Human Activity Recognition System to Benefit Healthcare Field by using HOG and Harris Techniques with K-NN Model

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ABSTRACT
The advancement of technology in recent years led to the development the human activities recognition (HAR) system in video . This type of system is one of an important areas for computer vision (CV) .This paper presents a system to help people who are suffered from a health problem and are stayed alone for long times especially the elderly , by recognizing three normal activities : (walking , drinking and eating) and six abnormal activities : (headache , vomiting , fainting , renal colic , intestinal colic , angina) , that are chosen from the daily life activities of elderly people . In this paper we proposed iterative thresholding for separating background from foreground and used two various techniques for features extraction Histogram Of Oriented Gradient (HOG) and Harris. Finally, K-Nearest Neighbors (K-NN) is used to classify normal and abnormal activities in video . The alarm system is activated when the system is recognized one of the abnormal activities by sending SMS email to the person who concerned with the status of the patient. The system is evaluated HOG with K-NN against with K-NN whether before and after using linear discriminant analysis (LDA) that is used to select the best features. Average recognition rate of HOG with K-NN before and after using LDA consecutively, 94.44% and 97.83% and average recognition rate of Harris with K-NN before and after using LDA Consecutively 87.65% and 93.51% for all normal and abnormal activities in our dataset.

General Terms
Human Activity Recognition System (HAR), computer vision, normal activities, abnormal activities.

Keywords
Thresholding, HOG, Harris, LDA, K-NN

1. INTRODUCTION
Beside dynamic scenes detection, classifying object, tracking object and description of behavior , human activity is an active and an important research subject in computer visions (CV) [1] . Human activity recognition system (HAR) has attracted many attention in the field of video analysis technology because of the increasing requests from many applications such as surveillance environments, entertainment environments , healthcare systems (hospitals, eldercare, home-nursing) and the increasing needing for safety and security has resulted in more research in intelligent monitoring [2][3].

In the literature, action recognition and activity recognition are the most common used terms .The term action is often confused with the term activity. Action usually refers to a sequence of primitive movements carried out by a single object, that is, an atomic movement that can be described at the limb level, such as a walking step. However, activity contains a number of sequential actions. For example, dancing activity consists of successive repetitions of several actions, such as (walking, jumping, waving hand) , etc. Activities can be placed on a higher level than actions [2].

Due to high increasing of the elderly people which are living alone and have health problems that is led us to design system to recognize normal and abnormal activities efficiently for elderly people in daily life ,i. e. monitoring their activities 24 hours in video[4]. In this research are recognize the three normal activities: (walking , drinking and eating) and six abnormal activities : (headache , vomiting , fainting , renal colic, intestinal colic , angina) are defined as an activities which need emergency medical help[4] . Single camera that are used to recognize human activities, this camera is put in different places indoor.

This paper proposes an approaches to complete the recognition for human activities recognition: iterative thresholding method for subtracting background ,HOG and Harris for extracting features and K-NN for classification the types of activities that is found in our dataset.

The alarm system is activated when the system is recognized one of the abnormal activities by sending SMS email to the person who concerned with the status of the patient. Whilst when the system is recognized one of the normal activities, the alarm step don't need to activate because the activity recognizes as a normal health activity .

2. RELATED WORK
In the past, most of abnormal HAR systems presented fainting or falling activities recognition systems[5,6,7]. In [5] Foroughi, Homa, et al in 2008 are proposed a novel approach for human fall detection based on combination of integrated time motion images and eigenspace technique. Integrated Time Motion Image (ITMI) is a type of spatio-temporal database that includes motion and time of motion occurrence. Applying eigenspace technique to ITMIs leads in extracting eigen-motion and finally multi-class Support Vector Machine is used for precise classification of motions and determination of a fall event. In [6] Caroline et al. in 2011 are proposed a new method to detect falls by analyzing human shape deformation during a video sequence. A shape matching technique is used to track the person's silhouette along the video sequence. The shape deformation is then quantified from these silhouettes based on shape analysis methods. Finally, falls are detected from normal activities using a Gaussian mixture model. In [7] Zafar et al. in 2013 are proposed a hierarchical HAR system to recognize abnormal activities from the daily life activities of elderly people living alone. This system have two levels of feature extraction and

activity recognition. The first level consists of R-transform, KDA, K-means algorithm and HMM to recognize the video activity. The second level consists of KDA, k-means algorithm and HMM, and is selectively applied to the recognized activities from the first level when it belongs to the specified group. The system is validated by a novel set of six abnormal activities; falling backward, falling forward, chest pain, headache, vomiting, and fainting and a normal activity walking .

