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Deep Learning Machine using Hierarchical Cluster Features

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Abstract
Deep learning of multi-layer computational models allowed processing to recognize data representation at multiple levels of abstraction. These techniques have greatly improved the latest ear recognition technology. PNN is a type of radiative basis for classification problems and is based on the Bayes decision-making base, which reduces the expected error of classification. In this paper, strong features of images are used to give a good result, therefore, SIFT method using these features after adding improvements and developments. This method was one of the powerful algorithms in matching that needed to find energy pixels. This method gives stronger feature on features and gives a large number of a strong pixel, which is considered a center and neglected the remainder of it in our work.
Each pixel of which is constant for image translation, scaling, rotation, and embedded lighting changes in lighting or 3D projection. Therefore, the interpretation is developed by using a hierarchical cluster method; to assign a set of properties (find the approximation between pixels) were classified into one.

Keyword: Scale Invariant Feature Transform (SIFT), Probabilistic Neural Networks (PNN), Hierarchical Cluster.

الخلاصة
التعلم العميق للنماذج الحسابية متعددة الطبقات بمعالجة التعرف على تمثيل البيانات على مستويات متعددة من التجريد. هذه التقنيات حسنت بشكل كبير أحدث تقنيات التعرف على الأذن. PNN هو نوع من الأساس الإشعاعي لمشكلات التصنيف ويستند إلى قاعدة اتخاذ القرار في Bayes ، مما يقلل من الخطأ المتوقع في التصنيف. في هذه الورقة ، يتم استخدام ميزات قوية للصور لإعطاء نتيجة جيدة ، وبالتالي ، استخدمنا طريقة SIFT احدى الطرق القوية لايجاد بكسل القوي وذلك بعد ما قمنا بتحسين وتطوير الطريقة التي تعتبر واحدة من الخوارزميات القوية في المطابقة المطلوبة للعثور على بكسلات الطاقة. توفر هذه الطريقة ميزة أقوى على الميزات وتعطي عددًا كبيرًا من البكسلات القوية ، والتي تعتبر مركزًا وتهمل الجزء المتبقي منها في عملنا.
كل بكسل منها ثابت لتغيرات الصور ، التدريج ، الدوران ، والإضاءة المدمجة في الإضاءة أو الإسقاط الثلاثي الأبعاد. لذلك ، يتم تطوير التفسير باستخدام أسلوب نظام تسلسل هرمي؛ لتعيين مجموعة من الخصائص (العثور على التقريب بين البكسلات) تم تصنيفها إلى واحد.

Introduction
The object in real scenes is recognized in the world cluttered features images that are not affected by nearby fuss or partial occlusion. The features must be at least constant in terms of lighting, 3D projection turns, and common object variations. On the other hand, features must be sufficiently distinct to identify specific objects among many alternatives. The problem of object identification is largely due to the lack of success in achieving these features. However, recent research on the use of dense local features has shown that effective recognition can often be achieved by using image descriptors that are sampled in a large number of replicable sites. So this in our way used some improvements, began with the SIFT and then an explanation of the proposed algorithm, with its improvement.
Scale Invariant Feature Transform (SIFT). This approach Transform an image into a large set of vector feature, each of which is constant for image translation, scaling, rotation, and embedded lighting changes in lighting or 3D

projection. Previous approaches to generating local features lack stability in scale and have been more sensitive to diacritical change and lighting change. SIFT features share a number of common properties with neuronal responses in the lower temporal cortex (LTC) in the primate vision.

Fixed features are effectively identified using the staging filtering policy. The first stage identifies key locations in scale space by looking for the locations that are the maximum or minimum of a difference-of-Gaussian (DoG) function. Each point is used to generate a vector feature that describes the Image Region Sampled Relatives scale space coordination framework. Features achieve partial persistence to local variations, such as affine or 3D projections, by blurring image gradient locations. This approach is based on a model of the behavior of complex cells in the cerebral cortex of mammalian vision. The resulting feature vectors are called SIFT keys. In the current implementation, each image is generated based on a command of the SIFT with 1000 keys, a process that requires less than 1 second of the calculation time.

SIFT keys derived from an image are used in the approach of nearest neighbors for indexing to determine candidate object models. The key combinations that correspond to a possible model are first identified through a Hough transform hash table, and eight-digit estimates in the lower squares to estimate model parameters. When at least 3 keys conform to the model parameters with the remaining residual, there is strong evidence for the presence of the object. Since there may be dozens of SIFT keys in the image of a typical object, it is possible to have substantial levels of occlusion in the image but retain high levels of reliability.

Probabilistic Neural Networks (PNN) is a kind of radial basis meshwork suitable for classification problem , it is based upon the Bayes classification rule for decision making which minimizes the expected error of classification, also based on Parson window estimation which appraisal the probability density use (PDF) for each class based on the breeding sampling [7]. In 1990, PNN was introduced by Donald Specht. Who was shown that the Bayes Parson classifier could be separated into a large Figure of simpleton processes implemented as a multilevel neural web and each of these process wholes could be tested independently in analog [8]. The functioning of PNN in object designation characteristics with reduced complexness, it has a very fast training speed, and the PNN can easily add new approach blueprint neurons to pattern layer. Unfortunately, PNN requires large memory because the pattern leaf node in pattern layer is just equal to the total number of training samples, which normally depends on the sample size of it and substantially causing high network complexity [9].

