A Textural Approach for Land Cover Classification of Remotely Sensed Image

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ABSTRACT
Texture features play a vital role in land cover classification of remotely sensed images. Local binary pattern (LBP) is a texture model that has been widely used in many applications. Many variants of LBP have also been proposed. Most of these texture models use only two or three discrete output levels for pattern characterization. In the case of remotely sensed images, texture models should be capable of capturing and discriminating even minute pattern differences. So a multivariate texture model is proposed with four discrete output levels for effective classification of land covers. Remotely sensed images have fuzzy land covers and boundaries. Support Vector Machine (SVM) is highly suitable for classification of remotely sensed images due to its inherent fuzziness. It can be used for accurate classification of pixels falling on the fuzzy boundary of separation of classes. Hence in this article, land cover classification of remotely sensed image has been performed using the proposed multivariate texture model MDLTP (Multivariate Discrete Local Texture Pattern) and SVM classifier. The classification accuracy of the classified image obtained is found to be 93.46%.

General Terms
Image Processing, Remote Sensing, Texture, Pattern Recognition

Keywords
Land use Land cover classification, multispectral image, texture feature extraction, texture segmentation

1. INTRODUCTION
Land cover refers to the biophysical attributes of the surface of the earth. Features of land covers include texture, shape, colour, contrast and so on. Land cover classification involves classifying the multispectral remotely sensed image into various land covers such as land, vegetation, water, etc. Some of the applications of land cover classification are town planning, conservation of earth's natural resources, studying the effects of climatic conditions and analyzing changes in land forms. Identification of a suitable feature extraction technique and classifier is a challenging task in land cover classification of remotely sensed images.

Texture based methods are widely used in applications like face recognition, content based image retrieval, pattern classification in medical imagery and land cover classification of remotely sensed images. Texture is a surface property that characterizes the coarseness and smoothness of land covers. Pixel based techniques classify a pixel depending on the intensity of the current pixel but texture based techniques classify a pixel based on its relationship with the neighborhood. Texture measures can capture macro as well as micro patterns as they can be captured by varying the size of neighborhood. Most of the texture based methods are rotation, illumination, scaling and color invariant and are robust and susceptible to noise. A variety of texture models are found in literature. The texture model, Local Binary Pattern (LBP) introduced by Ojala et.al [1] for gray level images was later extended for remotely sensed images by Lucieer et.al [2] as Multivariate Local Binary Pattern (MLBP). They concluded that MLBP model with uncertainty measure helped in identifying objects and yielded high classification accuracy. Algorithms using wavelet transform [3] and rotation invariant features of Gabor wavelets [4] were found for performing texture segmentation of gray level images and they reported that the results were promising. To provide better pattern discrimination, Advanced Local Binary Pattern (ALBP) [5] was developed for texture classification and applied on standard texture databases. It was proved that ALBP characterised local and global texture information and was robust in discriminating texture. Local Texture Pattern (LTP) [6] was formulated for gray level images and later extended to remotely sensed images as Multivariate Local Texture Pattern (MLTP) [8]. From the experiments, it was proved that MLTP model gave high classification accuracy. The Fuzzy Local Binary Pattern (FLBP) [7] was introduced as a fuzzy counterpart of LBP and its performance was proved to be better than its basic model. In Dominant Local Binary Pattern (DLBP) [9] histograms of dominant patterns were used as features for texture classification of standard textures. Local Derivative Pattern [10] was formulated for face recognition under challenging conditions. The Fuzzy Local Texture Pattern (FLTP) [11] used a fuzzy member function for pattern description. A novel face descriptor named Local Color Vector Binary Pattern (LCVBP) [12] was used to recognize face images with challenges. Two color local texture features like color local Gabor wavelets (CLGWs) and color local binary pattern (CLBP) [13] were found for face recognition and both were combined to maximize their complementary effect of color and texture information respectively. A comparative study [14] of the existing texture models namely MLTP, MLBP, MALBP, gabor and wavelet was performed by us and it was proved that MLTP outperformed other models in giving high classification accuracy.