3. DATABASE

In this paper, database that is registered for human activities monitoring in video, the table (1) below

Table 1. Described The Database

	Normal Activities	**Abnormal Activities**
Classes	- Number of activities = 3 - Verbs :walking , drinking ,eating	- Number of activities = 6 - Verbs: headache , vomiting , fainting , renal colic , intestinal colic , and angina
	The total of classes = 9	
Video	- Number of videos = 216	-Number of videos = 432
	The total of videos = 648	
	- Resolution = 640 × 480 pixels - Length of each video = 3 seconds - Frame rate = 25 frames / seconds - Static camera (canon 700D)	
Properties	- Homogeneous and limited variation background indoor - Performed by seven persons with various clothes, appearance, body and skin color .	

Fainting Headache Vomiting

Intestinal colic Renal Colic Angina

Walking Eating Drinking

Fig 1: Samples of our database for recognizing normal and abnormal human activities indoor

4. HUMAN ACTIVITY RECOGNITION (HAR) SYSTEM

In this paper our system is include the following levels :

1- Low level : This level contains background subtraction , feature extraction and classification .
2- Middle level : This level contains the human activities recognition models for recognizing normal and abnormal activities of single person.
3- High level : This level contains the application that is used HAR system in order to serve healthcare system , i.e. the application in this work is healthcare application.

4.1 Preprocessing

Two steps of preprocessing are prepared. First, "read video" , Each read video is consisted of sequence of frames that are number 90 frames. Every frame of the video sequences considers as a color image .Second, background subtraction ,the Iterative thresholding method is one type of global thresholding that is used in this step in order to dissociate the foreground (object) from background of the image.

4.1.1 Iterative Thresholding Method:

Iterative method is one of relatively simple methods, that does not require much specific knowledge of the image, and is robust against image noise . It represent special one-dimensional case of the k-means clustering algorithm, which has been proven to converge at a local minimum-meaning that a different initial threshold may give a different final result [8].

In [9] procedure to calculate intensity threshold *T* automatically that described by Gonzalez and Woods (2002) . The approach in [8] can be summarized as follows:

1- Make an initial estimate of *T*, for example the middle intensity. Segment the image histogram into a group G1 of intensities < *T* and a group G2 of intensities ≥ *T* and compute the mean of intensities $\mu 1$ and $\mu 2$ of the pixels $P(I)$ in the two groups as follows :

$$\mu = \sum_{I=0}^{N-1} I\,P(I) \qquad (1)$$

$$P(I) = n1 / N \qquad (2)$$

Where N is the total number of the pixels and $n1$ the number pixels with intensity I.

2- Compute a new threshold $T = 0.5(\mu 1 + \mu 2)$.

Repeat step 2 and 3 until the difference in success value of *T* is less than a predefined limit $|T - Tn| < 0.1$ (3)

Fig 3: An example of background removed

After the background subtraction step , the index of the binary images are calculated which has three color and then bring the coordinate of pixels that equal zero. This step solved to the problem of high similarities in postures of various activities .

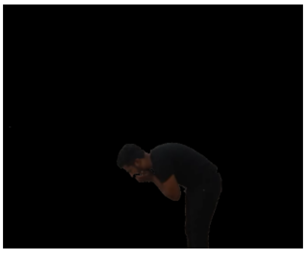


Fig 4: An example color image without background

4.2 Feature Extraction

Extraction of feature is played an important roles in image processing[10] . Feature extraction is the main step in HAR system; features that are extracted useful for pattern recognition and/or classification [11]. It is desirable to extract features which are focused on discriminating between classes. In this stage the characteristic of segmented object is extracted such as colors , motions , silhouette and shape . In General , features can be classified into four classes:) space-time information, local descriptors , frequency transform , body modeling)[3]. In this paragraph introduces various types of feature extraction techniques which are used in image processing , where reviews the definitions and notations and using of these the techniques.