Literature Review

In this paragraph, we will review the range of research that has been used SIFT to extract the features as shown below:-

A reliable matching method for extracting static fixed features between images is having different views of object or place. Features are fixed for image rotation, scale, distortion, 3D view change, add noise, and change the illumination. The features are highly distinctive, which means a single feature of the images can be correctly matched with a large probability of a large database of features from many images. The paper also describes features of object recognition. The matching of individual database features is recognized by known object attributes has been presented [1].

Describes a new algorithm called Scale Invariant Feature Transform (SIFT), by using SIFT reliable matching features between images are extracted to different views of the same object. extracted features of the images are highly distinct and are fixed on the scale and orientation of the image. property is extracted in four steps. In the first step, the locations of potential interest points in the image are calculated by detecting the maximum and minimum difference of Gaussian (DoG) filters that are all applied click image at different scales. Then, by eliminating the points there is a low contrast detected locations the points are refined. Then based on the local image features the orientation is set to each key point. Finally, each key point is calculated as a local feature descriptor. This descriptor is converted to the key direction point based on the local image gradient to provide orientation invariance has been presented [2].

The new matching technique chart is described on the Sift to determine the face system based on features extracted from facial images. The paper investigates the performance of recognition techniques based on graph matching topology in SIFT properties. This topology matching graph is constant to the rotation, scale, and translation. Matching facial projections to the images represented by a graph can be matched new images by maximizing the function of similarities by looking at the similarities of local features and spatial distortions. To discover the best features of the SIFT facial query features and a two-graph database based on matching techniques that have been developed. This technique is used to deal with the pseudo-pair assignment reduce the number of features in the database. Two matching algorithms are used to find matching feature points in the database and facial image query. The advantage of the system is that it increases system performance based on SIFT features. The results obtained show the ability of the system to handle lighting changes and irregularity occur in the database or face image of the query. The accuracy results identified in improving matching techniques can increase system performance even in the same space representation feature has been presented [3].

Determine the different arrangement of the SIFT features that can be used to reduce the number of SIFT features to identify the face. This method checks the number of irrelevant features to be matched in order to simplify the task at hand as well as increases the recognition accuracy. This system shows that the reduction is more than 4 times the number of accounts and 1% increase in the accuracy of recognition have been presented [4].

A new method called FSIFT to overcome FSIFT inaccuracy. The method is obtained by calculating the SIFT method at predetermined fixed positions of the image described during the training phase. Determining the key points of predefined spatial locations will help eliminate the optimal threshold and split the facial image when the advanced approaches gain greater lighting stability than other SIFT modifications. The experiment is conducted on the Extended Face database Yale B (EYB) have been presented [5].

The Proposed Ear Classification System

Primary structure of the proposed Ear Classification system is consist of two phases; training phase and testing phase. Figure 1 is shown the structure of our proposed recognition system. Now we explain each step in Figure 1.

Preprocessing Module

The first module of the proposed system is preprocessing. The main focus of this module is to detect the skin area in the ear image, localize and extract each of the ear clips. This module is a critical task for both extraction and task recognition features. This module consists of three main stages; each stage includes several steps, as follows:

1. Brightness Preprocessing

The proposed technique is used as preprocessing of the way to improve the brightness of the image for the purpose of showing the detail image well because sometimes the image capture process is taken as appropriate or inappropriate for the conditions in which the brightness of the images is increased proportionally between 0 and 255[6].

2. Skin Color Modeling Step

HSV color space is suitable to represent the color of the human ear skin has been used and has been displayed based on color when needed to indicate the color properties numerically; the description of color with intuitive values, based on the concept of color, saturation, and tone. The hue determines the dominant color in the region (such as red, green, and blue); Saturation measures the color space in proportion to its brightness.

Density, lightness, or value is associated with color. The intuition of the components of color space and the explicit distinction between luminance and coloration properties made these color spaces popular in the work on skin color segmentation. Equations (1), (2) and (3) represent conversion rules to obtain values (H, S, V) of the desired color space [6]. After image color conversion applied, HSV is used to detect skin segmentation. The skin color has value 1 if the skin region and the others have value 0.

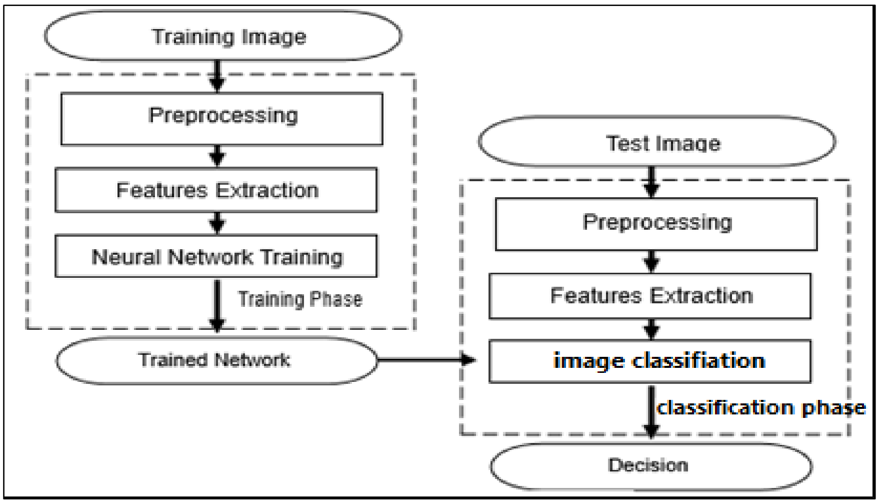


Figure 1. Primary structure of proposed classification system

3. De-Noising Step

- **Median Filter**

For reducing the noisy pixels that may appear after Skin segmentation, a median filter is applied. The median is just the middle value after ascending all the values of the pixels in the neighborhood; the median has half the value in the neighborhood. After applying median filter the resulted image became blur image.

