THE REPUPLIC OF TURKEY

BAHCESEHIR UNIVERSITY

# FALL DETECTION BY USING RGB-D CAMERA

Master Thesis

Muataz Akram Hassan Hassan

ISTANBUL, 2016

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NATURAL AND APPLIED SCIENCES

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**DEPARTMENT OF COMPUTER ENGINEERING**

Name of the thesis: Fall Detection By Using RGB-D Camera
Name/Last Name of the Student: Muataz Akram Hassan
Date of the Defense of Thesis:2/9/2016

The thesis has been approved by the Graduate School of Natural and Applied Sciences.

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This is to certify that we have read this thesis and we find it fully adequate in scope, quality and content, as a thesis for the degree of Master of Science.

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## ACKNOWLEDGMENTS

This Master thesis was carried out at Bahcesehir University Graduate School of Natural and Applied sciences under the supervision of Dr. Tarkan Aydın .

I would like to Thank Dr. Tarkan Aydın for his valuable advises ,his ideas and limitless help and over all the time taken to accomplish this thesis.

Secondly, I would like to thanks my friends that have always been encouraging me and support my decisions. And most importantly I have infinite gratitude for my family, my source of power and inspiration, that help me and support me in all the way during the phases of my life .

Lastly, I would like to dedicate this work for my brother Souhaib Akram ,may his soul rest in peace, and for the city that wait a war with an indefinite date Mosul.

# ABSTRACT

FALL DETECTION BY USING RGB-D CAMERA

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September 2016, pages 52

The proportion of older people is increasing day by day in the world. More than 33% of home residence people are 65 years old or above and 66% of those in home care are suffering from fall one or more than one times in the year. The fall leads to the fear of doing daily life activities and the loss of confidence to live alone. In addition, It generates dangerous injuries that may lead to death sometimes. Therefore, It is necessary to provide assistance as soon as possible. The computer vision systems will give us a good technique to analyze the attitude of the person and recognize the abnormal actions.

Proposed  is based on extracting some features from skeleton joints and we applied it to the classifiers to detect the fall and find which classifier is the best. We utilized the kinect to get the information of skeleton and weka for classification .

Also, the ethical issue is the privacy of the person. we used the Kinect RGBD cameras which deal with the depth information to protect the identity of the person and preserve his privacy.

**Keywords:** Fall Detection, Kinect Camera, Older people

# ÖZET


RGBD KAMERA KULLANARAK DÜŞMELERIN TESPIT EDILMESI

Muataz Akram Hassan

Bilgisayar Mühendisliği Bölümü

Tez Danışmanı: Asst. Prof. Tarkan Aydın

Eylül 2016, 52 Sayfa

Dünya üzerinde yaşlı insanların oranı günden güne artmaktadır. Evde bakılan insanların %33'ünden fazlası 65 yaş ve üstüdür. Bu evde bakılan nüfusun %66'sı yılda bir veya iki kez düşme tehlikesi ile karşı karşıyadır. Düşme korkusu günlük yaşam aktivitelerini yapmalarını engellemekte ve tek başına yaşayabilme güvenlerini yitirmelerine neden olmaktadır. Ayrıca bu düşmeler ciddi yaralanmalara ve hatta ölümlere sebebiyet verebilmektedir. Bu yüzden, yaşlılara destek sağlamak amacıyla ( Bilgisayarla Görme) sistemleri insan davranışını incelemek ve normal olmayan aksiyonları saptamak için iyi bir teknik olarak kullanılabilir.

Öneriler yöntem, iskelet eklemleri üzerinden bazı bilgiler elde ederek bunları sınıflandırıp düşmeleri saptayarak ve hangi sınıflandırıcının en iyisi olduğu belirlemeye dayalıdır. İskelet bilgilerini elde etmek için Kinect ve sınıflandırma için Weka kullanılmıştır.

Ayrıca, kişinin özel hayatı bir etik sorun olarak görülebilmektedir. Bu amaçla kişinin kimliğini ve gizliliğini korumak için Kinect RGBD kameralar kullanılmıştır.



**Anahtar Kelimeler**: Düşme tespit, Kinect kamera, Yeşli insanlar

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## ABBREVIATIONS

ARFF : Attribute-Relation File Format

COM : Center of Mass

GMM : Gaussian Mixture Model

HAR : Human Activity Recognition

HMM : Hidden Markov Models

ISTE : Integrated Spatiotemporal Energy

KNN : K- Nearest Neighbors

LHMM : Layered Hidden Markov Model

MHI : Motion History Image

NI : Natural Interaction

OpenNI : Open Natural Interaction

RGBD : RGB Depth

SCMPM : Single class mini max probability machine

SDK : Software Development Kit

SIMBAD : Smart Inactivity Monitor

SMO : Sequential Minimal Optimization

SVM : Support Vector Machine

WEKA : Waikato Environment for Knowledge Analysis

# 1. INTRODUCTION

According to the research of the United Nations the number of seniors has increased three times during the past 50 years and it will be more than the three times again in the next 50 years[1]. The rate of people who are more than 60 years old is growing faster[2].The highest proportions of old people is in European countries and expected to stay at least the next 50 years.

And more than 33% of home residence people are 65 years old or above and 66% of people who live in home nursing suffered from fall at least once yearly [3].Not less than 66% of seniors have encountered a fall can fall once more [4].

Therefore, falling is a great danger for the older people and cause injuries that even lead to death if the assistance wouldn't come in time. In addition to physical injuries, they are psychological consequences like loss of confidence to live alone and lack of independence.

Fall is representing a big challenge for our society that motivates us to offer solutions and technology will help us to find a system that provide a good life quality for elder with lowest cost of healthcare.

## 1.1 DEFINITION OF THE FALL

Actually, we don’t have one definition for fall and it can be defined in various methods depend on what is the study focus but the most common definition and used in many researches is 'unintentionally coming to the ground or some lower level and other than as a consequence of sustaining a violent blow, loss of consciousness, sudden onset of paralysis as in stroke or an epileptic seizure'[5].

## 1.2 THE MAJOR REASON OF THE FALL

The falls can happen anywhere but over half of all falls occur at home while a person is doing the activities of daily life . Falling is a real threat to our ability to live on our own.

The most common factors of fall are the normal changes of aging like Impaired vision and not to wear glasses or poor hearing also some diseases which lead to dizziness such as Diabetes. The lack of exercise and muscle weakness, especially in the legs do increase a person's risk of falling Addition The side effects of some medicines can make you lose your balance and make you fall , All of these reasons can cause to fall.

## 1.3 CLASSIFICATION OF METHODS TO FALL DETECTION

The classification of fall detection methods is ill-defined process and complex. The categories of the approaches are different from a study to another and there is no system accepted by the unanimous scientific circles because there is not a common framework for data acquisition.

Therefore, they are more than one classification for the methods to detect the fall and in our approach we will divide to three methods.

A. Detect Fall by Ambience Device
B. Detect Fall by Wearable Sensor Device
C. Detect Fall by Computer Vision

We will describe each one of them and study their strength, weakness and we will propose the one that ensures the safety, security and an available independence in life for the elder.

### 1.3.1 Detect Fall by Ambience Device

Is the first system we will highlight it. It  includes some sensors like infrared sensors, microphones and vibration sensors. This technique depends on noticing the vibrations caused by falling on the ground. We will get the data by setting up several sensors in the place to take the data of the people when they are close to them. We can be divided into presence device and posture device.

The strength of this approach is not Intrusive mean you don't need any device to wear it but on the other hand the big problem of this system is the noise coming from environment what leads to many false alarms. The use indoor is the second disadvantage adding it is least effective if we compare with other systems.

### 1.3.2 Detect Fall by Wearable Sensor Device

The principle of this domain depends on wearing  miniature sensor devices to detect fall and uses accelerometer, gyroscopes sensors  to physical activity monitoring and get more information about the patient’s position. Wearable sensor including motion device and posture device.

The advantage of this technique, the patient can use it whenever and  it’s more accurate than an acoustic system, weight light and water resistant also we have some shortcomings it isn't comfortable for users  and we should consider the battery life in same time it does not give us solutions if the patient is unconscious or forget to wear it.

### 1.3.3 Detect Fall by Computer Vision

This technique used the image and video to recognize the fall and the big advantage in this system we can monitor more than one person for 24 hour and that gives us a huge database to detect all cases like unconscious person or stress state and we don't need to wear any device like wearable sensor. Recently with the decrease rapidly of the prices of cameras increases the use of this system but the shortage of this approach is the privacy of the person. The challenge of fall detection by video is detecting the abnormal event from other activities of the life. We can classify computer vision to two types: methods using: RGB camera and methods using depth cameras. The classification of fall detection methods in Fig 1.1 and the general fall detection system based computer vision in Fig 1.2

**Figure 1.1: The classification of fall detection methods**

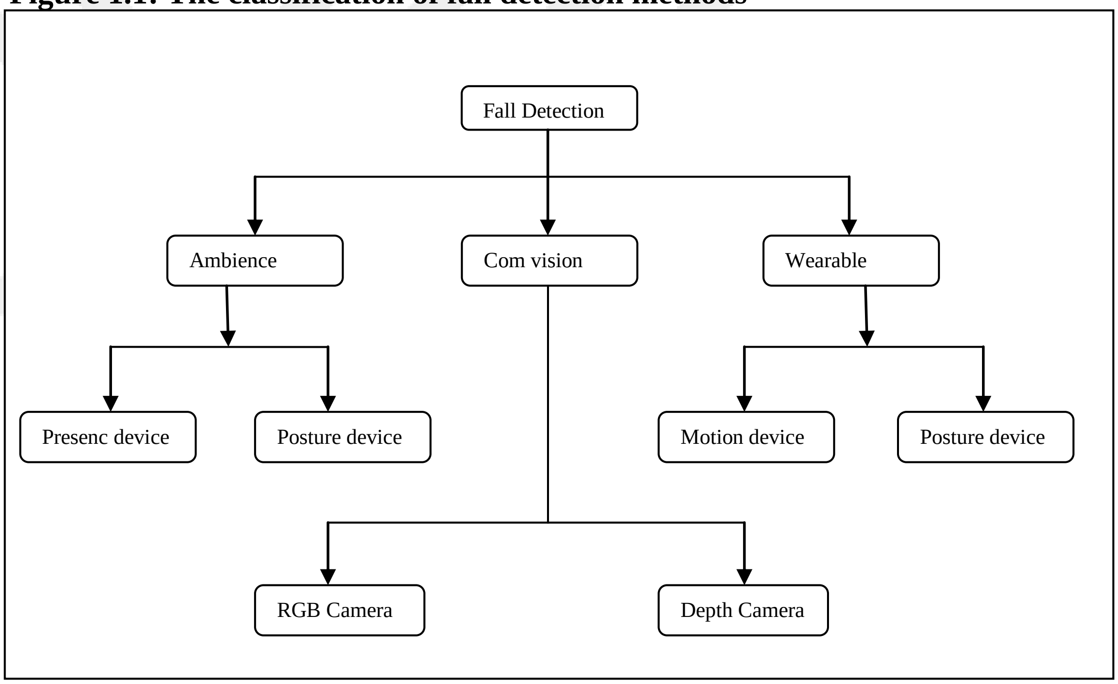
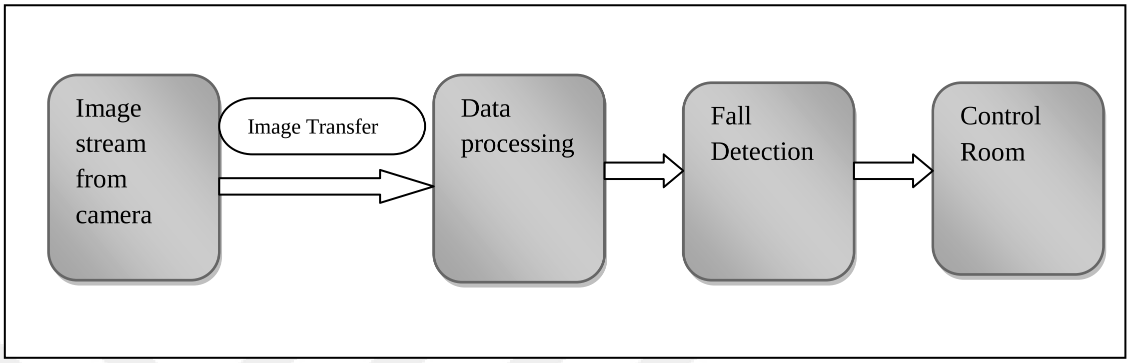