Support vector machine (SVM) is a binary classifier but can be used for multiclass classification following suitable approaches. The advantage of SVM over other classifiers is that SVM allows a marginal region on both sides of the linear or non linear boundary of separation of classes and classifies the pixels within the support regions based on measures of uncertainty and reliability. This ensures that uncertain pixels that fall in the support or boundary region are assigned exactly correct class labels. Among many classification algorithms used for texture based classification of remotely sensed images, Support Vector Machine [15], Relevance Vector Machine [17] are reported often in literature. Hermes et.al [15] suggested that SVM was more suitable for heterogeneous samples for which only a few number of training samples were available. Ge et.al [16] concluded that the SVM classification approach was better than K Nearest Neighbour classification algorithm. Lu and Weng [18] performed a detailed survey of various classification algorithms including pixel based, sub pixel based, parametric, non parametric, hard and soft classification algorithms. They summarized that the success of an image classification algorithm depended on the availability of high quality remotely sensed imagery, the design of a proper classification procedure and analyst's skills.

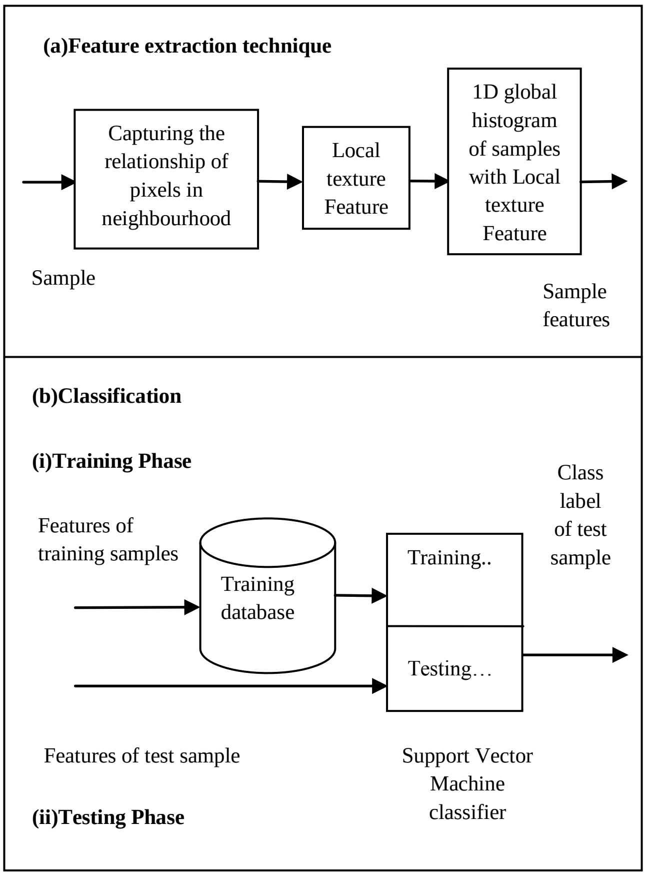
Among the texture models mentioned earlier, only LBP, LTP, wavelet and Gabor wavelet have been extended to remotely sensed images already. The challenge in spectral methods is that they produce features of high dimensionality. So dimensionality reduction may be required prior to classification. At the same time, the multivariate texture models MLBP [2] and MLTP [8] yield high classification accuracy on remotely sensed images using at most three discrete levels. So it is expected that if we increase the number of discrete levels, we can more precisely model the elationship between neighbour pixels. Motivated by this, a multivariate texture model with four discrete levels is proposed for land cover classification of remotely sensed images. Incorporating fuzziness either during feature extraction [7, 11] or classification can improve the classification accuracy of pattern classification and recognition problems. Support vector machine is a fuzzy classifier often used in classification of remotely sensed images. Moreover it converges quickly and needs only a minimum number of samples for classification. Justified by these facts, the proposed multivariate texture model is combined with SVM classification algorithm for performing land cover classification of remotely sensed images. The objective of this research work is to propose a multivariate texture model, Multivariate Discrete Local Texture Pattern (MDLTP) for land cover classification of remotely sensed images that gives high classification accuracy.

2. METHODOLOGY

2.1 Outline of the proposed methodology

The proposed approach has texture feature extraction part as shown in Fig.1 (a) and classification part as shown in Fig.1 (b). During feature extraction, the centre pixel of each 3x3 neighbourhood of a sample is assigned a pattern label using the proposed local texture descriptor. The 1D global histogram is formed to characterise the global feature of the sample.