- **Masking Window**

To achieve the process of obtaining the region of interest ,we need to get rid of the noise in the image surrounding the ear such as hair depending on the proportion and fit at this stage is used to remove noise in order to obtain the best region of the interrupt of the ear, which will be based on the principle of Sample in the match, Improve the results of region of interest .

4. The Region of Interest by using Masking

- **Canny Edge Detection Stage**

The best way to extract the best edges was using the canny method but not in its usual way because the canny method when using the original image in the process of the catcher did not give me good results but gave me the process of generating sample so the canny method used here is the use of two angles each corner look has a Kernel value and a sigma for each of hence will give me the angle of the point and its edge not only the edges.

- **Generating Sample Stage**

After performing the process of detecting the edge by using the canny method through which the weak and strong edges are detected. Here we will use the weak edges to generate the samples because we do not need the shape of the ear, but we need to random points to find the matching and extraction of the ear area and even this must generate sample until we measure through the convergence with the ear by rotating the ear at certain angles.

- **Logical Operation Stage**

After the process of generating a sample, we carry out the logical operations with the original image and all the sample until it is to find points similarity and difference the by calculating (XOR) and relying on probability zeros and units on all the possibilities calculated by the If the zeros more than the units are rejected and if the units more than 90% is acceptable if less are rejected and then cut the area of the ear.

- **Dailition Operation**

The difference between weak and strong points in the representation of the edge is a set of convergent pixels to obtain the strong edge. The canny algorithm separates the strong from the weak from the edges. The force always draws from the edge. The weak are always neglected because it does not have the edge properties to obtain the powerful pixel energy points that are extracted by the Sift algorithm, the energy pixels will be extracted between the strong and weak edge because they determine the structure of the ear and thus make the sift only work on the edges, Therefore, the way of Dilation is used here is the difference between the strong and the weak points of the strong points that carry either the weak points are ignored.

5. Scale Invariant Feature Transform

In our proposed transformation the system will be used to extract stronger features from ear image. SIFT system is that can extract local feature, the main idea of SIFT is to find extreme points in scale space, extract invariant when location, scale, rotation, illumination changed. Now we explain the steps of feature extraction by using SIFT:

- **Interest Points with Multiple Scale**

The first step is detected Interest Points to find locations with the stable feature. In the SIFT proposed, Interest Points detection based on Laplacian-of-Gaussian (LoG) filters with multiple scale space:

a) Laplacian-of-Gaussian (LoG) filters

LOG filters, which primarily respond to distinct glamorous fountains surrounded by dark region or vice versa. Unlike filters used for known corner detectors, LOG filters are altruistic, meaning they are not sensitive to direction. To select points of interest across multiple scales, a measurement area representation of the input image is created by repeatedly smoothing the image with a sequence of small Gaussian filters. The difference between images is used in the layers of the meter next to the approximation of the LOG filter in each scale. Points of Interest (POIs) are finally selected by finding the local maximum in the 3D LOG scale space.

Scale Space

The goal of using a filter is to improve the images so the application of SIFT made its first steps to improve the image through the use of Gaussian filter to get a smooth image and then we calculate the scale space is represented by four levels of scale so that one is smaller than the other, we have to reduce the size of the image by taking each image input and calculate the mean of every four pixels of the image the result is smooth image and those four levels one depends on the other, so that each exit of the image becomes an entrance to another so that Becoming one smaller than the other meaning pushes the exact details of the image. Each image takes five levels of Gaussian blurring so that each image is different in scale and blurring and blurring exceeded the problem of scale because I at any level I exceed it and this is a key point very high that I have 20 image extraction feature.

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \qquad (1)$$

Where

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{(-x^2+y^2)/2\sigma^2} \qquad (2)$$

b) Different of Gaussian

Blur image is work on it as searches overall image scales and locations to identify key points by using a Difference-of-Gaussian (DoG) function and as a result, the edges are formed because the edge is produced by using two blur images.

$$D(X, Y, \sigma) = L(X, Y, K\sigma) - L(X, Y, \sigma) \ldots \qquad (3)$$

- **Key Point Selection and Refinement**

The main points were identified in three steps: first step detection of extreme points in the DoG area, the second step improved position by local interpolation, and finally elimination of edge response.

a) Detection of Extreme Points in the DoG

This is approximated by the DoG of the input image in different scales. Each pixel takes maxima or minima of the difference-of-Gaussian images and compares it with its neighbors 26 in 3×3 regions at the current and adjacent scales, and take the highest pixel or less pixel of these areas and thus we get the points located at the extrema of a DoG pyramid of the input image are identified as candidate key points. Next, at each candidate key point location, a detailed model is fit to determine the accurate location and scale based on measures of the key point's stability by using Equations 1, 2, and 3.