**Figure 1.2: General fall Detection system based computer vision**




## 1.4 PRIVACY AND ACCEPTANCE

One of the challenges that facing fall detection in general was the privacy and how we can available the approach which preserve the privacy and acceptable by the elderly .It is not easy for older people to accept put the cameras in their houses and recording their life for 24 hour.

In our model, we have provided comfortable method and unobtrusive for elder where we treat with this problem by using the Kinect RGBD cameras which deal with depth information to protect the identity of the person preserve his privacy.

More than 33% of home residence people are 65 years old or above and 66% of people who live in home nursing suffered from fall at least once yearly

# 2. LITERATURE REVIEW

In the area of fall detection they are many researches[6][35] and the detect of the fall depend on the methods which used to gather the data. We can categorize to three types : Ambience based fall detection, Wearable sensor fall detection and Computer vision fall detection. In this review we will focus on last one.

In the filed of the ambience ,they using Array-Based Detectors to develop a method called as Smart Inactivity Monitor (SIMBAD).This method depended on the low-cost, array-based infrared sensors[6]. Other method depended on the vibration of the floor and sensing of the sound , and utilizes the processing of the signal and the pattern of the recognition algorithm to detect the unusual action among different activities of the life. used by Zigel at [7].

In the second method(Wearable sensor ), they designed an embedded system to detect the fall that utilizes two kinematic sensors put on two places on the body thigh and chest. The gyroscope and accelerometer had utilized in the sensor module of kinematic and by microcontroller processing the data locally to get fast answer [8]. To detect the fall in this system they used the accelerometer to be able identify the person position and sending the warn by short messages (SMS) .They used two-stage in algorithm of fall detection and the device wearing on the user waist. [9]. They used many triaxial acceleration sensor devices to sensing the pose of injured body, when the fall event occurred the device send the data to computer by wireless transmission devices for more analysis and take a decision. [10].

In the last decade the computer vision systems boomed in the healthcare industry. The studies and researches have expanded in this field here we will clarify some of the earliest research for the fall detection and as we know the intelligent surveillance system should be strong to the problems of image processing and one of the strong points come from choosing the camera so our review will be based on the type of the camera used in the system so we will divide to two categories RGB Camera and RGBD camera.

## 2.1 RGB CAMERAS

The first category of the computer vision systems to fall detection and the earliest attempts and researches in this way. Analyzing the person's bounding box in the image is one of the most commonly and simple methods[11,12,13].

They utilized audio and video to detect the fall. They computed the wavelet transform by using the signal motion of a person and this value used as an input for HMM-based classification. In addition of HMMs of Audio channel they reach to the final decision[11]. The simple method recognizing between a few common activities by using hidden Markov models to see how the performance of the features[12]. They present a system depending on two things detect the object and the fall model uses . To recognize the moving of the person used a Gaussian mixture model (GMM) to apply adaptive background subtraction method and the fall model analyze a features set like horizontal, aspect ratio and vertical gradients of an object to fall detection[13]. Other studying Try to find the fall at inactivity zone like bed and chairs by analyzing The silhouette of the person and the 2D image velocity. The fall detect with special thresholds. The camera was set up in the ceiling at a height of 2.6 m to avoid the occluding [14] .

Other methods used fuzzy logic [15,16,17].

In the first one ,they proposed multi view system to detect the fall by using a layered hidden Markov model (LHMM) to describe the motion. The system proposed to utilize a multi-view setting, The low-level steps are implemented separately in each view that leading to extracted the features of a simple image suitable with achievement of real time. after that the unit of fusion combine the output of each camera to give a point of view independent pose classification[15]. The other one proposed a system to recognize the live activity of the person by linguistic summarization. They analyzed voxel person and a fuzzy hierarchy to detect the fall which each output of level using as input for the next level[16]. In the last one, the system depend on detect of the human prior to posture recognition and used some features designed to describe the person's silhouette[17].

[18][19] To detect the fall they used a single calibrated camera to track the head with 2D ellipse that utilized to calculate the localization 3D head. In case person standing was good result but errors happened with a falling person (oriented of the head) . The progress here is to represent the head they are using an oriented 3D ellipsoid which is tracked with a particle filter through the video sequence.

And some systems used multi camera and it is more difficult to implement than a single camera. [20] More than one cameras are utilized to coverage many rooms. Each room has a single camera for monitoring. The camera hand off is deal with distorting the body's appearance in the new view by means of homograph [21]. To recognize the fall would analyze the volume distribution along the vertical axis and when the major part of this distribution is unusually close to the ground during a particular time period the alarm would be triggered. [22] Video features are extracted and applied one class classification techniques to decide if the new cases in the ‘fall region’ or outside of it to recognize the fall from other activities like walking ,sitting, crouching ,standing or lying. They used 4 various ways; K-center, K nearest neighbor, OCSVM and single class mini max probability machine (SCMPM) and find that SCMPM achieves the overall best performance among them.

Other approaches used posture of the body and many different ways [23,24,25,26,27,28].

The fall detect by analyzing human behaviors by classifying the position of the monitored person[23]. They used the sensor of an asynchronous temporal contrast vision that features sub-millisecond temporal resolution. They recognize the fall when big change happen in the centroid of the person significantly and quickly [24]. They used the variance ratio to detect the fall and a Principal Component Analysis to get the direction of the person to improve their recognition results they used a head tracking module[25].

[26] They made a research to know the receptivity of the older people about Intelligent video monitoring system. The study focuses on two main part:

to explore their receptivity towards the system (cameras, computer at home) and to explore their perception related to the data transmitted and the transmission modes.

[27] They detect the fall by analyze the integrated spatiotemporal energy (ISTE) map which contain the motion and the time of motion event and they used it as a features. Other studying, proposed a hierarchical human activity recognition (HAR) method to recognizing between the fall and the daily activities life .The system consist of two levels of feature in case the activities belongs to the specified group , they applied it selectively from the first level. The approach is well to recognize between the highly similar activities[28] .

## 2.2 RGB DEPTH CAMERAS

The use of this technology for fall detection was not common because it was expensive but after the depth sensing technology spread like Microsoft Kinect. The researches in this field start increasing more and more. The earliest utilization of depth camera for fall detection was in 2010 when they utilized the type of the cameras is Time-Of-Flight and hanging on the wall to observe scene and to recognize the fall event the study used the distance from the floor plane to the center of the human body and the backbone direction of the person. The fall happen when the distance of a human centroid is lower than certain threshold to the floor [29].

The other approach of utilized kincet camera is getting depth images. The study used two features to detect the fall 3D centroid to ground distance & body velocity if the human silhouette centre height relative to the floor less than a threshold fall is occurred and in case if the person is not appearing in the scene they analyze the velocity of body before occlusion happening. The histogram analysis of a V-disparity image used to detect the ground plane. The system detected many of fall events but with many false positive however the method still cannot robustly represent a correct human position[30].

The study [31] Using the 3D bounding box without referring to the floor to analyze the depth information to detect the fall when the composite vector of width and depth and the velocities of height are gone over certain thresholds and there is no motion the fall has happened. The results were acceptable but the searching can be mathematically tedious.

The other study depend on joints of person by using skeleton information to get the orientation of the body to indicate if the fall happened or not. The fall is occurring when the distance between the spine and floor is less than threshold and the main direction of the body is parallel to the floor. The disadvantage of this study is the sight , Tt will always be vertical for the camera and that means they cannot recognize when the fall happens in other directions[32].

Other system detect the fall based on collect the information of normal color and map of the depth . They obtain the motion by the depth and map of the RGB by using MHI to get motion and HU to extract the features from MHI then classify the fall by using SVM[33].

In other approach ,they propose a system providing more independency for elder by using Kinect RGB D cameras to identify five activities based on depth information and the RGB video will keep continue monitoring when the person go outside the domain of the camera. A hierarchy classification schema is designed to strong distinguish of five activities. It recognizes the fall from other similar activities like fall down from standing position , fall down from the seat, sitting on the seat, and sitting on the ground[34].

The system propose a statistical method . They used two Kinect cameras to best cover of the scene and they take a decision depending on catching the movement of the person thought the last frames. They are utilizing Bayesian framework to combine the features and recognize the fall. In this experiment, all data of training collected from a particular standpoint and the data of test gathered from different standpoint This assessment protocol is a good method to know the robust of the technique to camera displacement [35].

