissimilar feature sources for encoding the facial image. Three descriptors (Histograms of Oriented Gradients (HOG), LBP, Global Descriptors (GIST)) were researched to extract the facial features based on block division.

Tran-Trung and Hoang [44] have presented hand gesture recognition applications at current years, like robotics, electronic commerce, human-machine interaction, electronic sports, and assistance to people with hearing disabilities. The document presents a strategy to hand gesture recognition in multi-view cameras. The presented strategy was assessed at HGM-4 reference dataset with LBPs.

Qin et al. [45] have presented a novel opinion on a few cases of different representations of facial images were helpful with facial recognition and appropriately diminishing that image resolution could be helpful for better classification of facial images. Furthermore, the idea appears to be helpful in serving people enhance facial recognition systems at real world.

Mi et al. [46] have introduced PCA depend strong feature extraction methods to treat the image with its transferred vector, leading to the latent information loss performed with images. PCA depending on block norm minimal using block norm. Performance was assessed with multiple datasets and outcomes were likened to other PCA-based methods.

Liu [47] have presented a feature recognition system for related human face key opinions. The experimental outcomes show the recognition time of suggested system was< 0.7 s, SNR > 24 dB, the recognized accuracy was > 90%.

Mehta et al. [48] have presented a development of automated assistance systems based on facial recognition. The relative study was performed to choose suitable detection, classified approaches as faster Region-based Convolutional Neural Network (R-CNN) as well as SVM classification outperformed its equivalent competitors.
Aiordachioaie et al. [49] have established thermal imaging of human faces of categorization purposes. Several data transforms were deemed with image processing, accompanied via information-based transformations, classification was considered. The result displayed that flexibility of toolbox depends on Discrete Cosine Transform (DCT) for feature selection.

Gnouma et al. [50] have suggested a supervised form via unsupervised learning with auto-encoder principle. Novel foreground detection depending on information removed as Gaussian Mixture Model (GMM) integrates uniform movement of optical flow magnitude. The outcomes demonstrate that the performance of the suggested strategy regarding with an irregularity in the performance of a stock, distortion of the form, point change, scale important changes.

Majhi and Pal [51] have presented retrieval scheme of image using block-level hybrid feature. The 1st level characteristics were created the DCT application; the 2nd-level characteristics were arrived that Singular Value Decomposition (SVD) processed. For the recovery mechanism, the similarity was scaled with five existing distance measurement systems to verify the performance. *Table 1* shows the Comparative analysis of literature review.

**Table 1** Comparative analysis of literature review

| **Author and year** | **Method** | **Advantages** | **Disadvantages** | **Performance** |
|---|---|---|---|---|
| Huang et al. [34] | Human emotion recognition depends on facial expression detection with the deep belief network | Accurately recognize the face | Human face images greatly in real environments based on difficult backgrounds and luminance | Face detection, FER was accomplished successfully |
| Belhouchette et al. [35] | Interest emotion recognition strategy with self-organising map along with motion estimation | Optimize the calculation time and enhance that recognition rate | Number of resources and calculation time are increased | Accurately recognize the face |
| Wei [36] | An innovative face recognition of non-controlled environment | Detecting the identity of individuals to monitor systems, security | Poor accuracy | The face detection, FER was accomplished positively |
| Zhang [37] | Improvement of face recognition technology based on intelligent image | Robust to the change of skin color and pose | The corner detection and texture matching of the face are carried out | The simulation outcomes show that the system had better feature matching and high recognition |
| Putri [38] | Indonesian ethnicity recognition depends on face image with Uniform Local Binary Pattern (ULBP) | Good feature matching and high recognition accuracy | High calculation time | Face detection and FER was accomplished successfully |