Taylor Series

Taylor series consists of two operation Gradient vector evaluated digitally at the key point and Hessian matrix evaluated digitally at the key point as shown Equation 7. Fine edges and ignore the insignificant edges can get by helping which determine the value of threshold and compare with $D(x, y, \sigma)$. Finding an extrema of the DoG values in this neighborhood, set the derivative of D to 0. The keypoint location is updated. All extrema with |D extremal| < 0.03, are discarded as weak extrema or low contrast points. Hessian matrix with edge wilan l has high maximal curvature, but very low minimal curvature.

$$\boldsymbol{D}(\mathbf{x}, \mathbf{y}, \boldsymbol{\sigma}) = \boldsymbol{D}(\boldsymbol{x_i}, \boldsymbol{y_i}, \boldsymbol{\sigma_i}) + \left(\frac{\partial \boldsymbol{D}(\mathrm{x,y,\sigma})}{\partial(\mathrm{x,y,\sigma})}\right)^{\boldsymbol{T}} \Delta + \frac{1}{2}\Delta^{\boldsymbol{T}} \times \left(\frac{\partial^2 \boldsymbol{D}(\mathrm{x,y,\sigma})}{\partial(\mathrm{x,y,\sigma})^2}\right)\Delta \quad (4)$$

$$(\hat{\ }\mathbf{x}, \hat{\ }\mathbf{y}, \boldsymbol{\sigma}\hat{\ }) = -\left(\frac{\partial^2 \boldsymbol{D}(\mathrm{x,y,\sigma})}{\partial(\mathrm{x,y,\sigma})^2}\right)^{-1} \left(\frac{\partial \boldsymbol{D}(\mathrm{x,y,\sigma})}{\partial(\mathrm{x,y,\sigma})}\right) \quad (5)$$

$$\boldsymbol{D_{extremal}} = \boldsymbol{D}(\boldsymbol{x_i}, \boldsymbol{y_i}, \boldsymbol{\sigma_i}) + \frac{1}{2}\left(\frac{\partial \boldsymbol{D}(\mathrm{x,y,\sigma})}{\partial(\mathrm{x,y,\sigma})}\right)^{\boldsymbol{T}} (\hat{\ }\mathbf{x}, \hat{\ }\mathbf{y}, \boldsymbol{\sigma}\hat{\ }) \quad (6)$$

b) Orientation

Compute the gradient magnitudes and orientations by applying Equations10,11 and 12 in a small window around the key point. Histogram of gradient orientation count is weighted by gradient magnitudes and a Gaussian weighting function. Usually, 36 bins are chosen for the orientation. Assign the dominant orientation as the orientation of the key point. In case of multiple peaks or histogram entries more than 0.8 x peaks.

$$\boldsymbol{L}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{\sigma}) = \boldsymbol{G}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{\sigma}) * \boldsymbol{I}(\boldsymbol{x}, \boldsymbol{y}) \quad \ldots (7)$$

$$\boldsymbol{m}(\boldsymbol{x}, \boldsymbol{y}) = \sqrt{\left(\boldsymbol{L}(\boldsymbol{x}+\mathbf{1}, \boldsymbol{y}) - \boldsymbol{L}(\boldsymbol{x}-\mathbf{1}, \boldsymbol{y})\right)^2 + \left(\boldsymbol{L}(\boldsymbol{x}, \boldsymbol{y}+\mathbf{1}) - \boldsymbol{L}(\boldsymbol{x}, \boldsymbol{y}-\mathbf{1})\right)^2} \quad (\mathbf{8})$$

$$\boldsymbol{\theta}(\boldsymbol{x}, \boldsymbol{y}) = \mathbf{tan^{-1}}(\boldsymbol{L}(\boldsymbol{x}, \boldsymbol{y}+\mathbf{1}) - \boldsymbol{L}(\boldsymbol{x}, \boldsymbol{y}-\mathbf{1}))/\boldsymbol{L}(\boldsymbol{x}+\mathbf{1}, \boldsymbol{y}) - \boldsymbol{L}(\boldsymbol{x}-\mathbf{1}, \boldsymbol{y}))) \quad (\mathbf{9})$$

c) Descriptor SIFT using Hierarchical Cluster method

At this stage we draw the strong points needed by the SIFT method, by using the Hierarchical Cluster method, which takes the points obtained and calculates the distance between two points and takes the minimum distance, each time choose the lowest distance to be Cluster and continue until we get to the other Cluster consists and then take points The middle between the two formation process for the casters is nailed because it does not contain a specific condition to stop.

In our method, we used the rate as a stopover because we needed the nearest distance between the points to find a cluster. Take the distance and collect them and divide their numbers so that I can know the distances that are close to the divergent. If the rate is lower, it is required if it does not go away. This method helps us to determine the number of the cluster within the mean error. This is the resulting cluster. We take the center point of each of the clusters by calculating the mean and taking the center point. Each point of the cluster completes our number k. Then I will again use a force field using k-mean and then extract force field feature extraction for ear .the strong features are selected by calculating the mean and standard deviation for each point in the descriptor, which is represented by five vectors. Here is the computation of the points which represents the strong points. Also, calculate all the points that were extracted by calculating the mean and standard deviation, but here we notice a difference points between each ear image. So Normalization work to take the points extracted also the mean and the deviation of the qualitative will become a point 10 features of the cluster and 10 of the comprehensive points of SIFT have for each image permission 20 features.