Other studying used the depth camera to get the data. Where they used the depth images that got it from the camera to calculate the data of the skeleton of the body [36]. Look to the table 2.1

**Table 2.1: Literature Review**

| Reference | Intermediate Data | Features | Classifier | Actions | Notes |
|---|---|---|---|---|---|
| [11] | Bounding Box | Audio signal Wavelet transform applied aspect ratio | HMM | Fall | |
| [12] | Bounding Box | height to Width ratio off diagonal terms from the covariance matrix | HMM | Fall | |
| [13] | Bounding Box | Accept ratio, horizontal and vertical gradients ,orientation | Thresholding | Fall | |
| [15] | Bounding Ellipse | Angle between vertical direction and principle axis | Layered HMM | Fall | |
| [16] | 3-D Silhouette | Centroid, eigen -based height, similarity of the major orientation with vertical direction | Fuzzy inference | Fall | Multiveiw |
| [17] | Bounding Box | Width, Height , Centroid Oreintation of vertical axis | Fuzzy logic system | Fall, Laying, Squatting, Sitting ,Standing | Adaboost for Human Detection |
| [18] | -- | 3D head position velocity | Thresholding | Fall | Head is tracked |
| [19] | Silhouette | Silhouette Edge points | Shape context matching GMM | Fall | |
| [20] | Silhouette | Vertical & Horizontal projection probabilities | HMM | Fall 4 postures | Multi view |
| [21] | 3-D Silhouette | Vertical volume distribution ratio | Thresholding | Fall | Multi view |
| [22] | 3-D Silhouette | | One class clasiffiers | Fall | Multi view |
| [23] | Silhouette | Shape, Area,color distribution, average motion vector, Vertical & Horizantal projection | Bayesian Classifier | Standing, Sitting, Crouching, Lying | Track-based classificati on to detect fall |
| [24] | Moving Pixels | Centeroid Vertical velocity | Thresholding | Fall | Kinect |
| [25] | Bounding Ellipse | Orientation of the main axis, Variance ratio, Temporal change of head position | Multi Frame Gaussian | Fall | Head: skin-colored |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | blob two camera |
| [27] | Silhouette Ellipse | Weighted motion history image, orientation and axis of ellipse | Thresholding | Slip , Fall | |
| [28] | Silhouette | R transform, Kernel discriminant analysis | HMM | Falling backwad,falling forward,chest pain,headache, vomiting, tainting | |
| [29] | 3-D Silhouette | Centroid to ground distance | Thresholding | Time of flight camera | |
| [30] | Silhouette | 3D centroid to ground distance & velocity | Thresholding | Fall | |
| [31] | 3-D Bounding Box | Width, Height, Depth, Height velocity | Thresholding | Fall | |
| [32] | Bounding Box Skeleton | Audio sensor Features of bounding box, Major axis from skeleton joints | Thresholding | Backward fall,Forward fall,Lateral fall,neutral | Head, Shoulder, Spine, Hip,Knees for major axis, No fusion |
| [33] | Silhouette | Motion history image Hu moment | SVM | Fall | kinect |
| [34] | Bounding Box skeleton | Width-height ratios Angles between joints | Hierarchical SVM | fall down from standing position , fall down from the seat, sitting on the seat, sitting on the ground | kinect |
| [35] | Bounding Box | Total head drop Maximum speed Smallest head height Fraction of frames where head drops | SVM | Fall | kinect |

# 3. IMPLEMENTATION

In our methods we used  Microsoft visual studio C++ as a programming language for execution. And another libraries had utilized  like OpenNI (to video and  image processing) and we used one RGB Depth camera for monitoring. We will explain our approach for fall detection. we selected some of the features and applied them to classifiers to compare which one of them is better. We utilized the weka for classification. We got the information of the skeleton joints from the openni and applied them to weka

## 3.1 THE DATASET

The Kinect camera of Microsoft utilized to build the data for the experiences. We are concerned to recognize falls from different activities. To achieve this aim, we structured a dataset that containing the life activities of elderly. Our recording consist of 2000 frames. It had a length of two minutes. There is one actor in the scene and The recording contains the activities  of daily life like standing ,gaiting and running .The  fall happened between 1600 to 1800.

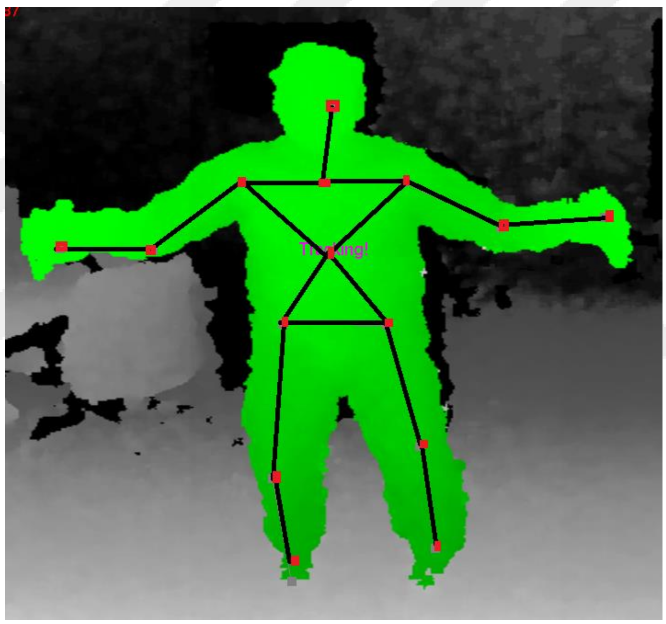
## 3.2 KINECT AND OPENNI

Microsoft released Microsoft Kinect(Fig.3.2)  in 2010 and it became one of the popular techniques to capture video where it used infrared to build image depth information After that it has been widely used in the medical field because it is comfortable for the elder and accurate for skeleton detection and it's not affected by illumination.

OpenNI (Open Natural Interaction) is  software created by PrimaSense and made open source, it uses natural user interfaces along with organic user interfaces and improves on their interoperability to be used by Natural Interaction devices. It will help us to extract the depth information and the joints of the body.

The Microsoft Kinect SDK makes available skeletal joints tracking, which allows researchers to study fall detection by analyzing the human body joints. The skeleton contains 20 joints coordinates to track the person in each frame. In this study, we used only 15 of them to recognize the fall. The joints used were torso, neck, head, left hip, right hip, right knee, right foot, right shoulder, right elbow, right hand, left knee, left foot, left shoulder, left elbow and left hand. See Fig 3.1

**Figure 3.1: 15 Skeleton Joints Finding by openNI**



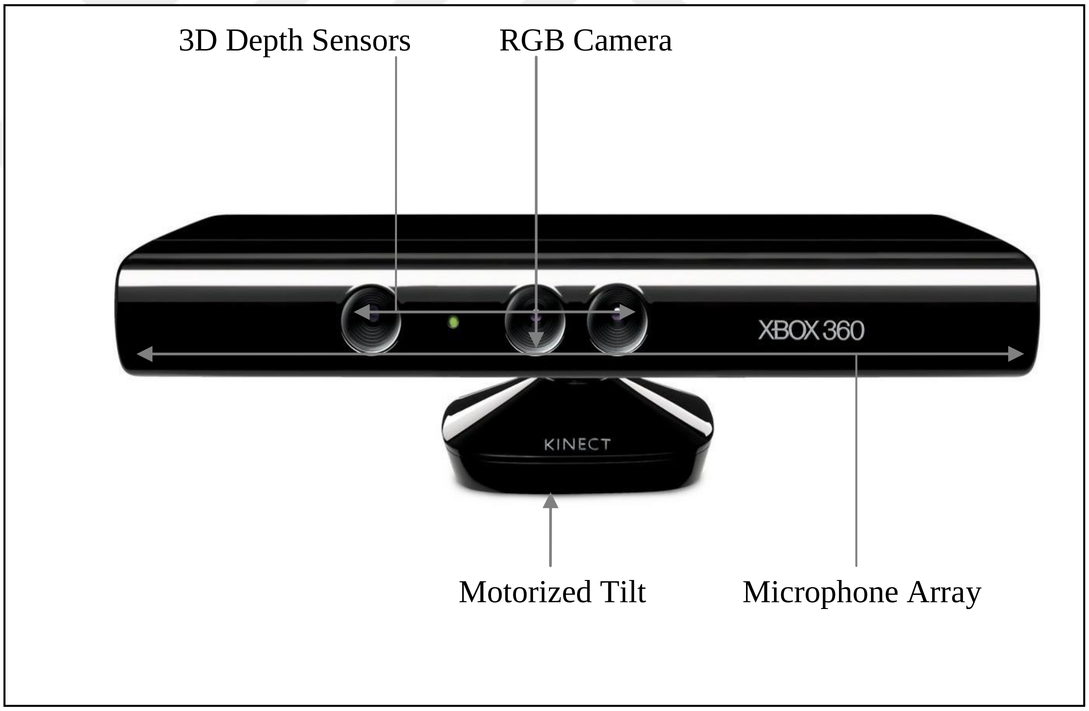
## 3.3 TRACKER ALGORITHM

The User Tracker algorithm provides access to one half of the algorithms provided by NiTE. Scene segmentation, skeleton and floor plane detection. The first aim of the algorithm of the User Tracker is to discover all of the active persons in a specific scene. It individually tracks each human it finds, and provides the means to separate their outline from each other and from the background. Once the scene has been segmented, the User Tracker is also used to initiate Skeleton Tracking and

Pose Detection algorithms. Each user is provided an ID as they are detected. The user ID remains constant as long as the user remains in the frame. If a user become outside the coverage of the camera, or tracking of that user is lost, the user may have a different ID when he is detected again.

The purpose of the skeleton algorithm is to analyze a user outline supplied by the User Tracker algorithm, and to locate the position of that user's joints in space (eg knees, elbows, head, etc). Wherever joints are not visible, the algorithm will make a best guess about the joint. For all data calculated, confidence values are also created to help an application understand if the algorithm is sure about the data, or if it is "guessing".

**Figure 3.2: Kinect Camera**




*Source: Google*

### 3.4 THE FEATURES EXTRACTION

The next step for our method is to get important information about the movement of the objects which will help us to extract the features to detect the fall. The selection of the features should be improving the process of machine learning and lead to more robust models.

We should select the features that will provide us good description for the movement of the objects in the scene. These attributes will play a crucial role in the classification process. We should take into account the less number of the features what means the device can work faster. And as we know, The represented of the body by 15 skeletal joints positions.