4.2.1 Background Of Histogram Of Oriented Gradient (HOG)

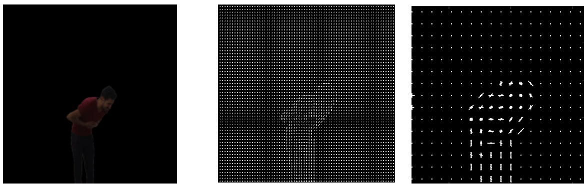
In [12] the first proposed of histogram of oriented gradient (HOG) descriptors for human detection were by Dalal and Triggs 2005 . HOG have so good descriptor for detecting human . At present HOG features are utilized on a large scale in object detection and object recognition. Body shape is describe through extraction the directions of edge or directions of gradient in the window[13].

HOG has sizable success in recognition and object detection The major concept of HOG features is that object shape and appearance are described via the distribution of edge directions. This is performed by separating the window of image into 64 blocks where each block is consist of 2*2 cells. Histogram of gradient direction or edge orientation is computed for each pixel in a cell. HOG descriptors which is pointed to combined histogram entries form the descriptor blocks [13]. Generally, the HOG can be summarized in the following steps :

1- Gradient Computation [14]: Gradient computation is the first step for HOG feature computation , that is calculated gradient of image for each pixel in ,$S_X \times S_Y$ (window size (pixels)) detection window . The following equations (4) and (5) are computed gradient for *X* and *Y* direction .

$$gx = \partial I / \partial x = f(x+1,y) - f(x-1,y) \qquad (4)$$

$$gy = \partial I / \partial y = f(x,y+1) – f(x,y-1) \qquad (5)$$



gx : gradient for *X* dirction & *gy :* gradient for *Y* dirction

The pixel value for *(x, y)* position in an image *I* is represented by *f(x, y)* .

2- Gradient Magnitude And Orientation Computation [14] : The second step for HOG feature computation , that is calculated gradient magnitude and orientation , these are done by The following equations ,(6) equation is calculated gradient magnitude M and (7) equation is calculated gradient orientation Ө .

$$M(x,y) = (gx^2 + gy^2)^{1/2} \qquad (6)$$

$$\Theta (x,y) = \tan^{-1}(gy/gx) \qquad (7)$$

3- Orientation Binning : The orientation binning includes creating the cell histograms. Every pixel computes the weighted vote for an edge orientation histogram channel relyed on the orientation of the gradient element centered on it, and the votes are cumulative in orientation bins over the regions of local spatial that are called cells. Cells can be either radial or rectangular [12]. After computing gradient angle and gradient magnitude for each pixel in a cell, the value of magnitude is specified to bin ranging from (0-180) degrees (When inter-bin distance (Ө dist) is 20° over 0~180°, N is determined as 9) .High magnitude values are considered as a part of edge directions and low values are ignored [13][14] , i.e. the gradient utilized in conjunction with nine channels of histogram (00-200) ,(200-400) ,(400-600),(600-800), (800-1000),(1000-1200),(1200-1400),(1400-1600),(1600-1800) implemented best in the detection of human [13].

4- Normalization [40] : Strengths of gradient differ over a vast range owing to local differences in foreground-background and illumination contrast, therefor efficient local contrast normalization turns out to be major for well performance [12]. This step is applied to normalize contrast into each block, the are two representative normalization schemes are offered in equations (8) and (9) [14].

$$\text{L1-norm: } \{C / (\| B_k \| + \varepsilon)\} \qquad (8)$$

$$\text{L2-norm: } \{C / (\| B_k \|^2 + \varepsilon^2)^{1/2}\} \qquad (9)$$

In these above equations :

Bk : is represented dimensional vector for a block .

C : is represented each element in the vector .

ε: is a small constant that utilized to avert(avoid) division by zero.

The dimension of each block is determined by the number of orientation bins in the block.

5- Descriptor Blocks : Features that are extracted from every cell, and cells are concatenated to every other to structure a descriptor of block. The final descriptor is acquired via the concatenation of whole the blocks features in the window [13].