Probabilistic Neural Network Architecture (PNN)

The Probabilistic Neural Network (PNN) is a multilayer feedforward, supervised learning algorithm and performs its operations using four layers: an input layer, a pattern layer, a summation layer, and an output layer as shown in Figure 2 :

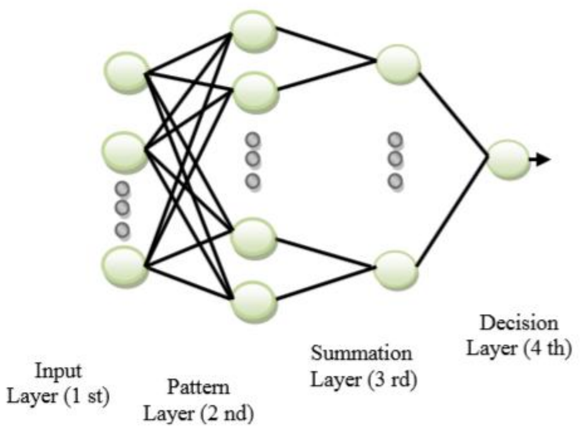


Figure 2: Probabilistic Neural Network Architecture

Input layer also called is distribution layer, which is fully connected to the pattern layer, the input features vector (x) are distributed to all neural node in pattern layer. The pattern layer contains one neuron for each training sample. In the pattern layer, each neuron node computes the distances between the input features vector and the training samples and produces a vector which elements estimate how close the input to a training sample, any distance metric like Euclidean distance, squared Euclidean distance and Manhattan distance can be used for computing the distance [10]. Each neuron performs a Gaussian function (radial transfer function) which can be simplified as in Equation 10:

$$\boldsymbol{G}(\boldsymbol{x}) \leftarrow \mathbf{exp}(-\frac{\boldsymbol{D}(\boldsymbol{x},\boldsymbol{y})}{\mathbf{2}\boldsymbol{\sigma}^{\mathbf{2}}}) \quad (10)$$

Where

G: represent the output of a neuron pattern node.

X: is the input features vector to be assigned to class Ci

D(x,y): is the distance between the input features vector and the pattern vector that belongs to the specific class, (Euclidean distance has been used in this paper).

σ: is smoothing factor

The pattern layer neurons which belong to the same class are connected to the same summation neuron node. In the summation layer, there is one neuron node for each class, sums the outputs of pattern layer for each class and produces outputs which represent the probabilities of that class (obtain and estimate probability density function of the class), as Equation 11.

$$\boldsymbol{O}(\boldsymbol{x}) = \frac{\mathbf{1}}{\boldsymbol{nj}}\sum_{\boldsymbol{j}=\mathbf{1}}^{\boldsymbol{nj}} \boldsymbol{G}(\boldsymbol{x}) \quad (11)$$

Where

O(x): the output of summation node i for class Ci

nj: the number of samples in pattern layer of class Ci.

G(x): represents the output of pattern node i.

Finally, the decision layer picks the maximum one of these probabilities, and provides the target class for the input features vector [11], as Equation 15.

$$\boldsymbol{Target\ class}(\boldsymbol{x}) = \boldsymbol{max}\left(\boldsymbol{O}(\boldsymbol{X})\right) \quad (15)$$

The standard deviation decision should remain for the majority. The value of σ affects the results of PNN recognition and is carefully classified. More than one algorithm can be used to determine the range of the smoothing element. In this search, the minimum and maximum standard deviation value are used after calculating the average vector of each category to determine the range.

Results and Discussion

The experimental results are obtained from our proposed Ear classification system, are shown as:

Preprocessing Image stage:

The enhancement processing applied to the color image as shown in Figure 3.

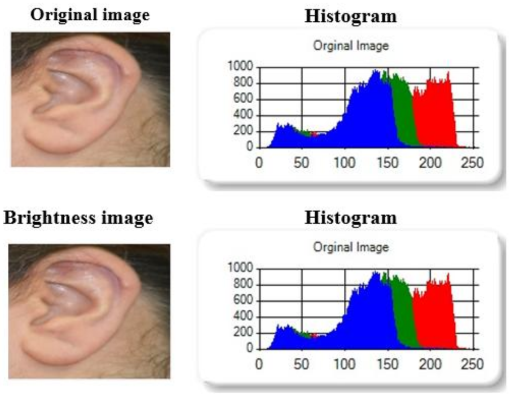


Figure 3: The preprocessing stage.

Color Model Conversion stage:

The results of converting color image model to HSV model as shown in Figure 4.

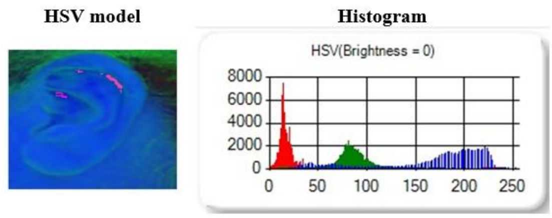


Figure 4: Color conversion

Skin Segmentation stage:

The skin segmentation of HSV ear image as shown in Figure 5.

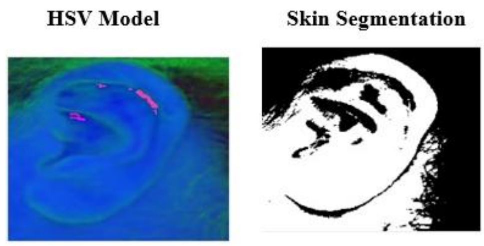


Figure 5: Skin segmentation

De-Noising step:

Remove noise and get rid the excesses of hair and others. As shown in Figure 6.

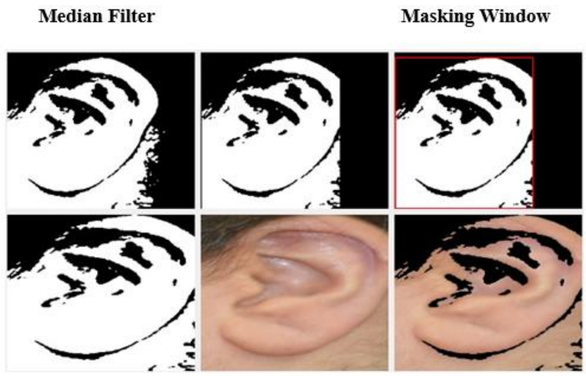


Figure 6: De-Noising Stage.