$s_i^n\ (x,y,z) \in \mathrm{R}^3$

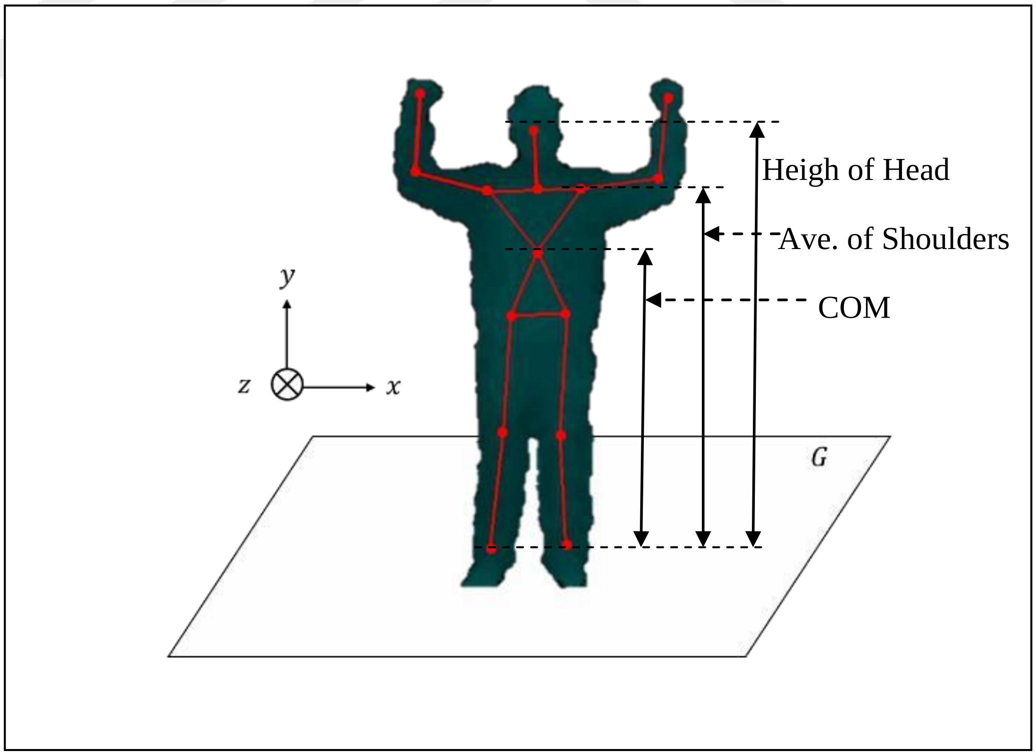
where $i$ is the index of the skeletal joint and $n$ indicate to the time means the number of the frame. Table 3.1

The standard vector should be perpendicular on the floor in all the cases and here it is represented by (y) component of a joint position. In some cases y is not perpendicular on the floor like if the camera moved or the floor was slanted and we treat with it by calculate the distance between the features and the floor.

**Table 3.1: The Names of 15 skeleton Joints**

| S | Skeletal Joints | S | Skeletal Joints |
|---|---|---|---|
| S1 | Head | S9 | Torso |
| S2 | Neck | S10 | Left Hip |
| S3 | Left Shoulder | S11 | Right Hip |
| S4 | Right Shoulder | S12 | Left Knee |
| S5 | Left Elbow | S13 | Right Knee |
| S6 | Right Elbow | S14 | Left Foot |
| S7 | Left Hand | S15 | Right Foot |
| S8 | Right Hand | | |

**Figure 3.3: Skeleton joints and ground plane $G$**




*Source: Reference[36]*

### 3.4.1 The Height of Head

The first thing that we can notice when the fall occurred is a large change in the height of the body. The height of the head can be one of the best features which indicates the fall because it's readily observable .And as we know, the openNI provided us the joints of the body (skeleton data) such as head, hands and feet so we will use height of head which is represented by the distance between the head and the ground as a first feature in our method to determine the fall .The fall is detected when the value of the head of height decreased significantly comparing with the previous cases. Shown in Fig 3.3 It is represented by equation below.

$$f1(n) = s_1^n(y) \tag{3.1}$$

### 3.4.2 The Velocity of The Upper Part of The Body

The change in the velocity of the upper part of the body is taken as another feature for fall detection. we used the average of the shoulders heights to the floor to indicate the upper body speed. Fig 3.3.We selected the shoulders joints because they are more stable comparing with other joints of body. We can note the velocity of the upper body will increase when initiating fall. It is given by the equation below.

$$f2(n) = (s_3^n(y) + s_4^n(y))/2 \tag{3.2}$$

$$f3(n) = f2(n) - f2(n-1) \tag{3.3}$$

### 3.4.3 The Center of Mass

The center of mass (COM) is the point on an object at which the weighted relative position of the distributed mass sums to zero and we selected it as a third feature for our method to determine the fall . It is represented as a line from the center of mass to the floor Fig 3.3and it should be perpendicular on the ground as we mentioned before. When the fall is occurred the distance between the COM and the floor will decrease and this will be our feature to detect the fall.

The equation is given bellow

$$f4(n) = s_9^n(y) \tag{3.4}$$

### 3.4.4 The Body Orientation

The orientation of the person is the other feature we used to trace the fall. The direction of the fall is represented by the angle and to find this angle we need two vectors .First of them is the human body vector(U) that represent the difference between two points. One of them the head joint (H) and the second is the average between the feet joints (AV) . Fig 3.4 and Fig 3.5

And the calculation of the average of feet joints is

$$(AV_{x,y,z}) = ((LF_x + RF_x)/2 , (LF_y + RF_y)/2 , (LF_z + RF_z)/2) \tag{3.5}$$

Where LF : Left foot , RF: Right foot

While the computation of the human body vector

$$U_{x,y,z} = ( H_x - AV_x , H_y - AV_y , H_z - AV_z ) \tag{3.6}$$

The second vector(N) is the vector perpendicular onto xz-plane. And the equation of the angle(θ) between two vectors U and N is

$$\theta = \arccos\left(\frac{U.N}{\|U\|\|N\|}\right)$$

$$f5(n) = \theta(n) \qquad (3.7)$$

When the person is in normal situation like standing or walking the theta will be zero or is very little because the vector of the body will be identical or in same direction with the N vector which is perpendicular on the xz-plane but the case will change when the person has fallen because the body vector will make angle with N vector. Fig 3.6

**Figure 3.4: U Vector**

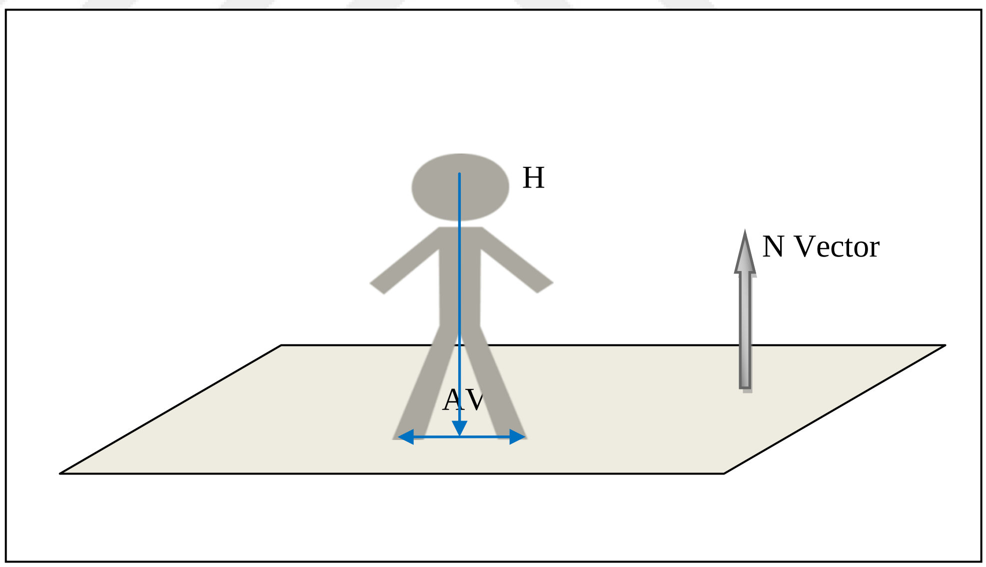


**Figure 3.5: U vector parallel with N vector**

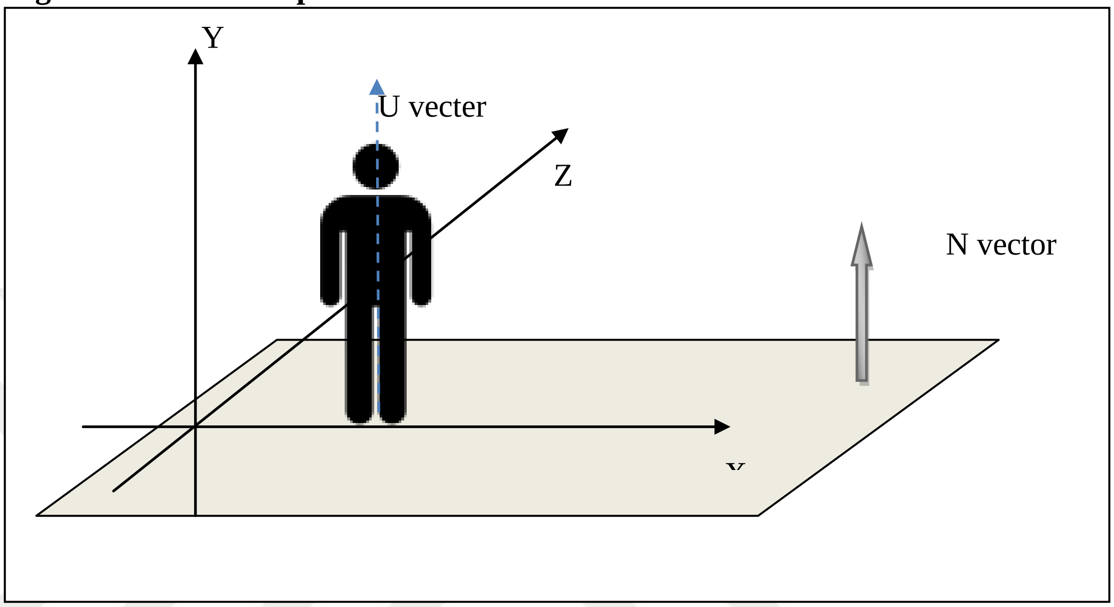
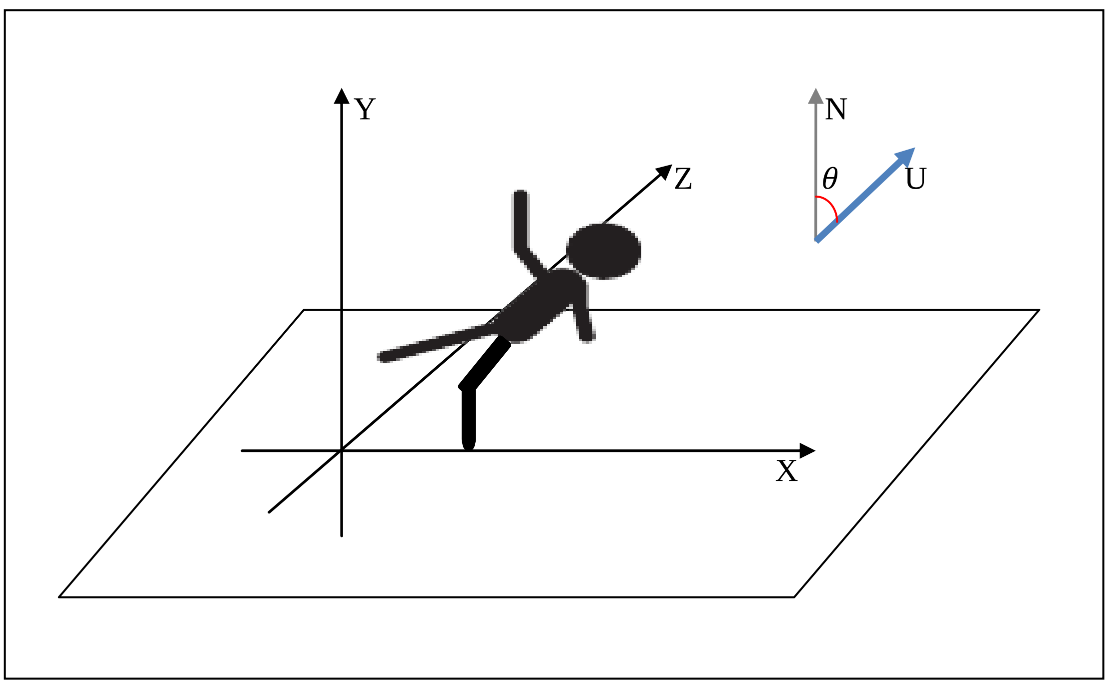



**Figure 3.6: The Orientation**



### 3.4.5 The Bounding Box

The Depth MetaData of Openni are used to create a 3D bounding box which contains the human shape. The geometrical dimensions of this box are monitored frame by frame, to retrieve the subject's posture, and to detect falls.