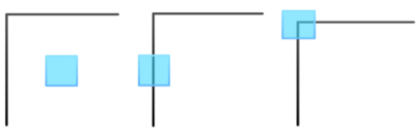
In our work the cell size with [32 32] is selected , because it is more affects to the information in each cell , i.e. for example, when cell size is [32 32] the number of shapes is few but the amount of information is more and the time of execution is faster, but if the cell size is [8 8] (the default cell size in HOG), the number of shapes is more, but the amount of information is less and the execution is slower. Algorithm 3.2 show the steps that are followed to

calculate the HOG features , and the resulted HOG features for one image of one of abnormal activity (intestinal colic), (as in figure (5) , and the output was HOG features vector of size (1x 9576)

4.2.2 Background Of Harris

The Harris corner detection algorithm is one of the easiest algorithm which used for extracting feature point in an image. It is developed by C. Harris and M. Stephens in 1988 , detects the location of corner points within an image . The major concept is to locate points of interest where the neighborhood displays edge in more than one direction : these would be the corners of the image [15] [16].

Corner points are utilized to define features because they have “good defined position and can be strongly detected”. Corner detection is generally approach utilized in computer vision systems for extracting certain types of features and conclude the contents of an image. Corner points are originally unique and are great interest points due to their invariance to rotation, translation, ,noise and illumination . Because of the corner points have intrinsic properties, that led the Harris corner detection algorithm has been used overly for computer vision applications, like : image registration, motion detection, panorama stitching, video tracking, three-dimensional modeling, and object recognition [17] . The corner can be considered as the intersections of two well-defined edges. The Harris corner detection algorithm seeks for corner points via looking at areas in an image that is contained high gradient values in all directions. The window is recursively scanned across the X and Y gradients of the inputted image, and if highly changings in intensity exist in multi directions, then a corner is conclude to exist in the current window. Figure (6) shows the various kinds of regions that can exist within an image [17] .



Flat Region **Edge Region** **Corner Region**

Fig 6: Directional intensity change types [17]

The Harris corner detector is based on the autocorrelation of image intensity values or the values of image gradient. The gradient covariance matrix is given by equation (10) :

$$G_{x,y} = \begin{bmatrix} \left(\frac{\partial I}{\partial x}\right)^2 & \frac{\partial I}{\partial x}\frac{\partial I}{\partial y} \\ \frac{\partial I}{\partial x}\frac{\partial I}{\partial y} & \left(\frac{\partial I}{\partial x}\right)^2 \end{bmatrix} = \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \qquad (10)$$

where *Ix* and *Iy* refer to the image gradients in the *x* and *y* directions . Harris corner detector consider the maximum and minimum eigenvalues, β *and* α , of the image gradient covariance matrix $G_{x,y}$ in developing corner detector . The ‘corner’ is said to happen when the two eigenvalues are large and similarity in magnitude. Harris which devises a measure utilizing the trace and determinant of the gradient covariance matrix as [15] [18] :

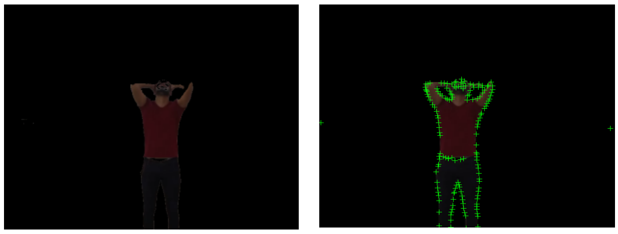
$$R=\alpha\beta - k(\alpha+\beta)^2 = \det(G) - k(\mathrm{Trace}(G))^2 \qquad (11)$$

Where k is specified constant; $k \epsilon ([0.04,0.06])$.

R : Corner strength , on the basis of R the pixels are classified as follows :

$R > 0$: Corner pixel , $R \sim 0$: pixel in flat region , $R < 0$: edge pixel .

In this paper Figure (7) show the result of Harris features points for one image of one of abnormal activity (headache) .



(a) **(b)**

Fig 7: Extracted feature using Harris , (a)) Image after background subtraction, (b) Detecting Harris feature

4.3 Dimension Reduction (DR) And Feature Selection

DR is an important task which is played a major role in statistics and machine learning and others . DR can be done via either reduce the number of features, a task called feature selection, or via reduce the number of patterns, called data reduction [19]. Data dimensionality reduction produce a compact low-dimensional encoding of a given high dimensional data set[20]. Beside of DR can be minimized the amount of storage needed via reducing the size of the data sets , DR can be helped to understand the data sets via discarding any irrelevant features, and to focus on the major important features, and DR can enable the detecting of rich information[21].