| Author and year | Method | Advantages | Disadvantages | Performance |
|---|---|---|---|---|
| Li [39] | Image Recognition depends on grey relational analysis | High recognition accuracy | Poor classification accuracy | Higher recognition speed and good recognition performance |
| Baker et al. [40] | Facial recognition enhancement using an artificial neural network by PCA | Detect people's identity to monitor systems, security and numerous practical fields | Diminish the dimensionality of face image | The outcomes show that the presented system was effective and extremely accurate |
| Shi and Tang [41] | Face recognition approaches depends on self-adaptive blocking LBP | To recover successfully the face recognition rate | The distribution of the bright, dark spot and other micro details cannot be completely fulfilled | The outcomes show that the presented system had great recognition rate and computational efficiency |
| Li and Cui [42] | 3D image reconstruction system of human maxillofacial defect imaging depends on matching block sample features | Three-dimensional image recognition and reconstruction of human maxillofacial defects | Human face image sample template matching, edge contour segmentation is mistreated | The simulation outcomes show that the presented system contains, the better ability to detect and detect features and can provide high precision |
| Nhat and Hoang [43] | Function fusion with HOG, LBP, GIST descriptors along with canonical correlation analysis of facial recognition | Improve the accuracy of face recognition systems | Poor classification accuracy | to recover efficiently that face recognition |
| Tran-Trung and Hoang [44] | Hand gesture recognition in Multiview cameras with local image descriptors | Good feature matching and high recognition accuracy | High calculation time | Face detection and FER were accomplished successfully |
| Qin et al. [45] | Discover alternative representations of facial images with facial recognition | Browse high resolution face images for better image ranking | The amount of used resources and calculation time is increased | Useful to help people improve facial recognition |
| Mi et al. [46] | Block-norm minimization based PCA | Good feature matching and high recognition accuracy | Latent information loss performed with images | It was efficiently depress the effect of corrupt blocks. |
| Liu [47] | A feature recognition system for related human face key points depends on the adaptive median filter | To eliminate that the image influence background on related key feature points recognition | Low efficiency and poor accuracy | Recognition accuracy was more than 90%, recognition good results. |
| Mehta et al. [48] | Real time image processing: integrated face recognition based automated attendance system | High recognition accuracy | Poor classification accuracy | Higher recognition speed and good recognition performance |
| Aiordachioaie et al. [49] | On processing, thermal images of human faces for classification purposes | Detecting that identity of individuals for monitoring systems | Correct representations and descriptors / characteristics of great recognition | The outcomes were hopeful and exhibit the flexibility |
| Gnouma et al. [50] | Stacked sparse autoencoder and binary motion image | Recover that accuracy of facial recognition systems | Minimum efficiency | The outcomes demonstrate that the efficiency of presented strategy regarding within discretion |

| Author and year | Method | Advantages | Disadvantages | Performance |
|---|---|---|---|---|
| | | | | under the performance |
| Majhi and Pal [51] | The image retrieval system depends on block level hybrid DCT-SVD fused features | Robust to the change of skin color and pose | the corner detection and texture matching of the face are carried out | The simulation outcomes show that the presented algorithm had great recognition accuracy |

## 2.1Research gap

One of a challenging research topic is human facial recognition method. The FER approaches contain GWT, AAM, and LBP. The GWT technique extracted face imagery texture information in several scales with direction attains better outcomes. But, the cost of time and the complexity of space is high. The facial expression dynamics can capture through analyzing locations of signs from AAM that is utilized for extracting shape feature. Though AAM can effectively get facial feature points, the fitting approach has a non-linear optimized issue, which has increased the calculation process to a more complex as well as computational complexity.

To overcome these issues, human emotion recognition based on block patterns of image and DWT is proposed. Here, DWT is utilized to extract the features of facial image for proposed algorithm due to its good localization characteristic. Before the application of DWT to an image whose emotions are to be identified, the image is divided into different block patterns, which is utilized in the remaining processing of the proposed algorithm. Among different evaluation parameters such as energy, covariance, correlation coefficients, etc., the dominant parameter energy is used to determine the emotions of the text image from the reference image. Finally, the proposed method increases the accuracy with less complexity during the face image recognition.

## 3.System description and methodology

DWT is proposed to capture the faces differences. Facial recognition can be done utilizing thresholding the range depending on the contact. Here, the wavelet change was motivated in the direction of light, facial pose and facial expression. The experiments utilized contact as well as start values to ensure greater consistency of product classification results. Encouraging test outcomes, the proposed algorithm is a viable and effective solution for recognizing faces, which leads to, well, practical use of forensic databases that exist in computerized human facial recognition applications. *Figure 1* shows the Block diagram of the proposed method.

The proposed system for emotion recognition is classified into three parts.