The 3d bounding box use 3 parameters to guess the body position we can calculate the 3 parameters width, height and depth of the 3D bounding box by the difference between the top and low points along the X, Y and Z dimensions.

$$H = |Ymin - Ymax| \tag{3.8}$$

$$W = |Xmin - Xmax| \tag{3.9}$$

$$D = |Zmin - Zmax| \tag{3.10}$$

The motion of the person is estimated by tracking the location of the 3D bounding box. We will calculate the proportion by divide the height of the bounding box on the width. In case the person is falling, the bounding box will change completely in both height and width, and as a result, the changing will happen in the ratio .

$$\text{Ratio} = \text{height} / \text{width} \tag{3.11}$$

$$f6(n) = \text{Ratio} \tag{3.12}$$

# 4. EXPERIMENT

## 4.1 DETERMINE THE FALL

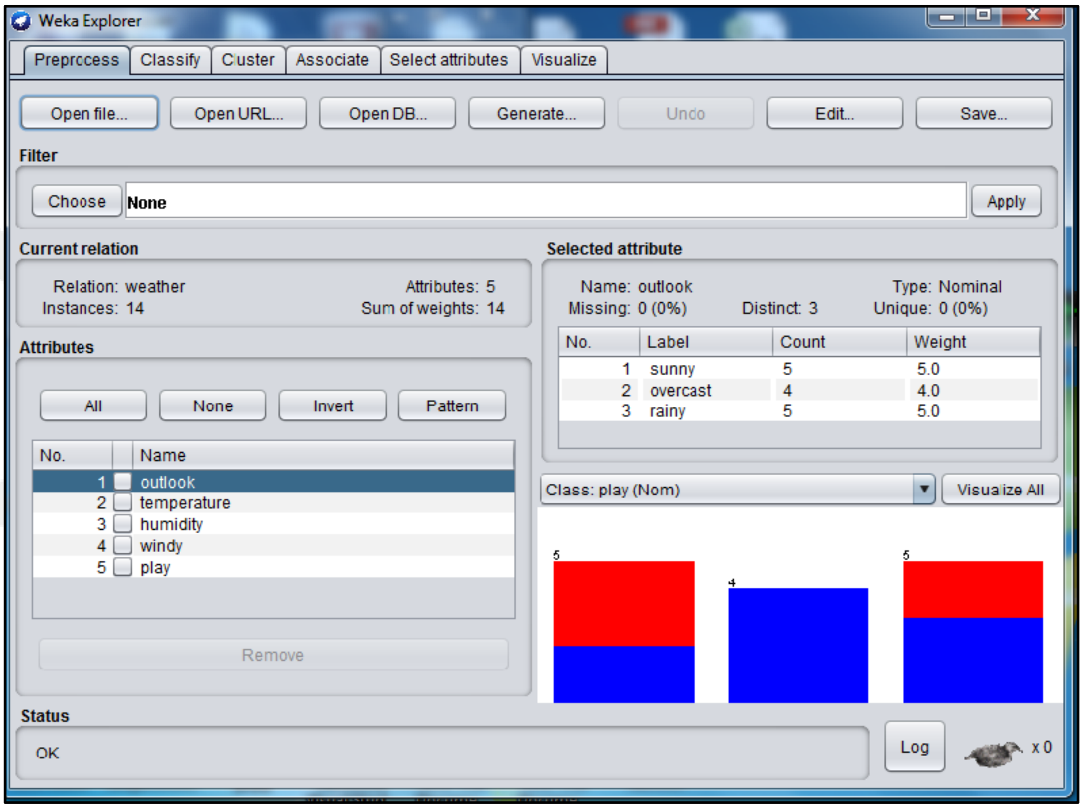
We got the data of skeleton joints from openni and made our program to extract the important features that will help us to detect the fall. After that , We send the data to the Weka to determine the fall. In Weka, we used three classifiers for our purpose. The Support Vector Machine , KNN and Bayes Naive . In the end of this section we will discover which one of them has better accuracy to detect the fall.

Our database consist of 1000 data frames and we have the data label, mean the number of the frame when the fall has happened and by watching the video we monitored the number of the frames to ensure when fall has occurred. we note that the fall happens at frame 1600 and stay in fall case until frame number 1800 back to the normal case. We indicated to the fall manually in the program in visual C++.

## 4.2 WEKA

Waikato Environment for Knowledge Analysis (Weka) is a software made in New Zealand at the Waikato University as an open source software. It was wrote by Java and distributed as a free software licensed by the terms of the General Public License (GNU). It’s includes a set of the algorithms of the machine learning and the tools of data preprocessing. Also it's supports many tasks of data mining like classification, regression, clustering and data preprocessing .The processing of the data as an arff file and the tool can read data from other file types such as csv file or SQL database and the data convert internally to arff form[37]. The arff (Attribute-Relation File Format) file is an ASCII text file that explains a register of instances participating a collection of attributes and it is less memory intensive, faster and better for analysis. The easiness of use provided to users make comparing various ways and determine those that are best option for the trouble that were prompted the researchers to frequent use its. Fig 4.1We can selected different classification, clustering and feature selection algorithms from the tool bar at the top.

**Figure 4.1: The Weka Screen**




*Source: Wikipedia*

## 4.3 THE ATTRIBUTE AND DATA

In the database every attribute has own statement that determine the name and the data type of that attribute. The order of attributes announced  the column location in the data part of the file. As an example, if the attribute is the fourth one announced after that ,Weka estimates all the attributes values that will be detect in the fourth comma delimited column.

The data should be familiar with weka and it distribution to columns and rows. The columns should be equal with our attributes and last column will be representing the class.

### 4.4 CROSS VALIDATION FOLDS

Cross validation is a method for evaluating how the outcomes of the statistical analysis will release to set of the data independent. In any application, the aim of the classes prediction to guess how accurately the predictive pattern and how is it behave in practice. The cross validation results will use to predict the performance of the classifier in practice and to select the model or classifier.

In our technique, applying the algorithm to build a classifier from the data. We selected 10 folds to cross validation and that means the label data will distribute to 10 equal size groups. Each set will divide into two parts As an example 90% of the data had utilized to training and 10% of the remaining data had utilized to testing. The operation will repeat for other groups from 2 to 10 and generates more classifiers. The result of a single estimation will be the averages of the performance of the 10 classifiers outcome from 10 groups.

### 4.5 THE CLASSIFICATION

In general ,the classification is the operation of utilizing a pattern to estimate unidentified values (output values), by utilize a number of identified values (input values) And to achieve the classification, firstly we require to pattern the relation between the inner and the outer variables. This operation includes learning a patern utilizing the data in which both the input and the output variables are existent. Also the opinion of the expert can be utilized to construct/improve a pattern. The pattern can be utilized to predict the output value by only using the input data.

The classification of the algorithm should be able to recognize the falls from other daily life activities. So, after obtaining the vector features from the video sequence analysis, we have developed a way to utilize these features to the classification of an event of the fall from other events that took place at the scene. The input of the classifier will be the features vector and classify the movement of the person in the scene according to the values of the features vector .The results of the classifier should be significant and related with the movements of the human like walking, falling down, sitting down, ... etc.

We used seven attributes as an inputs for classifiers .The ratio between the height and the width of the bounding box . The average of shoulders to compute the velocity of upper body, center of mass ,height of head and orientation . Our task is only to determine if the fall occurred or not so we will classify to two classes 1 and 0. Zero if fall is not happened and one if fall is occurred .We used three different methods for classification .

a -SVM( Support Vector Machine)

b -The k-NN algorithm

c -The Naive Bayes

We will describe each one of them and how they work , also we will review the results that we have obtained from the experiments.

## 4.6 DESCRIPTION

In total, They are 978 instances and as we can see in the Figure 4.2 the blue class is containing 931 instances. It is equal zero and that means the fall did not happen. On the other hand , The red class consist of 47 instances and It is equal one and that indicates the fall .