The region of Interest Stage:

Canny Edge Detection: In this stage we are applied canny edge detection on the resulted image of the de-Noising stage, to cut the interested region as shown in Figure 7.

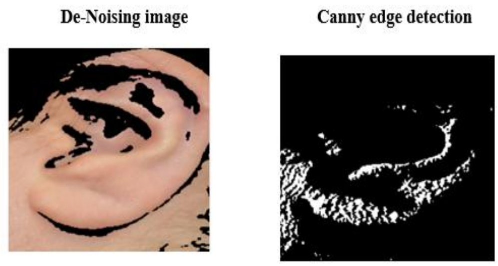


Figure 7: Edge Detection by using The Canny Edge Detection Method

Generation sample: generation sample using weak canny edge detection and rotation for a suitable masking for all ear images as shown in Figure 8.

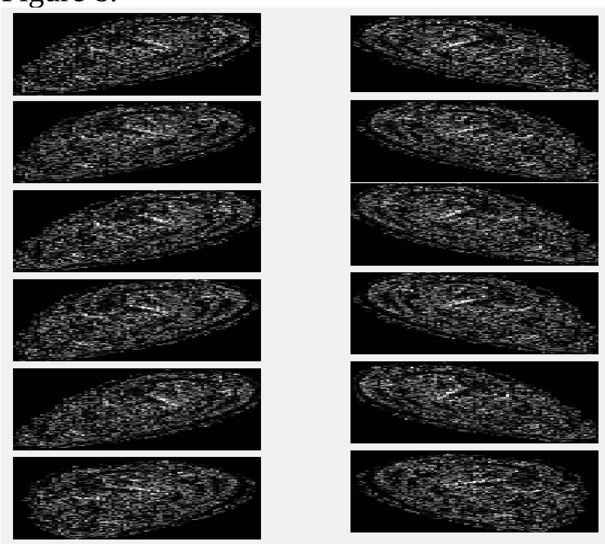


Figure 8 Generation Sample by Weak Canny Edge Detection

1. **Region Of Interest:**

a cut of ear image by all steps use shown in Figure 9

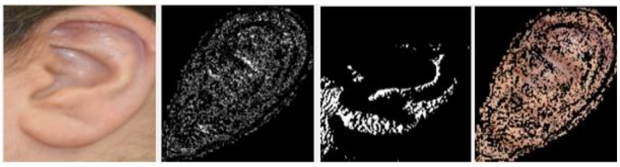


Figure 9. The region of interest for all steps

2. **Logical operation:** find points similarity and difference the by calculating XOR as shown in Table (1).

Scale Invariant Feature Transform

i. Interest Points at Multiple Scale

1. **Scale space:** scale space is represented by four levels of scale so that one is smaller than the other,

Table (1) explain similarity and difference XOR

No	Name Picture	(1+1)(0+0)	(0-1)(1-0)
1	l1\0.bmp	62.254%	37.746%
7	R1\0.bmp	60.056%	39.944%
5	l1\-10.bmp	57.332%	42.668%
2	l1\5.bmp	56.674%	43.326%
3	l1\-5.bmp	55.080%	44.920%
4	l1\10.bmp	54.839%	45.161%
11	R1\-10.bmp	54.643%	45.357%
6	l1\20.bmp	53.976%	46.024%
8	R1\5.bmp	52.837%	47.163%
9	R1\-5.bmp	52.150%	47.850%
12	R1\20.bmp	52.080%	47.920%
10	R1\10.bmp	51.470%	48.530%