1. Block pattern of the image (text /reference image)
2. Use of DWT
3. Extraction of features and its comparison

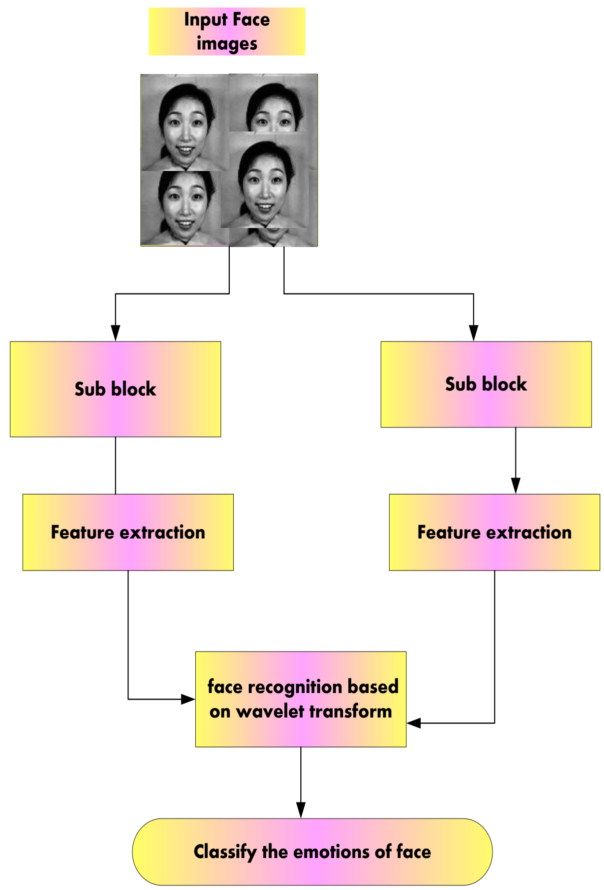



**Figure 1** Block diagram of the proposed method

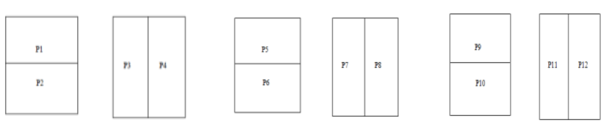
### 3.1Block pattern of the image (text /reference image)

Normally, the face is a part of the body that is either used in face recognition techniques or emotion recognition systems. Face recognition is comparatively easy as in emotions micro expressions are involved that remain on for milliseconds or microseconds to face.

Thus, capturing the micro expression is a little tedious and complicated. Furthermore, muscle movements of the face play a vital role in understanding emotions, and these muscle movements vary from person to person. However, the changes in emotion employ a change in the positions of muscles that generate different variations in the lines which are formed on the face. These formed lines change the energy of a specific part of the face. Hence, in the proposed algorithm, before feature extraction by DWT, the face (emotions to be recognized) is divided into specific block patterns which are utilized to measure different parameters such as energy, covariance, correlation coefficient etc.

The division of block pattern is elaborated as follows:

1. Text image is initially divided into two parts vertically and horizontally, named as $P_{1,}$ $P_2$ and $P_3$, $P_4$, respectively.
2. Again, the blocks of images$P_1$ and $P_2$ are further divided vertically and horizontally into two parts, namely, $P_{5,}$ $P_6$ and $P_7$, $P_8$, respectively.
3. In this fashion, each block of the image is divided vertically and horizontally into sub-blocks.
4. This division of the block may extend to a large number of sub-blocks, but in this proposed algorithm, it is limited up to 12 by extensive observation. The block division hierarchy is shown in *Figure 2*.




a. Division of Test image b. Division of block P1/P2 c. Division of block P3/P4

**Figure 2** Block division hierarchy for generation of pattern

## 3.2Detailed description of DWT algorithm for face reorganization

In this manuscript, the DWT is generally utilized Transform in image process. This DWT method provides high accuracy, high speed with less computational complexity and DWT is capturing the differences in faces. Face recognition depends on contact can be done through utilizing threshold.

The DWT decay an image as a set of depended functions named wavelet; decay is defined as "resolution" of imagery. DWT acts a signal multiple resolution analysis along localization in both times, frequency domain. The 2D-DWT filter is applied as a set of banks, which includes a continuous plan of high and pass filters. The final outcomes derived are a decay of input image as 4 non-overlapping multi-resolution sub bands: LL, LH, HL, HH. The sub-band LL signifies coarse-scale DWT coefficients, sub-bands LH, HL, HH denote the fine-scale of DWT coefficients. HH is discovered for face recognition.

The detailed explanations of the DWT algorithm are given below:

Step1. Every face reorganization image decomposes with the help of DWT.

Step2. HH band of decayed imagery is utilized to more process.

Step3. HH band resizes to original image size.

Step4. Every resizing image is divided into sub images.

Step5. Convert every sub picture as a column data matrix. Each of them expresses in order to D-by-N. Then the decomposition equation is given as $K_j = \{k_{j1} + k_{j1} + \ldots k_{jM}\},\ j = 1,2,..L\ ,M$ is represented as the total count of images.

Step6. Calculate the average value for each sub-image.

Step7. Subtract the average value from the column data matrix of every subimage, then vertically centralized column data matrix as $K_{nj} = \{\vec{k}_{j1} + \vec{k}_{j1} + \ldots \vec{k}_{jM}\},\ j = 1,2,..L$

Step8. Rearrange components to obtain square matrix.

Step9. Gather Eigen values, Eigenvectors, diagonal values of square matrix as, $H_j = \{H_{j1} + H_{j1} + \ldots H_{jP}\},\ j = 1,2,..L\ ,$

Here, $P$ is represented as the sub image feature. Then attain trained data base matrix $Y_{mj} = L_{xj}{}^T Z_{xj} = \{Y_{j1} + Y_{j2} + \ldots Y_{jP}\} = 1,2,..L$

Step10. Replication same process for row data matrix.

Step11. Lessen the required feature size $Y_{mj} == \{Y_{i1}{}^T + Y_{i2}{}^T + \ldots Y_{iP}{}^T\} i = 1,2,..L$

Step12. The steps above are repeated to create feature 2 for the entire picture without DWT.