In the Figure 4.3 we can see the class description for each attribute and we have seven attributes each one of them is representing a single feature that we utilized to determine the fall

**Figure 4.2: The Instances**

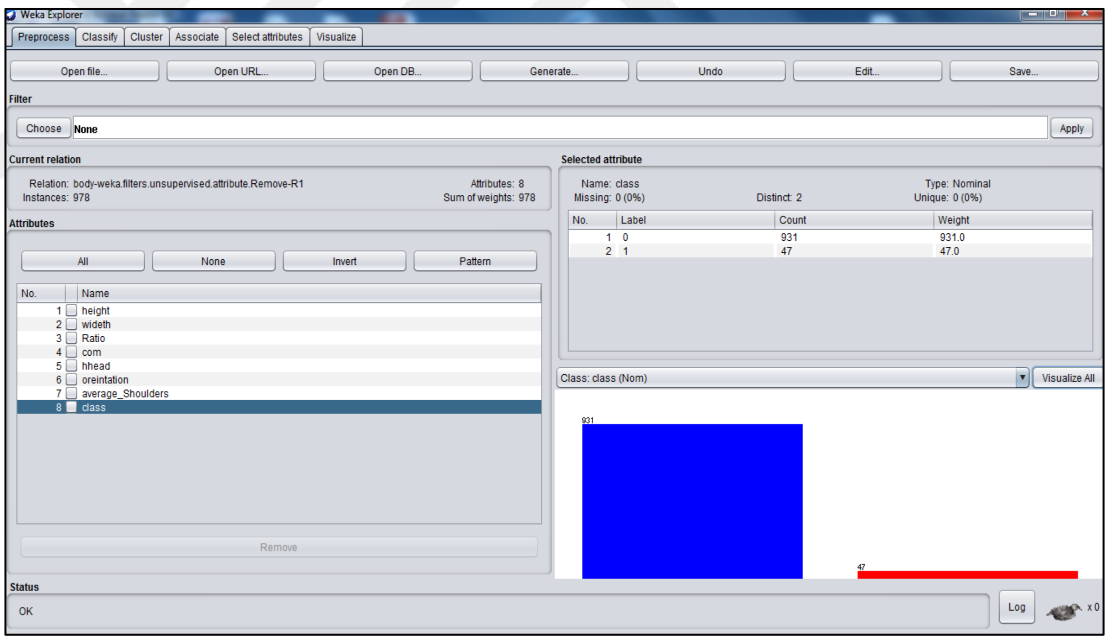
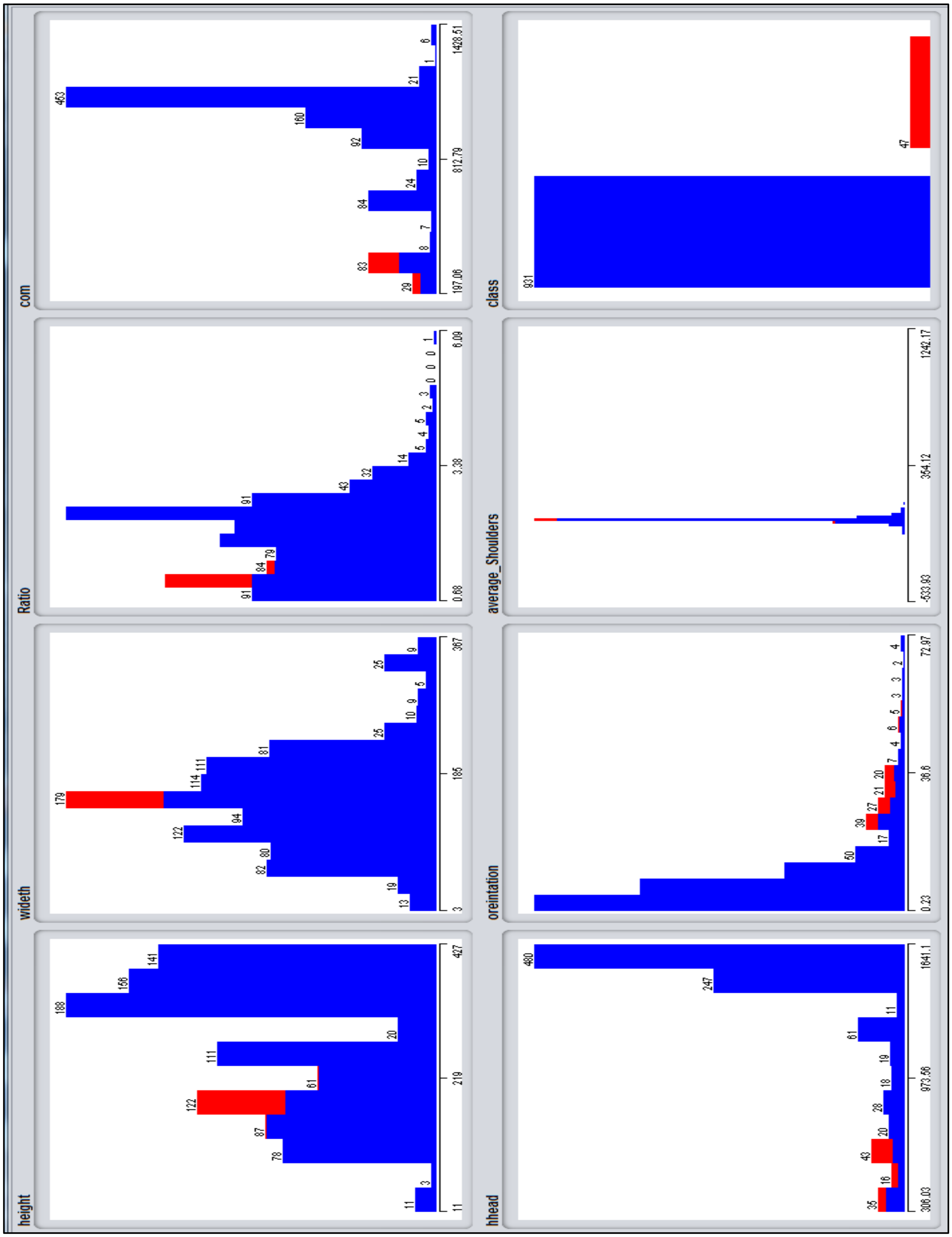


**Figure 4.3: Distribution of the attribute In Naiv Bayes**



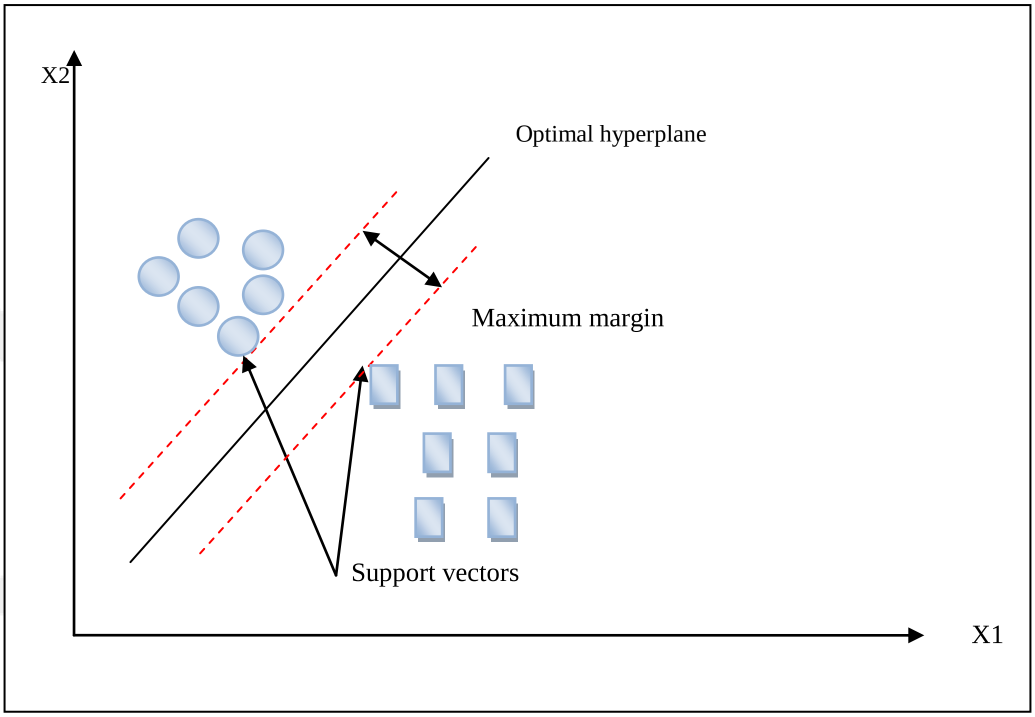
### 4.5.1 The Svm

SVM( Support Vector Machine) is a good method to classification the data .We used it to distinguish the fall from other daily activities. It is a technique under the list of supervised learning models in Machine Learning it is analyzing data to be used for regression and classification analysis. The older SVM algorithm was created in 1963 by Alexey Ya. Chervonenkis and Vladimir N. Vapnik and over the years it has developed until 1995 to the current standard incarnation (soft margin).

The main aim of the svm is to design a hyperplane. It will classify all the training vectors in two classes. The best select when the hyperplane that departs the most extreme margin from both classes. The margin is this separation between the hyperplane and the nearest components from the hyperplane.

In other words, the attribute is the estimator variable is and a transformed attribute which is utilized to determine the hyperplane is called a feature. The mission of choosing the best representation is known the feature selected. A features set which characterize a single state is known as a vector. So the purpose of SVM modeling is to detect the best hyperplane which isolates between the vector clusters in a manner which make two classes first of them contain the states of target variable are on one side of the plane and the second include another cases on the other side of the plane. The support vectors are the closer vectors to the hyperplane are. Show the Fig 4.4

**Figure.4.4: The SVM Classifier**




### 4.5.1.1 The benefits and drawbacks of support vector machines

The strength of support vector machines are impact in high dimensional spaces. And It is efficient in situations where the samples number less than the dimensions number. Also it has memory efficiency where we can use a collection of training points in the function of the decision (known as a support vectors) It is multilateral, what means we can specify many Kernel functions for the selected function Common kernels are provided, but also it is possible to identify custom kernels.

The first disadvantage of support vector machines is when the samples number is less than the features number, the technique is possibility to give low execution.

Secondly the SVMs is not give the probability of the guess immediately , these are computed utilizing an expensive five-fold cross- validation.

#### 4.5.1.2 kernel Function

Kernel function is a non linear function learned by linear learning machine in a high dimensional feature space while the capacity of the system is controlled by a parameter that does not based on the dimensionality of the space this is known kernel trick which means the kernel function transform the data into a higher dimensional feature space to make it possible to perform the linear separation.

So the data is not linearly separable but we use kernel function that gives a modular matter to learn nonlinear patterns utilizing linear models only we should exchange the kernel with the inner products. All the calculation stay as efficient as in the original filed and the kernel parameter is the exponent which controls the scale of the polynomial.

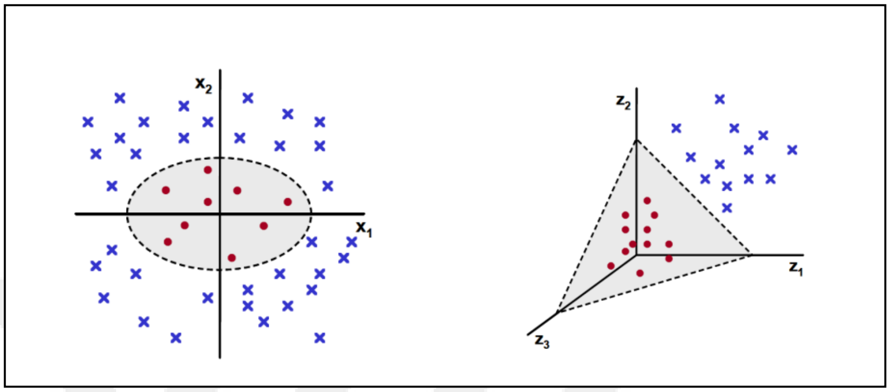
The polynomial kernel : $K(x, y) = \langle x, y\rangle^{\wedge}p$ (4.1)

And we change the value of the exponent to see the influence on the results on SVM classifier

Example about how Kernel work . Fig 4.5

Each example defined by a two features $x = \{x_1, x_2\}$
No linear separator exists for this data
Now map each example as $x = \{x_1, x_2\}$ $z = \{x_1^2, \sqrt{2}\, x1x2, x2^2\}$
Each example now has three features ("derived" from the old representation)
Data now becomes linearly separable in the new representation

**Figure 4.5: Kernel Work**




### 4.5.1.3 The Weight

In our approach we changed the weight and exponent in kernel function to make the performance of SVM better.