The multiclass SVM classifier works in two phases as shown in Fig. 1(b). In the training phase, training samples are extracted from distinct land cover classes of remotely sensed images. Texture features in the form of 1D global histogram of training samples are used to train SVM classifier. In the testing phase, test samples centred around each pixel of remotely sensed image are extracted, 1D global histogram is found and given as input to SVM. The SVM classifier finds the optimal hyper plane of separation and returns the class label based on its prior learning of training samples.



2.2 Local texture feature extraction using Discrete Local Texture Pattern (DLTP) – Proposed Texture Model

The proposed texture model DLTP, extracts local texture information from a neighbourhood in an image. Let us take a 3x3 neighbourhood where $g_C, g_1, \cdots g_8$ be the pixel values of a local region where the value of the centre pixel is g_c and $g_1, g_2 \cdots g_8$ are the pixel values in its neighbourhood. The relationship between the centre pixel and one of its neighbour pixels (g_i) is described in equation '(1)'.

$$DLTP = \begin{cases} L(NS, PS) & U \le 3 \\ 166 & Otherwise \end{cases}$$

$$P(g_i, g_c) = \begin{cases} -1 & if\ g_i < (g_c - n) \\ 0 & if\ (g_c - n) \le g_i \le g_c \\ 1 & if\ g_c < g_i \le (g_c + n) \\ 9 & if\ g_i > (g_c + n) \end{cases} \quad (1)$$

Here 'n' is the threshold which is set to express the closeness of neighbouring pixel with the centre pixel. The value $p(g_i, g_c)$ stands for output level assigned to i[th] pixel in the neighbourhood. The discrete output levels are fixed numerically to -1, 0, 1 and 9 to assign unique pattern values during individual summation of positive and negative values later. The output levels characterize the neighbourhood pixel relation. Concatenation of these levels in a neighbourhood gives us a pattern unit. The sample calculation of pattern unit for n=5 is shown below.

$$\begin{bmatrix} 206 & 194 & 201 \\ 203 & 201 & 198 \\ 212 & 210 & 202 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 9 & -1 \\ 1 & & -1 \\ 0 & 0 & 1 \end{bmatrix} \rightarrow 1 \quad 9 \quad -1 \quad -1 \quad 1 \quad 0 \quad 0 \quad 1$$

The total number of patterns considering all combinations of four output levels with the number of pixels in the neighbourhood (P) equal to 8 will be 4^8. This will lead to increase in number of bins required when these local patterns are accumulated to characterise global regions. In order to reduce the number of possible patterns, a uniformity measure (U) is introduced as defined in equation '(3)'. It corresponds to the number of circular spatial transitions between output levels like -1, 0, 1 and 9 in the pattern unit. Patterns for which U value is less than or equal to three are considered uniform and others are considered non uniform patterns. The gray scale DLTP for 3x3 local region is derived as in equation '(2)'. The value PS stands for sum of all positive output levels including zero and NS stands for sum of all negative output levels in the pattern unit. To each pair of (NS, PS) values, a unique DLTP value is obtained from the lookup table 'L' for all uniform patterns and 166 will be assigned for non uniform patterns.

$$U = \left| s(g_{P-1} - g_c) - s(g_0 - g_c) \right| + \quad (2)$$

$$\sum_{p=1}^{P-1} \left| s(g_p - g_c) - s(g_{p-1} - g_c) \right| \quad (3)$$

where s(x,y) = $\begin{cases} 1 & if \quad |x - y| > 0 \\ 0 & if \quad otherwise \end{cases}$ and

$$PS = \sum_{i=0}^{P-1} p(g_i, g_c) \quad if \quad s(p(g_i, g_c)) \geq 0$$

$$NS = \sum_{i=0}^{P-1} p(g_i, g_c) \quad if \quad s(p(g_i, g_c)) < 0 \quad (4)$$

The lookup table (L) provides unique pattern values to the different combinations of NS and PS values and it can be generated using the following pseudo code listed below.

```
INITIALIZE  L (0:8, 0:72) =0
SET Pattern Label (m) =1
Generate 4^8 possible pattern units
FOR each pattern unit do
    Find uniformity measure (U)
    IF U<=3
        Find NS and PS
            IF (L (NS, PS) ==0)
                SET L (NS, PS) =m
                INCREMENT m=m+1
            ENDIF
        ENDIF
ENDFOR
```

The maximum negative sum (NS) is 8 as there can be eight -1's. The maximum positive sum (PS) is 72 as there can be eight 9's. So the size of the lookup table is (8 x 72). All entries in the table are filled sequentially starting from 1 to 165 which characterise unique pattern labels. Zero entries in the lookup table show that those patterns will never occur. This scheme provides 165 uniform patterns and one non uniform pattern.