Figure 10: Explain of Scale Space With octave

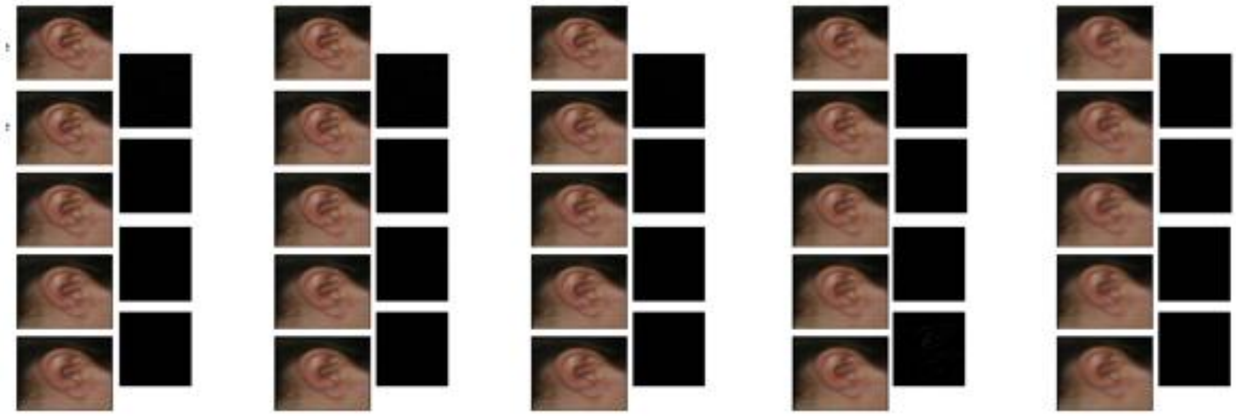


Figure 11: Dog Scale Space Constructions

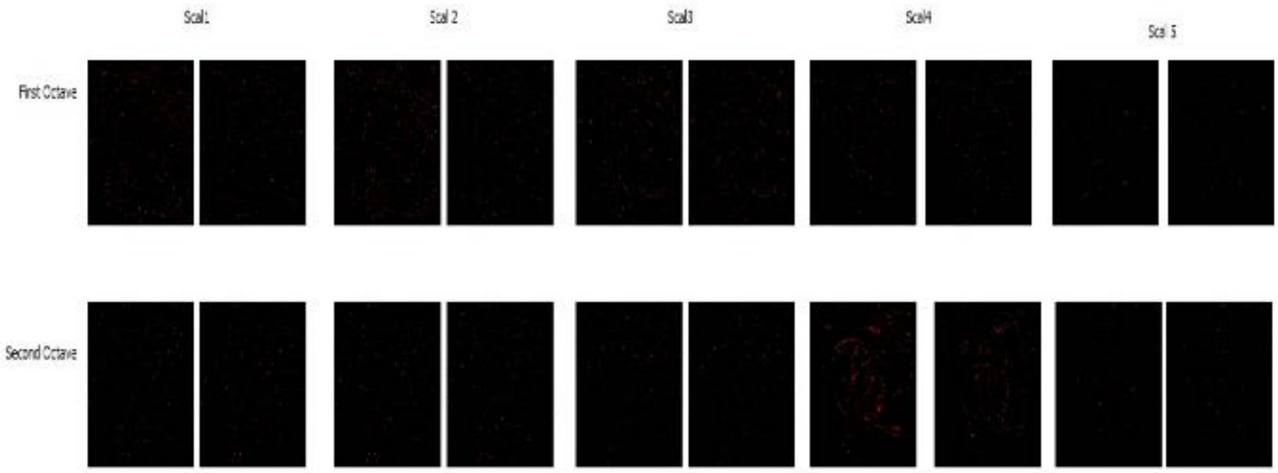


Figure 12 Extreme scale space in the DoG

1. **Different of Gaussian:**

Searches overall image scales and locations to identify key points by using a DoG function shown in Figure 11.

ii.Key Point Selection And Refinement

1. **Detection Of Extreme Points in the DoG:**

DoG of the input image in different scales shown in Figure 12.

2. **Find Key Point:**

SIFT feature extraction for ear shown in Figure 13, Table(2) and Figure 14.

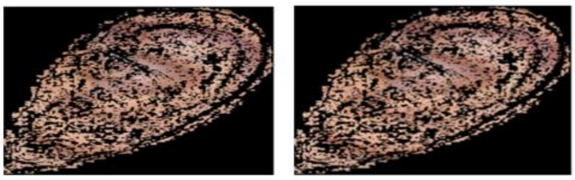


Figure 13: key point of SIFT feature extraction

Tabel(2) Explain Of SIFT Feature Extraction of descriptor

ori	sd-oct	Sd	V	U	subintrvl	OCTAVE	INTERVAL	Y	X	ID
0	6.517376	13.03475	221	3	0.147089	1	1	4.643679	222.9899	1
0	5.832095	11.66419	214	4	-0.33374	1	1	6.128718	215.6424	2
-2.95558	5.866834	11.73367	181	17	-0.30804	1	1	18.95663	183.3132	3
-2.95558	6.235128	12.47026	223	19	-0.04453	1	1	20.98531	225.0102	4
0	6.062938	12.12588	213	25	-0.16573	1	1	27.00673	214.9537	5
0	6.432249	12.8645	140	32	0.090185	1	1	33.98672	142.0021	6
0	6.236657	12.47331	219	38	-0.04347	1	1	40.00613	220.9858	7
0	6.433535	12.86707	143	39	0.091051	1	1	40.9972	144.9837	8
0	5.825703	11.65141	110	43	-0.33849	1	1	45.01551	112.0132	9
0	6.384666	12.76933	177	46	0.058049	1	1	47.98657	179.0017	10
...	...	...	...	...	...	...	...	...	...	...

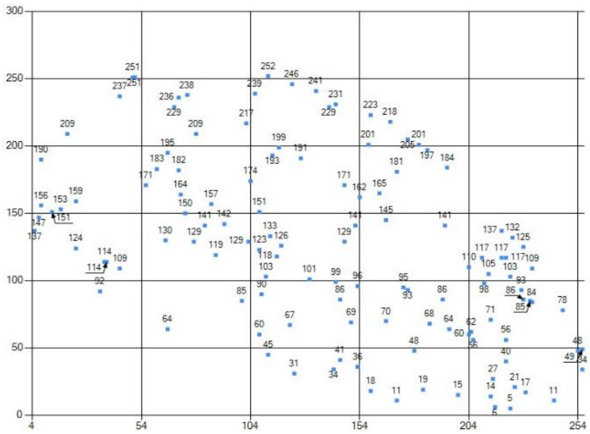


Figure 14 Draw Key Point in Coordinate

3. **Hierarchal Cluster:** find force field features SIFT method shown in the Table (3), Figure 15 and Figure 16.