We have the C parameter which is representing the weight in SVM .When we changed the C the performance of classifier will improve. The weight will make the hyperplane more sensitivity. The C parameter trades off misclassification of training examples against simplicity of the decision surface. A small C makes the decision of the surface more smoothly, while the goal of increasing the C is to give the model flexibility to choose more support vectors samples to classify all training examples correctly.

### 4.5.1.4 The Svm In Weka

In Weka ,We have more classifier support SVM such as $SMO_{reg}$ ,SGDtext and SMO. We will use the last one SMO (Sequential Minimal Optimization) that is one method to fix the training problem of the SVM. This implementation wordly replaces transforms nominal attributes and all missing values into binary ones. Also it normalizes every attributes by default. (In that state the output coefficients are depend on the normalized data, not the original data and this is so significant for interpreting the classifier). SMO uses the heuristics to division the problem of the training to the smaller problems that can be solved analytically.

In total we have 978 instances. SVM will estimate how many instances will classify as a correct and how many instances are incorrect. In the first situation of the SVM when weight is 30 and exponent is 1. We had 949 instances as a correct case and 29 as incorrect while the accuracy was 97.0348% and when we increased the exponent to 5 and kept the weight as 30 in the second situation. The performance of SVM improved where we got 960 instances as a true and 18 instances as a false and the accuracy was 98.1595 %. In the last case of SVM we raised the weight to 50 and kept the power at 5 . The accuracy became 99.182 % and that was the best performance for SVM where we obtained 970 instances as a correct and just 8 cases as incorrect.

Here , we can see the influence of changing the weight and the power of kernel equation on the performance of the SVM from results of weka.

**Table 4.1: SVM Results**

Ex= 1, weight= 30

| Class | TP Rate | FP Rate | Precision | Recall | F Measure | MCC |
|---|---|---|---|---|---|---|
| 1 | 0.638 | 0.013 | 0.714 | 0.638 | 0.674 | 0.660 |

Ex= 5, Weight= 30

| Class | TP Rate | FP Rate | Precision | Recall | F Measure | MCC |
|---|---|---|---|---|---|---|
| 1 | 0.979 | 0.018 | 0.730 | 0.979 | 0.836 | 0.837 |

Ex= 5, Weight= 50

| Class | TP Rate | FP Rate | Precision | Recall | F Measure | MCC |
|---|---|---|---|---|---|---|
| 1 | 1.000 | 0.009 | 0.855 | 1.000 | 0.992 | 0.920 |

### 4.5.2 The Naive Bayes Classifier

It is a classifier depend on Bayes' Theorem with an presumption of independence among predictors and It is one of the classifiers under the listed of simple probabilistic in machine learning.

In other words, the classifier of Naive Bayes presume which the existence of a particular feature in a class is not related to the existence of any another feature. As an example, a fruit may be considered to be an apple if it is red, round, and about 3 inches in diameter. Even if these features depend on each other or upon the existence of the other features, all of these properties independently contribute to the probability that this fruit is an apple and that is why it is known as 'Naive'.

The model of the Naive Bayes is simple to construct with no complexed iterative parameter prediction that makes it especially benefit for very large database. Along with simplicity, Naive Bayes is common to outperform even highly sophisticated classification techniques.

In some kinds of probability models, the classifier of Naive Bayes can be trained so perfectly in a supervised learning setting. In many practical applications parameter estimation for the models of the Naive Bayes exploits the technique fully. The Naive Bayes advantage is that it only demands a little amount of training data to predict the parameters essential for classification.

The equation below

$$P(c\backslash x) = \frac{p(x|c)p(c)}{p(x)} \quad (4.2)$$

$$P(c\backslash x) = P(x_1\backslash c)P(x_2\backslash c) \ldots\ldots\ldots\ldots\ldots P(x_n\backslash c)P(c) \quad (4.3)$$

$P(c\backslash x)$ is the posterior probability of *class* (c, *target*) given *predictor* (x, *attributes*).

$P(c)$ is the prior probability of *class*, $P(x)$ is the prior probability of *predictor*.

$P(x\backslash c)$ is the likelihood which is the probability of *predictor* given *class*.

#### 4.5.2.1 Naïve Bayes in Weka

According to Bayes classifier in Weka , Naïve Bayes utilizing predictor classes and Numeric predictor accuracy values are selected depend on the training data analysis. Therefore, the classifier considered as non updateable classifier (That actually mean the initialization of training instances will be zero in typical usage). The table below represents the normal description of the attributes in the classifier.

**Table 4.2: Description of the Attributes in The Naïve Bayes**

| Attributes | Mean | | Std. Dev | | Precision | |
|---|---|---|---|---|---|---|
| Height | 280.9013 | 170.4576 | 104.8311 | 7.141 | 4.6742 | 4.6742 |
| Width | 152.1316 | 148.6979 | 66.9217 | 3.3872 | 4.2824 | 4.2824 |
| Ratio | 2.0364 | 1.1317 | 0.7774 | 0.069 | 0.0092 | 0.0092 |
| COM | 944.1694 | 321.9536 | 233.2285 | 34.223 | 1.2935 | 1.2935 |
| Height of Head | 1395.259 | 528.1085 | 292.9819 | 83.541 | 1.4387 | 1.4387 |
| Orientation | 9.1572 | 31.3952 | 10.9744 | 7.2751 | 0.0767 | 0.0767 |
| Average Shoulders | 1.5065 | -1.0331 | 51.2357 | 13.9643 | 1.8676 | 1.8676 |

In the results, we can note the accuracy of Bayes Naive was 98.7% and that means the device has a high performance. Where we had 966 instances as a correct and 12 as an incorrect. The table below represent the results according to weka.

**Table 4.3: The Results of Naïve Bayes Classifier**

| Class | TP Rate | FP Rate | Precision | Recall | F Measure | MCC |
|---|---|---|---|---|---|---|
| 1 | 0.957 | 0.011 | 0.818 | 0.957 | 0.882 | 0.879 |

### 4.5.3 The Knn

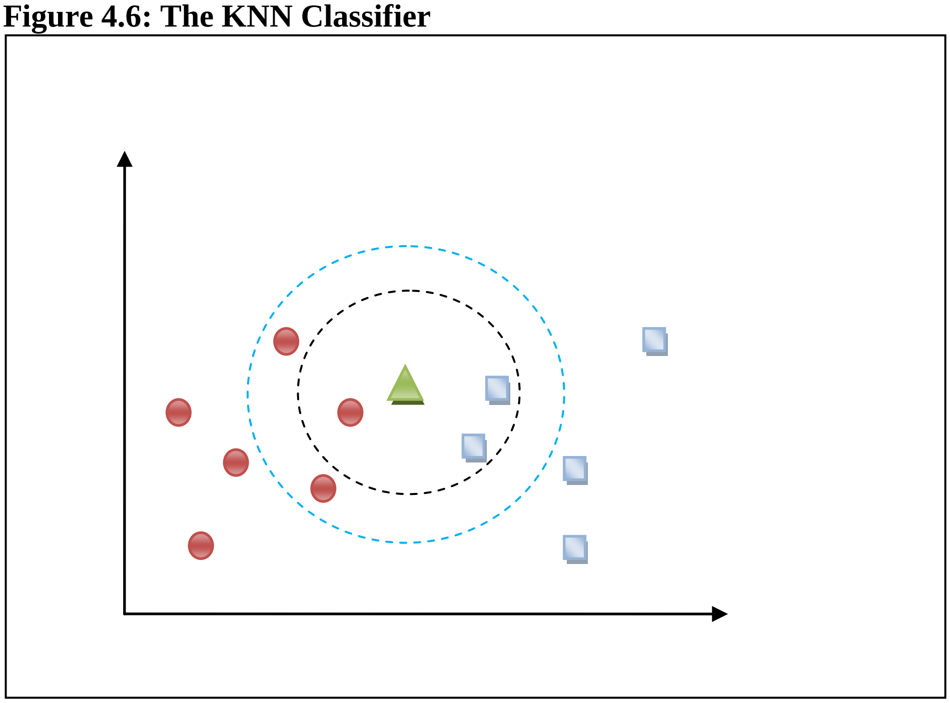
The KNN is one of the easiest algorithm of the machine learning that all available cases are saved and new cases classified depending on the measure of the similarity. It is more commonly used in classification than regression.

KNN is an non parametric technique and that means it didn't do any assumptions on the underlying data distribution. It is a lazy leaning . That means it didn't utilize the data points of training to make any generalization. Which means , The training phase is very minimal or they are no training case and that means the training phase is very fast..

In the Fig 4.6 , It's illustrate the Knn classification. We have classes of square and circle as a training vectors. Our task is to estimate (classify) the triangle depend on a choose number of its closest neighbors. In other expression, we need to know whether the triangle will be classified as a square or a circle. The knn algorithm will identify the k nearest neighbors of the triangle.

In case k =3 , we will make a circle with triangle as a center just as big as to enclose only three data points on the plane. As a result, The triangle will be classified as a square . In case k =5 the triangle will belong to the circle class.

**Figure 4.6: The KNN Classifier**



#### 4.5.3.1 The Knn in Weka

KNN represented under the lazy classifier in Weka and we can select appropriate value of K. We got our outcomes by using IBK which representing the KNN in weka . In case one we have 978 instances, the classifier indicate 972 as true and 6 as incorrect. The accuracy was 99.3865 %. In the other case when we changed the k = 5 we have 13 cases as incorrect and 965 cases as a true while the accuracy decreased to 98.6708 %. and that's because most of our dataset is defined as a non fall. The accuracy will increase in case the data of fall equal the data of not fall.

**Table 4.4: The KNN Result**

K=1

| Class | TP Rate | FP Rate | Precision | Recall | F Measure | MCC |
|---|---|---|---|---|---|---|
| 1 | 1.000 | 0.006 | 0.887 | 1.000 | 0.940 | 0.939 |

K=5

| Class | TP Rate | FP Rate | Precision | Recall | F Measure | MCC |
|---|---|---|---|---|---|---|
| 1 | 0.936 | 0.011 | 0.815 | 0.936 | 0.871 | 0.867 |

## 4.7 THE INFLUENCE OF FEATURES ON THE ACCURACY

In our approach, we need to know which feature more important than others and more effect on the accuracy and which one less important or not active so we excluded each feature and calculated the accuracy in all classifiers.