Feature extraction and dimension reduction can be combined in one step, there are different techniques are used to accomplish this purpose such as principal component analysis (PCA),linear discriminant analysis (LDA), Singular Value Decomposition …. etc… .[22]. In this thesis is utilized LDA method to minimize the dimensionality of the feature space .

4.3.1 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is one of the most important a supervised dimension reduction techniques [4] , which is represented a very major tool in a wide difference of problems. It is common utilized in machine learning problems such as : face and gesture recognition ,pattern recognition, , feature extraction , data dimensionality reduction and data classification [23][26].The LDA is proposed by R. Fisher in 1936, so it also known as Fisher discriminant analysis (FDA) [25] .

The LDA is a “classical” method in the pattern recognition where it is utilized to find a linear combination of features that characterize or split up two or more classes of object or events. The result of combination may be utilized as a linear classification or, more common, for dimensionality reduction before it can be classified . The LDA works on only top Eigen values of small datasets. It don't work properly on large dataset because of its performancing scalability reduces on large datasets [26]. The idea of LDA can be summarized in the following steps [27] :

- Training set X ={ x(n) ∈ Rd$\}_{n=1}^{N}$, Y= { y(n) ∈ L$\}_{n=1}^{N}$, L={l1,l2,….,lc}.
- Define X_i as the feature set containing all feature samples with label l_i, and the number of sample of label l_i in X_i is denoted as N_i .
- Define the class mean vector as , the following equation (12)

$$\mu_i = \frac{1}{N_i} \sum_{x^{(n)} \in X_i} x^{(n)} \tag{12}$$

- Define the total vector mean as , the following equation (13)

$$\mu = \frac{1}{N} \sum_{n=1}^{N} x^{(n)} \tag{13}$$

- Define the between-class scatter matrix as the following equation (14)

$$SB = \sum_{i=1}^{c} N_i (\mu_i - \mu)(\mu_i - \mu)^T \tag{14}$$

Define within-class scatter matrix as the following equation(15)

$$\mathbf{S_w} = \sum_{\mathbf{i=1}}^{\mathbf{c}} \sum_{\mathbf{x^{(n)}} \in \mathbf{X_i}} (\mathbf{x^{(n)}} - \boldsymbol{\mu}_\mathbf{i})(-\boldsymbol{\mu}_\mathbf{i})^\mathbf{T} \tag{15}$$

4.4 Classification

After choosing suitable features from image or video, classification algorithms are the next step under consideration for recognizing activities of human for achieving good recognition execution , it is major to select an appropriate classification algorithm utilizing the selected features representation[3]. The general concept of classification is one of data analysis forms that extracts models describing important data classes. this models, called classifiers, predict categorical (discrete, unordered) class labels. The classification process of data consist of two-steps , The learning step (where a classification model is built) and the classification step (where the model is used for predicting class labels for data) [28]. Next are two approach for classification is used in this work to find the decision boundaries between the classes which are K-NN and Decision tree models .

4.4.1 K-Nearest Neighbor (KNN)

K-Nearest Neighbors (K-NN) method is one of the most important a machine learning algorithm, that is often utilized to classify objects based on the most similarity samples of training in the feature space, i.e. K-NN is based on closest training examples in the feature space. The classification is based on the distance between a set of inputted data points and training points. Different metrics can be utilized for determining the distance (Euclidean distance , Spearman distance , Mahalanobis distance and etc.) [3]. The Euclidian distance is the most common metric which utilized to measure distance , which is computed as the (16) equation. If we have two points *x*, *y* where each point is an n-dimensional vector, i.e. $x = \{x_1, x_2, \ldots\ldots, x_n\}$, $y = \{y_1, y_2, \ldots, y_n\}$. Distance function $d_E(x, y)$ between two points is defined by measuring their distance according to Euclidean equation[29] :

$$d_E(x, y) = \sqrt{\sum_{x=1}^{n} (x_i - y_i)^2} \tag{16}$$

The K-NN is supervised learning algorithm . If no model is learning from the training data that is called " lazy learning " ,K-NN from this type . In contrast , the eager learning methods they learn models of the data before testing [30].

The idea of K-NN is very easy and quite efficient in a lot of applications. It works as the following : Let *D* be the training dataset . Nothing on the examples of training is done. When the example of test is presented, the K-NN is comparing *d* with each example of training in *D* to calculate the similarity or distance between them . The *k* most closest(similar) example in *D* are then chosen. This set of examples is named the K-nearest neighbors of *d*. *d* then takes the most recurrent class among the *k* nearest neighbors .