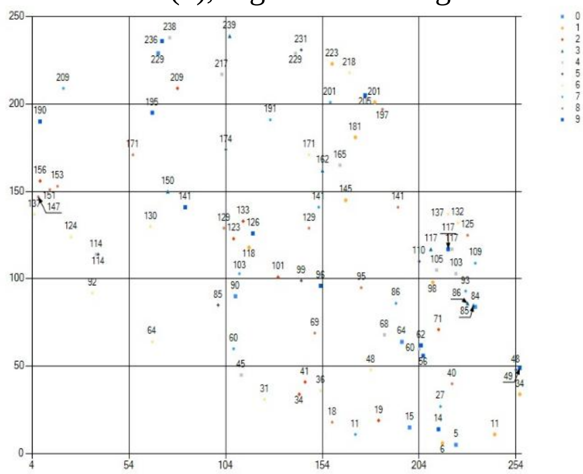
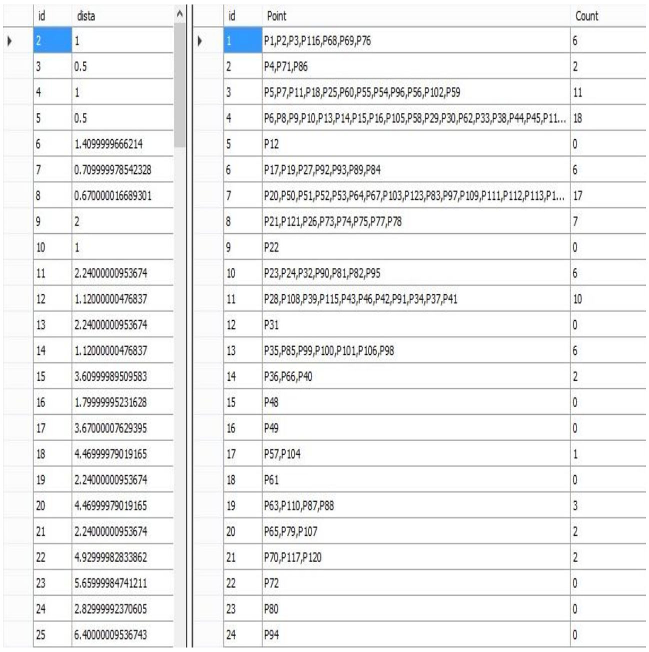


Figure 15 this key point extraction of hierarchal cluster

Table (3) calculation distance of an all key point



id	dista
2	1
3	0.5
4	1
5	0.5
6	1.4099999666214
7	0.709999978542328
8	0.670000016689301
9	2
10	1
11	2.24000000953674
12	1.12000000476837
13	2.24000000953674
14	1.12000000476837
15	3.60999989509583
16	1.79999995231628
17	3.67000007629395
18	4.46999979019165
19	2.24000000953674
20	4.46999979019165
21	2.24000000953674
22	4.92999982833862
23	5.65999984741211
24	2.82999992370605
25	6.40000009536743

id	Point	Count
1	P1,P2,P3,P116,P68,P69,P76	6
2	P4,P71,P86	2
3	P5,P7,P11,P18,P25,P60,P55,P54,P96,P56,P102,P59	11
4	P6,P8,P9,P10,P13,P14,P15,P16,P105,P58,P29,P30,P62,P33,P38,P44,P45,P11...	18
5	P12	0
6	P17,P19,P27,P92,P93,P89,P84	6
7	P20,P50,P51,P52,P53,P64,P67,P103,P123,P83,P97,P109,P111,P112,P113,P1...	17
8	P21,P121,P26,P73,P74,P75,P77,P78	7
9	P22	0
10	P23,P24,P32,P90,P81,P82,P95	6
11	P28,P108,P39,P115,P43,P46,P42,P91,P34,P37,P41	10
12	P31	0
13	P35,P85,P99,P100,P101,P106,P98	6
14	P36,P66,P40	2
15	P48	0
16	P49	0
17	P57,P104	1
18	P61	0
19	P63,P110,P87,P88	3
20	P65,P79,P107	2
21	P70,P117,P120	2
22	P72	0
23	P80	0
24	P94	0

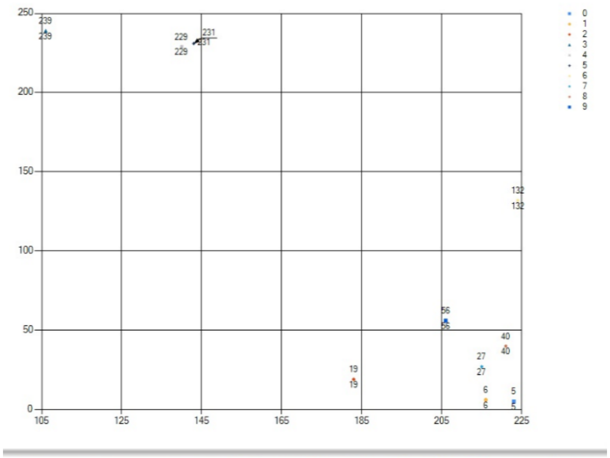


Figure 16 Force field feature extraction for ear

Conclusion

In this paper, we extracted the powerful properties using the Hercules Cluster method, which was invested in the SIFT method. We asked for counting operations so that we got strong properties that required using the method of SIFT to give the results of the strong because it is operating a basis explained which represents each point five vector. Therefore, the number of points generated until we derive the strong characteristics used Hierarchal Cluster, which clusters the points according to the mean errors and then, therefore, the number of key points generated until we derive the force field feature used Hierarchal Cluster, which classifies the points according to the mean and then gives the number of k. we use to make another classification using K-Mean. Here has to find force field points of extraction, applied the same features extraction techniques to obtain five features vectors, make features analysis to obtain (features have better discrimination power) that fed to the PNN with same structure to improve the classification.

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