In KNN classifier when k=1, according to results, they are not big difference in accuracy but we can distribute the features to three levels first level contains the width and the orientation as a features have most influence on accuracy. where we can notice the accuracy is low when we excluded them. In the second level, there are height, ratio, com and average of shoulders and they are not make difference in accuracy when we removed them. The height of head was in the last level and it was not useful where the accuracy increased when we excluded it.

When we increase the k to 5 the performance of the classifier is decreased and the effect of features on the accuracy changed.

We can classify the features according to influence on the accuracy to four levels. The width was the most effective on the performance. Followed it, the height and the orientation as a second features have influence on the accuracy. In the third level were the ratio and the average of shoulders as a non effect features. The com and the height of head as an inverse impact on the accuracy in the last level. Look Table 4.5

**Table 4.5: The influence of features on accuracy in KNN classifier**

| | The Accuracy when KNN=1 | The Sequence Influence of the Features | The Accuracy when KNN=5 | The Sequence Influence of the Features |
|---|---|---|---|---|
| Total Accuracy | 99.3865% | | 98.6708% | |
| Accuracy without Height | 99.3865% | 2 | 98.4663% | 2 |
| Accuracy without Width | 99.2843% | 1 | 98.1595% | 1 |
| Accuracy without Ratio | 99.3865% | 2 | 98.6708% | 3 |
| Accuracy without COM | 99.3865% | 2 | 98.773% | 4 |
| Accuracy without Height of Head | 99.591% | 3 | 98.773% | 4 |
| Accuracy without Orientation | 99.2843% | 1 | 98.4663% | 2 |
| Accuracy without Ave. of Shoulder | 99.3865% | 2 | 98.6708% | 3 |

According to results of the Naive Bayes classifier the most important feature was the width. Followed it the height and the ratio respectively. The other features(ratio ,com, height of head, orientation and average of shoulder) had a negative influence on the performance. Table 4.6

**Table 4.6: The influence of features on accuracy in Naïve Bayes  classifier**

| | The Accuracy of Naïve Bayes | The Sequence Influence of the Features |
|---|---|---|
| Total Accuracy | 98.773% | |
| Accuracy without Height | 98.4663% | 2 |
| Accuracy without Width | 96.6258% | 1 |
| Accuracy without Ratio | 98.5685% | 3 |
| Accuracy without COM | 99.182% | 5 |
| Accuracy without Height of Head | 99.2843% | 6 |
| Accuracy without Orientation | 99.182% | 5 |
| Accuracy without Ave. of Shoulder | 98.8753% | 4 |

In the SVM classifier we change the exponent and the weight to get higher accuracy so in first case where the weight is 30 and the exponent is 1 the highest impact on the performance was the height of head feature and after that, the width and the com while the orientation was the third important feature by affecting on the accuracy. the ratio and average of shoulders were fourth and fifth while the height was not effect on the rate of the accuracy.

In the second case of SVM while the weight is 30 and exponent is 5 the strongest feature was the width and the height had the secondly impact following it the orientation  etc.

In the third situation when the weight is 50 and exponent is 5 the most important feature was the width then the height of head and the third important feature was the orientation then the height and the other features respectively average of shoulders, com and ratio. Table 4.7

According to the results, we can notice the orientation had the big affect on the accuracy in first case in KNN classifier when k was 1 and the second important features when k was 5 in the second case. Also we can see, there are some features have a negative influence on the accuracy.

In SVM, the orientation had the third influence on the performance in all cases and they are no features had inverse impacting on the accuracy. While in Naive Bayes, the orientation was the worst if we compare with other classifiers where had a negative effect on the performance. And we can say , the feature that had the highest influence on the accuracy was the width in all classifiers

**Table 4.7 The influence of features on accuracy in SVM classifier**

| | The Accuracy of SVM Weight = 30 EX=1 | The Sequence Influence of the Features | The Accuracy of SVM Weight = 30 Ex=5 | The Sequence Influence of the Features | The Accuracy of SVM Weight = 50 Ex=5 | The Sequence Influence of the Features |
|---|---|---|---|---|---|---|
| Total Accuracy | 97.0348% | | 98.1595 % | | 99.182 % | |
| Accuracy without Height | 97.0348% | 6 | 97.546 % | 2 | 98.0573 % | 4 |
| Accuracy without Width | 95.3988% | 2 | 97.3415 % | 1 | 97.4438 % | 1 |
| Accuracy without Ratio | 96.6258% | 4 | 98.0573 % | 5 | 98.6708 % | 7 |
| Accuracy without COM | 95.3988% | 2 | 98.0573 % | 5 | 98.4663 % | 6 |
| Accuracy without Height of Head | 95.092% | 1 | 97.8528 % | 4 | 97.546 % | 2 |
| Accuracy without Orientation | 95.501% | 3 | 97.6483 % | 3 | 97.6483 % | 3 |
| Accuracy without Ave. of Shoulder | 96.9325% | 5 | 98.0573 % | 5 | 98.1595 % | 5 |

## 4.8 THE COEFFICIENT OF THE CORRELATION

The coefficient of the correlation also called r is the calculate of the strength how pairs of variables are related each one to another and the nature of that relationship between both of them. It is used to calculate the linear relation between pairs of variables and the result of the coefficient of the correlation should be between –1 and 1.

In case the value of correlation is positive (more than 0) mean the two variables are moving in the same direction. When the r = 1 it's mean the relationship between two variables is perfect. And when correlation is negative (less than 0) it's indicate to the each variable is going to the opposite side and when r is -1, that's mean the perfect negative relationship . And if the correlation coefficient of two variables is zero or close to zero(0.1,-0.1), it denotes that they are no linear relation between the variables.

In our method we used the Matlab to calculate the correlation coefficient between each feature and the class. Our results were moderate for the COM and Height of head. And weak for the Orientation, Height and the Ratio. For the Average of shoulder and width, they are no linear relationship. Table 4.8

**Table 4.8 The Correlation Coefficient**

| Features | The correlation |
|---|---|
| Height | -0.2275 |
| Width | -0.0072 |
| Ratio | -0.2474 |
| COM | -0.5046 |
| Height of Head | -0.5436 |
| Orientation | 0.4022 |
| Ave. of Shoulder | -0.0103 |

## 4.9 PERFORMANCE MEASURES

The definition of binary classification performance measures are based on following four parameters: True Positive(TP), False Positive(FP), True Negative(TN) and False Negative(FN) given by Error matrix (confusion matrix).

The sensitivity is the ability to recognizing the abnormal event and it is calculated by the proportion between the fall detection number and all falls which happened.
TPR or Sensitivity= TP/TP+FN
The specificity is the ability to avoidance the non false negative and it is the ability to recognize the unusual event in case if it is only happened .
Specificity = TN/ TN+FP

Accuracy it is ratio between the number of the true detect to all instances.
Accuracy = TP+TN/TP+TN+FP+FN

Matthews correlation coefficient is utilized to calculate the binary classifications quality.
MCC = TP * TN - FP * PN/((TP+FP)(TP+FN)(TN+FP)(TN+FN))$^{1/2}$

Precision or PPV = TP/TP+ FP
Look Table.3,Table.5,Table.6

# 5. THE RESULTS

we described the data collected from the fall detection device for the seven different types features and then used three classifiers to determine the fall. Same data was used as an input for the Support Vector Machine, Naive Bayes and The k-NN. And we selected 10 folds as a cross validation . As we know in Weka, the instances is representing as a data row and the data features are considered as an attributes. The simulation results show several parameters like correct instances, incorrectly instances ,The accuracy of correct instances, ,The accuracy of incorrect instances and other parameters. The Table 4.9 show the accuracies for three classifiers with seven attributes and 978 instances.

**Table 4.9: The Results of all Classifiers**

| | Correct Instances | Incorrect Instances | Accuracy for Correct Instances | Accuracy for Incorrect Instances |
|---|---|---|---|---|
| Naïve Bayes | 966 | 12 | 98.773% | 1.227% |
| IBK, K=1 | 972 | 6 | 99.3865 % | 0.6135 % |
| IBK, K=5 | 965 | 13 | 98.6708 % | 1.3292 % |
| SMO, EX=1,C=30 | 949 | 29 | 97.0348 % | 2.9652 % |
| SMO, EX=5,C=30 | 960 | 18 | 98.1595 % | 1.8405 % |
| SMO, EX=5,C=50 | 970 | 8 | 99.182 % | 0.818 % |

As obvious from the Table, KNN Classifier gives the highest accuracy 99.3865 % when k=1 and the performance is declined when we changed k=5 where the accuracy became 98.6708 %. Logically the accuracy should be increasing .

When we raise the k but it's decreased because the fall data is very few if we compared it with non fall data. The KNN takes 0 second to build the model. While the accuracy of the Naive Bayesian Classifier was 98.773% and took 0.03 second to build the model.

In SVM classifier, the accuracy was 97.0348 % in first case where the exponent is 1 and weight is 30 and took long time (0.85 second) to build the model. And when changed the exponent to 5 the performance getting better where the accuracy was 98.1595 % and the time was 0.33.In the last case we increased the weight to 50 and the performance was perfect where the accuracy was 99.182 % and the time spent to build the model reduce to 0.09 seconds. In SVM classifier, we saw the influence of changing the weight and the power of kernel equation on the performance.

when we take a look to the results , we can see the highest accuracy was in KNN (99.3865 %) when k=1 and decreased (98.6708 %) when k became 5 While the performance of SVM increasing gradually when we changed the weight and the power of kernel equation where the accuracy was 97.0348 % in first case and improved in the second case 98.1595 % till reached to perfect performance in the third case 99.182 %. So the SVM give us more flexibility to enhance the performance and when we compare the outputs of classifiers. We can see the SVM and KNN are so close but SVM more flexibility so the SVM Classifier should be our choice for classification.

# 6. CONCLUSIONS

In this project, we had developed a technique to recognize fall incidents in nursing homes automatically. Our method is based on got information from skeleton joints to extract the features. We extracted five features height of head, the velocity of the upper body ,center of mass ,the orientation of the person and the ratio of bounding box and we have used three classifiers SVM, the K-NN algorithm and the Naive Bayes to discriminate clearly a fall posture and we made a comparison between their results to know which one of them had best perform. The results showed that the performance is different from classification to another and the best choice was SVM classifier because more flexibility than other classifiers. However, the system can be implemented to detect fall incidents in elderly's houses and it has flexibility to fit other applications

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