Step13. Minkowski distance is utilized recover related images

Step14. Minkowski distance focuses on Euclidean space that is measured as both Euclidean generalization, Manhattan distance for receiving efficiency of more recognition. The Minkowski distance depends upon factor $L$ .

$$L = (a_1, a_2, \ldots. a_m) \quad (1)$$

Minkowski distance is utilized through p existence 1 or 2. In limited case of $L$ attainment infinity gets the Chebyshev distance.

$$F_d\left(x,z\right)=P_L\left(x,z\right)=\left(\sum_{a=1}^{m}\left|a_j-b_j\right|^l\right)^{j/l} \qquad (2)$$

Minkowski distance is frequently utilized when variables have been scaled on ration scales bycomplete0value.

### 3.3Extraction of features and comparisons

The different evaluator parameter which is derived from the frequency sub band of each block of text and reference image after application of wavelet transform is compared.

This evaluation is carried out in unique and specific ways, so the maximum match is obtained from the text and reference image based on different parameters. Based on this comparison, a conclusion is determined about the classification of emotions, like happiness, anger, sadness, etc. The comparative blocks of different patterns are shown in *Tables 2, 3,* and *4, 5*.

**Table 2** Basic block comparison

| Test imagery blocks | Reference imagery blocks |
|---|---|
| P1 | P1 |
| | |
| P2 | P2 |
| P3 | P3 |
| P4 | P4 |

**Table 3** Block comparison of P1/P2 test imagery

| Test imagery blocks of P1/P2 | Reference imagery blocks |
|---|---|
| P5 | P1/P2 |
| P6 | P1/P2 |
| P7 | P1/P2 |
| P8 | P1/P2 |

**Table 4** Block comparison of P3/P4 test image

| Test imagery blocks | Reference imagery blocks |
|---|---|
| P9 | P3/P4 |
| P10 | P3/P4 |
| P11 | P3/P4 |
| P12 | P3/P4 |

### 3.4Face recognition depends on wavelet transform Algorithm

Here, the document, depending on wave transformation and face recognition of PCA block, indicated with Wavelet Transform on Block PCA (WT-BPCA) that has 2 processes: trained and recognized process. The exact method as below:

A. Training process

(1) Initially, the images of faces are carried out wavelet transform.

(2) To process that image subspace based on the traditional PCA, the entire column is linked.

$Cj = A_j A_j T, \quad j = 1,2,3\ldots r)$

Here, $A_j$ =[ → Φ 1j , → Φ 2j ,…, → Φ Lj ],

(3) Compute Cj to obtain eigenvector Uj=[ u → j1, u → j2,…, u → jm] with SVD.

(4)To obtain that projection coefficient mj,

(5)Receive combined projection coefficient m, here m is: m= 1 r j= ∑wjmj

B. Recognition process

(1) In the trained process, the face imageries denote wave transforms, after removing minimum-frequency coefficients.

(2) Projected very block with equivalent eigenvectors and projection coefficient Ψ j (j=1,2,…,r).

(3) Obtain incorporated projection coefficient Ψ, Ψ = 1 r j= ∑w jΨ j (11) here Ψ j specifies sub-space image weight coefficient.

### 3.5Databases

In this work, the proposed model takes 4 FER datasets, such as FER 2013 [52], the extended Cohn–Kanade (CK+) [53], Japanese Female Facial Expression (JAFFE) [54], Facial Expression Research Group Database (FERG) [55].

**FER2013**: This is first developed in ICML 2013 challenges in representation learning [14]. It contains 32, 298 imageries of 48×48 resolution, mostly taken from wild settings. Initially, the training set contains 28,709 imageries, then the validation with test sets involves 3589 imageries. This dataset is generated by Google image search Application Programming Interface (API), then the faces are registered automatically. The faces are labelled as any 6 cardinal expressions along neutral. When likened with other datasets, FER has lots of variation in the imageries, via facial occlusion (mostly with a hand), partial faces, low-contrast images, eyeglasses.

**CK+**: This is a public dataset for the action unit together with emotion recognition. It contains posed and non-posed (spontaneous) expressions. A total of 593 sequences 400 images for training and 193 for testing.

**JAFFE**: It consists of 213 imageries of 7 facial expressions posed by 10 Japanese female models. In this dataset, 213 images were used, 180 images for training and 33 for testing. Every image is rated in 6 emotional adjectives by 60 Japanese themes [15].

**FERG**: This is a stylized character database with annotated facial expressions. It has 55,767 annotated face imageries of 6 stylized characters. The characters are modeled through MAYA. Originally, the training set has 50,767 imageries, and then the validation with test sets has 5000 imageries.