For example the figure (8) is shown two classes of data , positive (the filled squares) and negative (the empty circle). If *k*=1 , the test data point will be classified as negative , and if *k=2* ,the cannot be decided ,if *k*=3 the class is positive as two positive examples are in the K-NN.

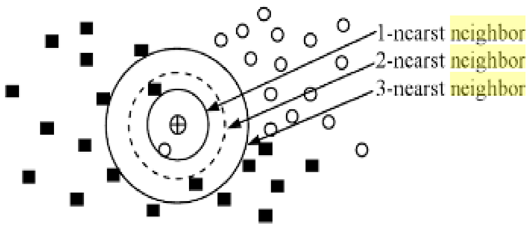


Fig 8: Example of K-NN classification[30]

4.5 Alarm System

Alarm is an important step that active only when the abnormality human activity happed, i.e. when an abnormal action is recognized , alert system is activated in the form alarm, referring to need of helping [31]. It plays an important role in securing and safety, increasing awareness, and giving an alert of a potentially dangerous situations.In this paper is utilized "Email" as type of alarm systems rather than hardwires, and that is simple and speedy because immediately destination person is alerted whether , (doctor , nurse , or any person responsible for the patient) when any abnormal human activity is detected will be send email right away .

5. EXPERIMENTAL RESULTS

This section illustrates the results of the proposed system implementation which used the video in the indoor to recognize the health type of human activities from these videos . HOG and HARRIS techniques with K-NN model are applied in order to obtain the best results. The success rate is calculated by using the following equation :

$$\text{Success Rate} = \frac{\text{Number of success states}}{\text{Total number of states}} \times 100\% \tag{17}$$

The results of the accuracy recognition that are obtained of implement K-NN model on the current healthcare human dataset is discussed ,the results is shown for HOG and HARRIS features that are utilized in this work. The table (3) is shown the recognition rate that are obtained before apply the method LDA technique with each type of feature .

Table 2. The results accuracy of K-NN for normal and abnormal activities for each class and the total classes before using LDA

Classes	HOG	Harris
Fainting	94.44	75
Vomiting	100	61.11
Headache	86.11	86.11
Angina	83.33	88.88
Intestinal Colic	100	94.44
Renal Colic	94.44	83.33
Walking	100	100
Drinking	97.22	100
Eating	94.44	100
Total	94.44	87.65

In figures (9) and (10) are the charts that presented the measure of the differences among features for each class and for total classes consecutively .

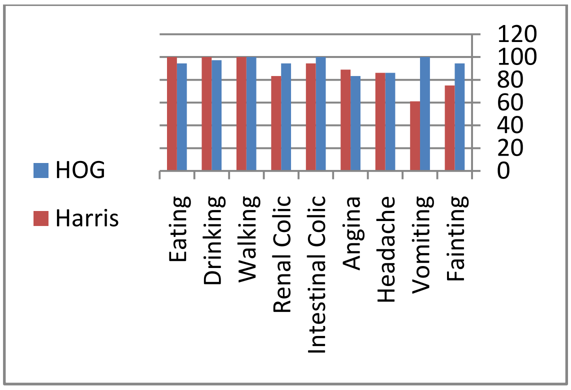


Fig 9: The results accuracy of K-NN for normal and abnormal activities for each classes before using LDA .

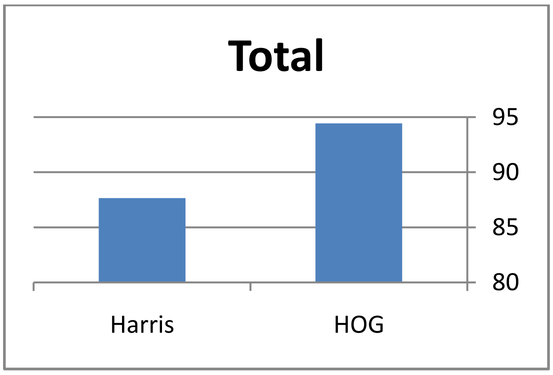


Fig 10: The results accuracy of K-NN for normal and abnormal activities for the total classes before using LDA.