2.3 Extending DLTP for multispectral bands

The proposed DLTP operator for gray scale image is extended as Multivariate DLTP (MDLTP). Among the multispectral bands, three most suitable bands for land cover classification are chosen and combined to form a RGB image. Nine DLTP operators are calculated in the RGB image. Out of nine, three DLTP operators (RR, GG and BB) describe the local texture in each of the three bands R, G and B individually. Six more DLTP operators describe the local texture of the cross relation of each band with other bands (GR, BR, RG, BG, RB and GB). For example, the GR cross relation is obtained by replacing the centre pixel of R band in its neighbourhood with the centre pixel of G band. Nine DLTP operators thus obtained are arranged in a 3x3 matrix. Then MDLTP is found by calculating DLTP for the 3x3 resulting matrix as shown below. This MDLTP histogram has only 166 bins.

$$MDLTP = DLTP \begin{bmatrix} DLTPg_i^R, g_c^R & DLTPg_i^G, g_c^R & DLTPg_i^B, g_c^R \\ DLTPg_i^R, g_c^G & DLTPg_i^G, g_c^G & DLTPg_i^B, g_c^G \\ DLTPg_i^R, g_c^B & DLTPg_i^G, g_c^B & DLTPg_i^B, g_c^B \end{bmatrix} \quad (5)$$

Where 'i' ranges from 0 to 7 (total number of pixels in 3x3 neighbourhood).

2.4 Global Description through 1D Histogram

The multivariate local texture descriptor describes the texture pattern over any local region. The global description of an image can be obtained through finding the histogram of multivariate local texture descriptor (MDLTP).

3. EXPERIMENTS AND RESULTS

3.1 Study Area and Data Used

The remotely sensed image under study is a IRS P6 (satellite), LISS-IV (sensor) image supplied by National Remote Sensing Centre(NRSC), Hyderabad, Government of India. The image has been taken in July 2007 and is of size 2959x2959. LISS-IV image has a spatial resolution of 5.8m. For study purpose, bands 2, 3 and 4 of LISS-IV data (Green, red and near IR respectively) are combined to form a RGB image and is shown in Fig.2. The remotely sensed image in Fig.2 covers the area in and around Tirunelveli city located in the state of Tamil Nadu in India. It extends to the suburbs of Nanguneri in the South, the outskirts of Palayamkottai in the East, the suburbs of Alankulam in the North West and the suburbs of Ambasamudram in the West. The Thamirabarani river runs across the diagonal region of the image. In the image, residential areas are either with closely packed buildings or with partially occupied buildings with shrubs and trees scattered then and there. Some irrigation tanks are present inside the city. Also in the south of Tirunelveli city leading to Nanguneri village several irrigation tanks and vegetation area are present. In the North, bare soil is scattered in some places on the way to Sankarankoil. In the West, on the way leading to Ambasamudram, paddy fields and vegetation are present on either sides of the perennial river. The LULC mapping is highly needed in this area to assess the urban area development and to conserve water resource by protecting the natural contour of Thamirabarani river course, because Thamirabarani river is the major water source for Tirunelveli and Tuticorin districts. An updated geological map has been selected as a reference for ground truth study of the same area. The experimental classes or training samples are the areas of interest extracted from source image in Fig.2 and are of size 16x16 and is shown in Table 1.

Table 1. Training samples and their descriptions

Class No	Actual Class	Sample Used	Description
C1	Vegetation-1		Crops with tender sprouts
C2	Vegetation-2		Thick forest like vegetation
C3	Vegetation-3		Mature and ripe crops
C4	Settlement		Residential area
C5	Water		Water in rivers and ponds
C6	Soil		Barren land with sparsely and randomly scattered shrubs