## 4.Results

Here, the simulation performance the HER-BP-DWT is proposed. The proposed method is simulated using MATLAB. Here, evaluation metrics, viz accuracy, sensitivity, specificity and precision are analysed. The performance of the proposed approach is likened with two existing approaches, like HER-CNN [56], and HER-BFA [57].

*Figure 3* depicts the test image. Here, the different block patterns named P1, P2 and P3, P4 horizontally and vertically respectively. The DWT applies to these block patterns that result from various frequency sub-bands: LL, LH, HL, HH. The coefficients of sub-bands are either integer numbers or floating numbers. The energies of these sub-bands are measured and utilized for the determination of the particular emotion based on the match with the energy of the blocks of the reference image. The Energy components of different test and reference images and frequency sub bands of blocks P1, P2 and P3, P4 are shown in *Table 5*. The test image provides smiley expressions. These expressions are substantially reflected in the blocks P2 and P4 so that it gives more information regarding smiley expression. Due to more smiley expressions in blocks P2 and P4, so the energy components of the same area.

**Table 5** Energy components of different test and reference images

| Block | Pic1 | Pic2 | Pic 3 | Pic 4 | Pic 5 |
|---|---|---|---|---|---|
| P1 | 4.6275 | 4.4232 | 4.2828 | 3.3676 | 4.0607 |
| P2 | 4.4274 | 4.6045 | 4.5259 | 3.4538 | 4.7435 |
| P3 | 4.0210 | 4.1100 | 4.0137 | 2.69255 | 4.0348 |
| P4 | 5.0338 | 4.9176 | 4.7950 | 4.1959 | 4.7685 |
| P5 | 4.5478 | 3.7611 | 3.6875 | 2.4487 | 3.9711 |
| P6 | 4.7043 | 5.4478 | 5.3643 | 4.5988 | 5.5140 |
| P7 | 5.3857 | 5.2213 | 5.1945 | 3.8919 | 5.1955 |
| P8 | 3.8693 | 3.9876 | 3.8573 | 3.1556 | 4.2895 |
| P9 | 4.7073 | 4.3875 | 4.2258 | 3..7930 | 4.0240 |
| P10 | 5.3604 | 5.4478 | 5.3643 | 4.5988 | 5.5140 |
| P11 | 5.4223 | 5.2719 | 5.2416 | 4.4025 | 4.9484 |
| P12 | 4.6454 | 4.5634 | 4.3485 | 3.9893 | 4.5883 |

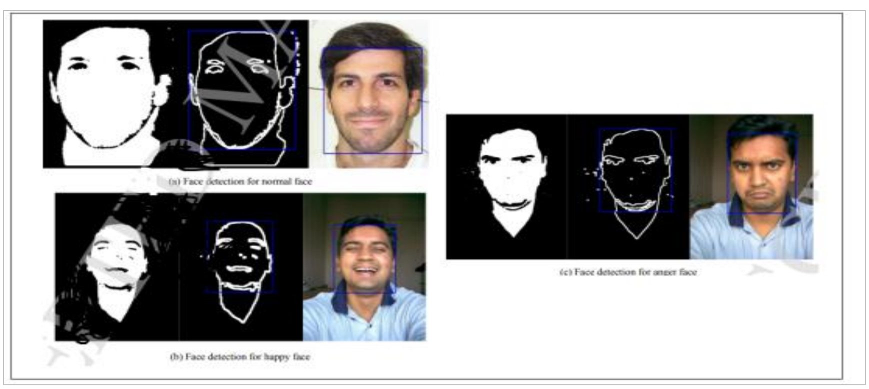



**Figure 3** Face recognition using DWT

Similarly, the reference image is subdivided into different blocks and its decomposition is carried out utilizing DWT that results in various frequency sub bands.

The experimentations are carried out using different test images which show different emotions, such as happiness, anger, sadness, etc. named Pic1to Pic5. The test images are used for experimentation are shown in *Figure 4.* Here, the energy details of the decomposed components are collected in the database, and these energy components are employed for recognizing that emotions by matching energy components of the test and reference image. The segmentation of reference image and the decomposition of its blocks into different frequency sub bands. *Table 6* shows, training and testing of the face recognition using DWT. On observing the table, the Accuracy, Precision, Sensitivity, Specificity of proposed BD-DWTA method shows better than the existing methods, such as human face recognition using HER-CNN and human face recognition using HER-BFA. Here, accuracy shows 99.55%, sensitivity shows 85.93%, Precision shows 92.43%, Specificity shows 90.74%, higher than the existing methods, such as human face recognition using HER-CNN and human face recognition using HER-BFA.