The table (4) are shown the recognition rate that are obtained after apply the LDA method . The figures (11) and (12) are presented the charts of the difference in the results accuracy of classes with K-NN model and LDA .

Table 3. The results accuracy of K-NN for normal and abnormal activities for each class and the total classes after using LDA

Classes	HOG	Harris
Fainting	100	88.88
Vomiting	100	86.11
Headache	100	94.44
Angina	94.44	100
Intestinal Colic	94.44	80.55
Renal Colic	100	91.66
Walking	100	100
Drinking	97.22	100
Eating	94.44	100
Total	97.83	93.51

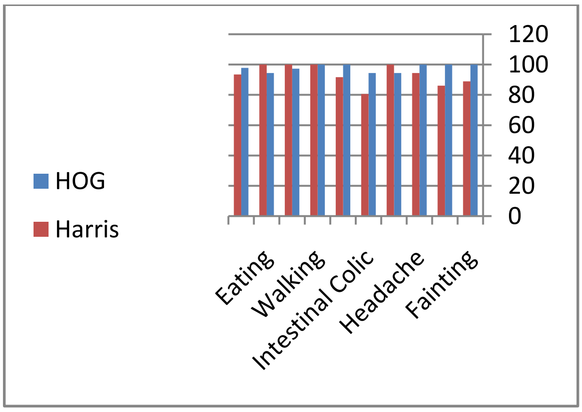


Fig 11: The results accuracy of K-NN for normal and abnormal activities for each class after using LDA .

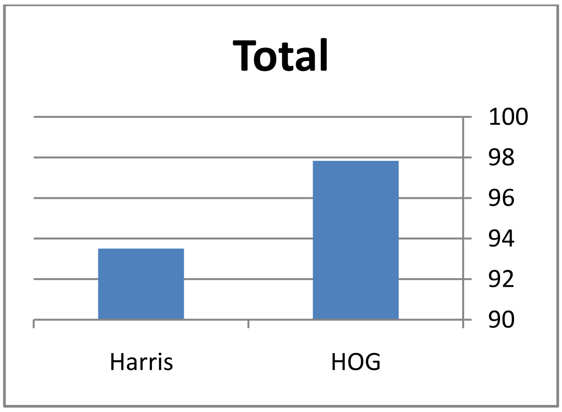


Fig 12: The results accuracy of K-NN for normal and abnormal activities for the total classes after using LDA.

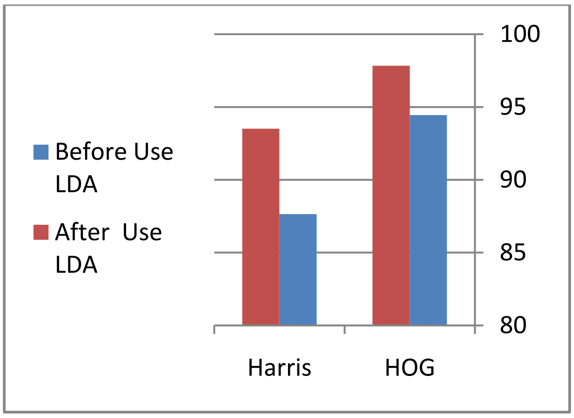


Fig 13: The comparative for accuracy of K-NN for normal and abnormal activities for the total classes before and after using LDA .

6. CONCLUSIONS

This research work, is proposed in order to recognize the normal and abnormal human activities for serving the healthcare fields . Our system is implemented by register database has three classes of normal activities and six classes of abnormal activities . The implementation of subtracted background from each frame ,in order to obtain images without background and is almost limited to the person's activity. This step is an important for increase accuracy and speed processing. In the preprocessing step , we can solved the problem of high similarities in postures of various activities different because some various activities that are seemed similar .Then LDA is used to select the best features , and to increase performance accuracy for both feature extraction techniques (HOG & Harris) . The results of K-NN model whether after or before using LDA the results was very good and encouraging. The accuracy performance of HOG is better than Harris , but the run time of Harris is less than HOG , i.e. Harris is faster than HOG.

7. FUTURE WORK

In future, the proposed method will be developed over other conditions by construct large database that have many activities daily life ,in several places with different background (indoor and outdoor) . In addition to this future development, SVM model will implement in order to recognize normal and abnormal activities instead of K-NN.

8. REFERENCES

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