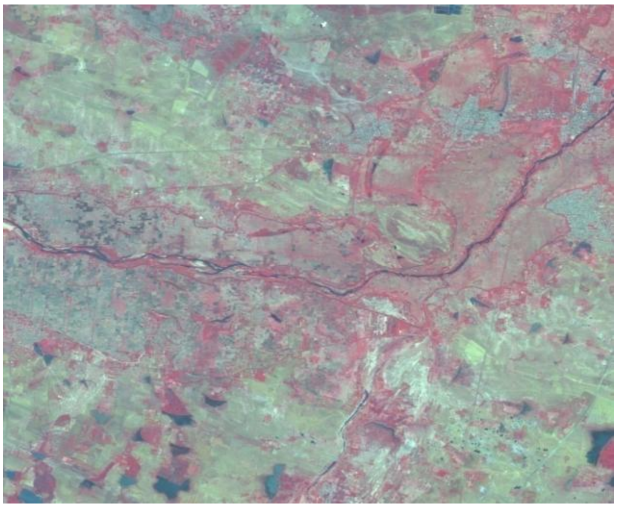


Fig 2: Remotely Sensed Image

3.2 Experimental Setup for Land cover classification of remotely sensed image with MDLTP

In experiments, the size of training and testing samples are kept same to get high classification accuracy. Since the size of the training sample was 16x16, the size of testing sample was also fixed to 16x16. The optimization problem of finding support vectors with maximal margin around separating hyper plane is solved subject to the tolerance value 'C' entered by the user. The parameter 'C' is the penalty assigned by user for training errors and is set to 1000. The classifier solves optimization problem with the help of polynomial kernel. A kernel specific parameter 'λ' is assigned prior to optimisation to 0.000000001. In training phase, the 1D histograms of training samples (found using the procedure given in Section II) were used to train SVM. In testing phase, the 1D histogram of testing samples found using the similar procedure were given as input to SVM. The classifier returned the class label. The classified image is shown in Fig.3. The MDLTP model discriminates well between various land covers because the micro patterns like Settlement and Vegetation-3 classes in Fig.3 are assigned distinct pattern codes. So these classes cluster densely. The thin diagonal line of water running across the image is clearly traced without discontinuity. The Vegetation-1 class which lies on either sides of Thamirabarani river is seen vividly. The Vegetation-2 class present around water tanks is also classified precisely.

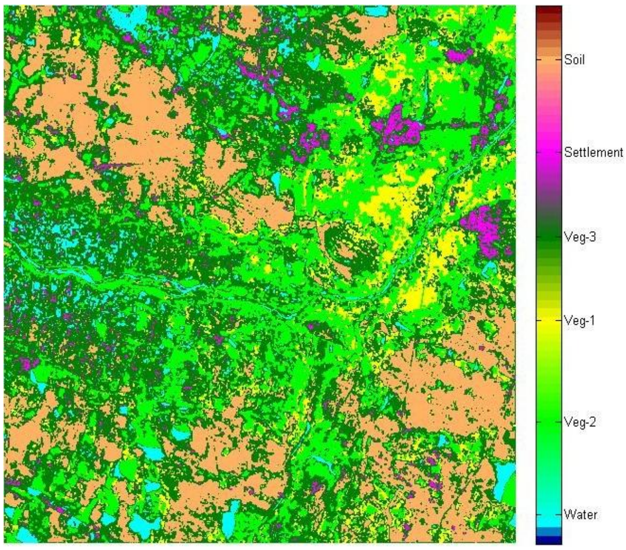


Fig 3: Classified image using MDLTP

3.3 Performance Metrics

The overall classification accuracy and Kappa coefficient are the performance metrics for assessing the classified image. To compute these values, an confusion matrix is built as follows. The size of confusion matrix is 'c x c' where 'c' is the number of classes. If a pixel that belongs to class c_i is correctly classified, then a count is added in entry (i,i) of confusion matrix. If a pixel that belongs to class c_i is incorrectly classified to class c_j, then a count is added to the entry (i,j) of confusion matrix. The diagonal entries mark correct classifications while the upper and lower diagonal entries mark incorrect classifications. Then the overall accuracy (P_o) can be found as follows.

Overall classification accuracy (P_0) = $$\frac{\sum_{i=1}^{c} x_{ii}}{n} \quad (6)$$

where 'n' is the total number of observations and

x_{ii} is the observation in row 'i' and column 'i' of error matrix. The classification accuracy expected (P_e) is found as below.