**Table 6** Comparison training and testing results face recognition using DWT

| **Methods** | **Accuracy** | **Precision** | **Sensitivity** | **Specificity** |
|---|---|---|---|---|
| HER-CNN | 83.55% | 75.49% | 70.84% | 80.54% |
| HER-BFA | 87.64% | 77.85% | 75.63% | 73.52% |
| HER-BP-DWT (Proposed) | 99.55% | 92.43% | 85.53% | 90.74% |


**Figure 4** Face recognition of happy, sad and anger using DWT

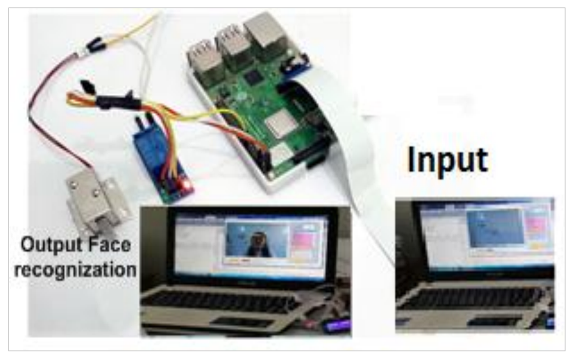



**Figure 5** Software and hardware implementation of face reorganization

## 4.1Software and hardware implementation of face reorganization

*Figure 5* shows the Software and hardware Implementation of the face reorganization system. To make the automatic door access system, the personal computer (PC) RS232 converter is linked through microcontroller via USB. When no face is detected in front of webcam, no signal is sent to the microcontroller. The door is closed because microcontroller does not receive any signal from PC, when a face is detected the name of the authorized person is displayed in the left corner of the noticing box in MATLAB GUI. Once the face is recognized, the door is opened automatically.

*Figure 6* shows the accuracy, sensitivity, specificity and precision of FER2013 dataset using human face recognition-based pattern block and DWT method. Here, the HER-BP-DWT method is analyzed with two existing methods, such as HER-CNN, HER-BFA. From the analysis, the proposed HER-BP-DWT method has an accuracy of 82% and 89% higher than the existing methods, such as human face recognition using HER-CNN and human face recognition using HER-BFA. The proposed HER-BP-DWT method has a precision of 80% and 89% higher than the existing method such as human face recognition using HER-CNN and human face recognition using HER-BFA. The proposed HER-BP-DWT method has a sensitivity of 83% and 84% higher than the existing method such as human face recognition using HER-CNN and human face recognition using HER-BFA.

The proposed HER-BP-DWT method has Specificity of 82% and 89% higher than the existing method such as human face recognition using HER-CNN and human face recognition using HER-BFA.

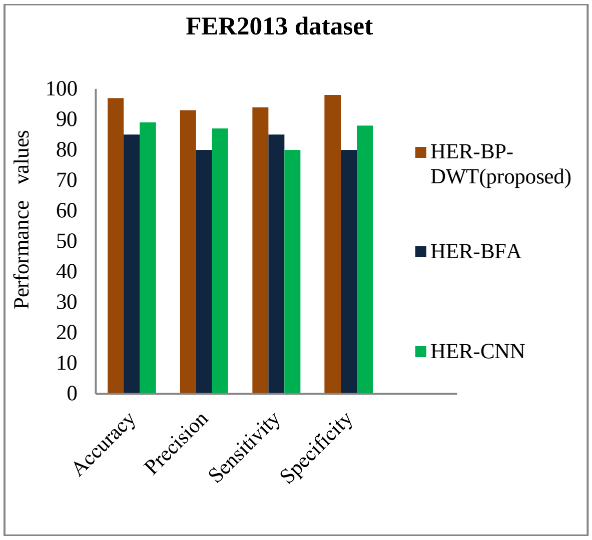



**Figure 6** Performance metrics of FER2013 dataset

*Figure 7* shows the accuracy, sensitivity, specificity and precision of CK+ dataset using human face recognition-based pattern block and DWT method. Here, the HER-BP-DWT method is examined with two existing methods, such as HER-CNN, HER-BFA. Here, the proposed HER-BP-DWT method has an accuracy of 80% and 89% higher than the existing method such as human face recognition using HER-CNN and human face recognition using HER-BFA.

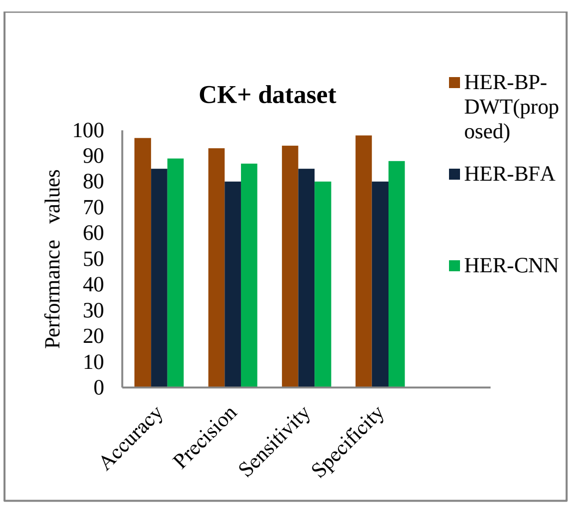



**Figure 7** Performance metrics of CK+ dataset

The proposed HER-BP-DWT method has a precision of 83% and 85% higher than the existing method such as human face recognition using HER-CNN and human face recognition using HER-BFA. The proposed HER-BP-DWT method has a sensitivity of 85% and 86% higher than the existing method such as human face recognition using HER-CNN and human face recognition using HER-BFA. The proposed HER-BP-DWT method has Specificity of 88% and 84% higher than the existing method such as human face recognition using HER-CNN and human face recognition using HER-BFA.