Accuracy expected (P_e) = $$\frac{\sum_{i=1}^{c} x_1 x_2}{n^2} \quad (7)$$

where x_1 is the marginal total of row 'i' and x_2 is the marginal total of column 'i'. Kappa coefficient is found using P_o and P_e as follows.

Kappa Coefficient = $$\frac{P_o - P_e}{1 - P_e} \quad (8)$$

3.4 Performance evaluation of classified image

In our experiments, a set of stratified random samples comprising of 2400 pixels were used for building error matrix. The performance measures such as classification accuracy and kappa coefficient described are found for the classified image in Fig.3 and shown in Table 2 and Table 3 respectively.

Table 2. Confusion Matrix of Proposed Model

	BG	C1	C2	C3	C4	C5	C6	RoT
C1	0	31	0	0	0	0	1	32
C2	0	1	249	15	0	2	0	267
C3	0	32	15	584	27	9	21	688
C4	1	0	7	8	340	9	21	386
C5	0	0	5	5	4	230	0	244
C6	1	2	0	1	8	0	771	783
CoT	2	66	276	613	379	250	814	2400

BG- Back Ground, RoT- Row Total, CoT- Cloumn Total

Table 3. Accuracy Totals of Proposed Model

Class Name	RT	CT	NC	PA %	UA %
BG	0	2	0		
C1	32	66	31	46.97	96.88
C2	267	276	249	90.22	93.26
C3	688	613	584	95.27	84.88
C4	386	379	340	89.71	88.08
C5	244	250	230	92.0	94.26
C6	783	814	771	94.72	98.47
Totals	2400	2400	2205		
Overall Accuracy= 93.46%			**Overall Kappa = 0.9156**		

RT- Reference Total, CT- Classified Total, NC- Number Correct, PA- Producer's Accuracy, UA-User's Accuracy

The proposed model MDLTP gives a classification accuracy of 93.46% and a kappa coefficient of 0.9156. The model performs well because the neighbourhood pixel relations are precisely captured with the help of four discrete levels. The window border effect usually seen in these boundaries of classified images is minimized by fixing a small window size of 16x16.

For evaluating the performance of the proposed model with the existing texture models, SVM multiclass classifier was used and the classification accuracies of various texture models were found and tabulated in Table IV. The existing texture based methods such as MLBP, MLTP, Gabor Wavelet and Wavelet were considered for comparison. From Table 4, it is seen that the texture models MLBP (with two discrete levels like 0 and 1) and MLTP (with discrete levels like 0, 1 and 9) yield 90.42% and 91.88% classification accuracy respectively. The difference in classification accuracies is mainly caused by the abilities of the texture models to trace the boundaries between different textures and to capture subtle pattern variations in micro textures.

Table 4. Performance Comparison of Proposed Model with Existing Models

Name of the feature extraction technique	Number of Bins in (texture model)	Overall Classification Accuracy (in %)	Overall Kappa Coefficient
MDLTP	166	93.46	0.9156
MLTP	46	91.88	0.8941
MLBP	72	90.42	.8759
Gabor Wavelet	-	91.88	0.8941
Wavelet	-	60.67	0.4743

The proposed model MDLTP performs better in these aspects and it requires 166 bins for modeling texture in 3x3 neighbourhood. Moreover, MDLTP features are low dimensional features found with minimum computational complexity. It can easily be extended for 5x5 and 7x7 neighbourhoods as well. The procedure for assigning pattern codes using positive and negative sums is proposed in this study.

4. DISCUSSION AND CONCLUSION

A multivariate texture model (MDLTP) is proposed for land cover classification of remotely sensed images. The advantages of the proposed model are threefold. Firstly, it gives stable results even for small window sizes and secondly, it requires only a minimum number of training samples in training phase. Thirdly, it captures additional uniform patterns. The SVM classifier augments the texture model by incorporating fuzziness in classifying land covers. From the experiments, it is proved that the proposed model yields 93.46% classification accuracy and outperforms other texture models taken for study, based on error matrix, classification accuracy and kappa statistics.

In future, it is proposed to incorporate fuzziness in the proposed texture model. It is also planned to extend the model for hyper spectral data. The proposed model may also inspire readers to go beyond four discrete levels to achieve high classification accuracy in applications like Face Recognition where high precision pattern discrimination is needed. The model can be hybridised with extreme learning machine or relevance vector machine classifier to yield better classification accuracy.

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