*Figure 8* shows the accuracy, sensitivity, specificity and precision of JAFFE dataset using human face recognition-based pattern block and DWT method. Here, the HER-BP-DWT method is examined with two existing methods, such as HER-CNN, HER-BFA. Here, the proposed HER-BP-DWT method attains accuracy of 82% and 84% higher than the existing methods, such as human face recognition using HER-CNN and human face recognition using HER-BFA.

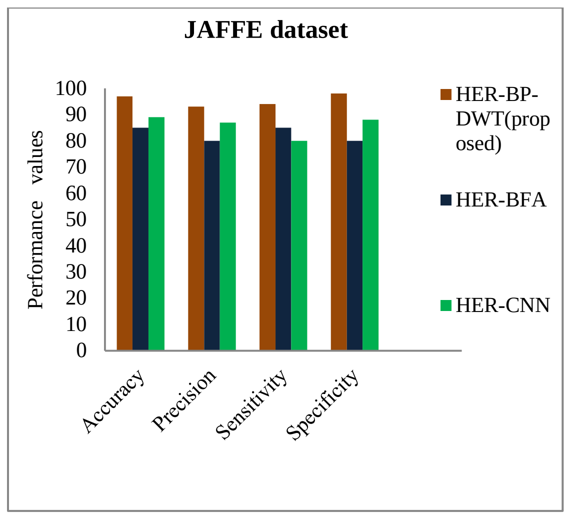



**Figure 8** Performance metrics of JAFFE dataset

The proposed HER-BP-DWT method attains precision of 86% and 89% higher than the existing methods, such as human face recognition using HER-CNN and human face recognition using HER-BFA. The proposed HER-BP-DWT method attains sensitivity of 84% and 82% higher than the existing methods, such as human face recognition using HER-CNN and human face recognition using HER-BFA. The proposed HER-BP-DWT method attains Specificity of 87% and 86% higher than the existing methods, such as human face recognition using HER-CNN and human face recognition using HER-BFA.

*Figure 9* shows the accuracy, sensitivity, specificity and precision of FERG dataset using human face recognition-based pattern block and DWT method. Here, the HER-BP-DWT method is analysed with two existing methods, such as HER-CNN, HER-BFA. Here, the proposed HER-BP-DWT method attains 84% and 87% accuracy higher than the existing methods, such as human face recognition using HER-CNN and human face recognition using HER-BFA. The proposed HER-BP-DWT method attains 83% and 85% precision higher than the existing methods, such as human face recognition using HER-CNN and human face recognition using HER-BFA. The proposed HER-BP-DWT method attains 84% and 87% sensitivity higher than the existing methods, such as human face recognition using HER-CNN and human face recognition using HER-BFA. The proposed HER-BP-DWT method attains Specificity of 82% and 87% higher than the existing methods, such as human face recognition using HER-CNN and human face recognition using HER-BFA.

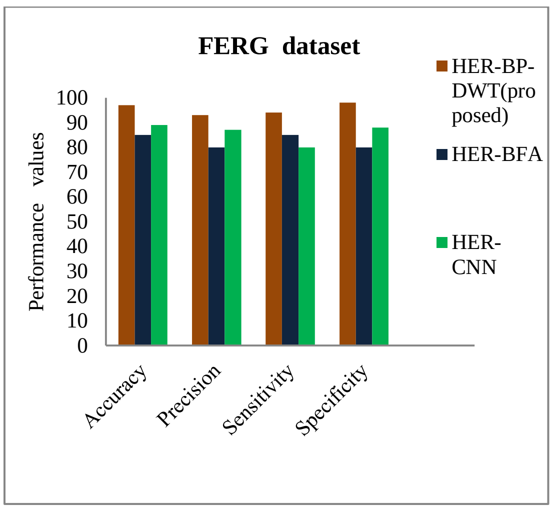



**Figure 9** Performance metrics of FERG dataset

## 5.Discussion

In this method four types of datasets are used, that are FER 2013, the extended Cohn–Kanade, JAFFE, and FERG. These datasets are compared with the existing methods, HER-CNN, HER-BFA approach in terms of accuracy, sensitivity, specificity, precision. In FER2013 dataset, the accuracy of FER 2013 dataset is 82% and 89% higher than the existing methods. The precision of FER 2013 dataset is 80% and 89% higher than the existing methods. The sensitivity of FER2013 dataset is 83% and 84% greater than the existing models, Specificity of FER2013 dataset is 82% and 89% greater than the existing models, viz human face recognition using HER-CNN and human face recognition using HER-BFA.

The accuracy of CK+ dataset is 80% and 89% higher than the existing methods. The precision of CK+ dataset is 83% and 85% greater than the existing models. The sensitivity of CK+ dataset is 85% and 86% greater than the existing models, Specificity of CK+ dataset 84% and 86% greater than the existing models, such as human face recognition using HER-CNN and human face recognition using HER-BFA.

In JAFFE dataset, the accuracy of JAFFE dataset is 82% and 84% higher than the existing methods. The precision of JAFFE is 86% and 89% higher than the existing methods. The sensitivity of JAFFE dataset is 84% and 82% greater than the existing models, Specificity of JAFFE dataset is 87% and 86% greater than the existing models, such as human face recognition using HER-CNN and human face recognition using HER-BFA.

In FERG dataset, the accuracy of FERG dataset is 84% and 87% higher than the existing methods. The precision of FERG is 83% and 85% greater than the existing models. The sensitivity of FERG dataset is 84% and 87% greater than the existing models, Specificity of FERG dataset is 82% and 87% greater than the existing models, viz human face recognition using HER-CNN and human face recognition using HER-BFA.

**Highlight of result**

- the performance metrics of accuracy for face recognition using HER-BP-DWT approach shows high accuracy 96.5%
- the performance metrics of specificity for face recognition using HER-BP-DWT approach shows high specificity 94.5%
- the performance metrics of sensitivity for face recognition using HER-BP-DWT approach shows high sensitivity 93.5%
- the performance metrics of precision for face recognition using HER-BP-DWT approach shows high precision 92.5%
- the proposed system is likened with two existing methods, viz HER-CNN and HER-BFA

### 5.1Limitations of this work

With the face database raise, face recognized rate will suffer. The face databases contain more public databases. Thus, the significant direction of future research is to uphold recognition rate stability under high databases.

A complete list of abbreviations is shown in *Appendix I.*

## 6.Conclusion

In this manuscript, an innovative method of block pattern is introduced for the recognition of different emotions. The block pattern is unique and simple that is followed in the proposed algorithm. The DWT is investigated to facial expression recognition. The energy components of different separated blocks are very much useful for the determination of the blocks match pattern, and hence different emotions are easily classified with proper accuracy and efficient way. The test image is classified into different kinds of emotions, such as sadness, disgust, cry, etc. efficiently. The experimental results show that the proposed BD-DWTA method is better than the existing methods. Here, accuracy shows 99.55%, sensitivity shows 85.93%, Precision shows 92.43%, Specificity shows 90.74%, higher than the existing methods, like HER-CNN [56] and HER-BFA [57].

### Acknowledgment

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### Conflicts of interest

The authors have no conflicts of interest to declare.

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## Appendix I

| S. No. | Abbreviation | Description |
|---|---|---|
| 1 | AAM | Active Appearance Model |
| 2 | AU | Action Units |
| 3 | BFA | Bimodal Fusion Algorithm |
| 4 | CK+ | Extended Cohn–Kanade |
| 5 | CNN | Convolutional Neural Networks |
| 6 | DCT | Discrete Cosine Transform |
| 7 | DFT | Discrete Fourier Transform |
| 8 | DRN | Deep Residual Network |
| 9 | DWT | Discrete Wavelet Transform |
| 10 | FACS | Facial Action Coding System |
| 11 | FD | Frequency Domain |
| 12 | FFT | Fast Fourier Transform |
| 13 | FER | Facial Expression Recognition |
| 14 | FERG | Facial Expression Research Group Database |
| 15 | GIST | Global Descriptors |
| 16 | GMM | Gaussian Mixture Model |
| 17 | GWT | Gabor Wavelet Transform |
| 18 | HER | Human Emotion Recognition |
| 19 | HER-BP-DWT | Human Emotion Recognition based on Block Patterns of Image and Discrete Wavelet Transform |
| 20 | HER-BFA | Human Emotion Recognition using Bimodal Fusion Algorithm |
| 21 | HER-CNN | Human Emotion Recognition using Convolutional Neural Networks |
| 22 | HOG | Histograms of Oriented Gradients |
| 23 | IoT | Internet of Things |
| 24 | JAFFE | Japanese Female Facial Expression |
| 25 | LBP | Local Binary Pattern |
| 26 | NN | Neural Network |
| 27 | PCA | Traditional Principal Component Analysis |
| 28 | R-CNN | Region-based Convolutional Neural Network |
| 29 | SOM | Self-Organizing Map |
| 30 | ULBP | Uniform Local Binary Pattern |
| 31 | WT-BPCA | Wavelet Transform on Block PCA |