**ÇUKUROVA UNIVERSITY**
**INSTITUTE OF NATURAL AND APPLIED SCIENCES**

**MSc. THESIS**

**Omar Ali Abbas AL-TEKREETI**

# OLIVE TREE CROWN DETECTION, DELINEATION AND COUNTING BY USING IMAGE PROCESSING TECHNIQUES

**DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING**

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**ABSTRACT**

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Year: 2021, Pages:141
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UAVs are rapidly improving and increasing to enhance satellite based remote discovery. UAV (Unmanned Aerial Vehicle) remote sensing and low altitude remote sensing (LARS) applications play a significant role in the environment. This thesis shows the utilization of LARS in agriculture especially in the farming for detection and counting the "olive trees" by the proposed algorithms in this study. The image acquired by RGB camera and the processing of detection and counting was by utilizing Digital Image Processing techniques and Machine Learning algorithms. Several methods preformed to get better results, the first method utilized Uneven Illumination Correction, Gaussian filter, Standard Deviation filter and Circular Hough Transform (CHT) to detect olive trees. The second method utilized Histogram Equalization (HE), Mean, Median, and Wiener filters with 3 unsupervised machine learning algorithms (Clustering technique) are K-means, Fuzzy C–means (FCM), and Expectation Maximization (EM) algorithms and Morphological Operations then Circular Hough Transform. The third method implemented supervised machine learning algorithms (Classification) are K-Nearest Neighbor, Linear Discriminant Analysis, and Support Vector Machine.



**Keywords:** UAV, Olive Trees, Image Processing, Machine Learning algorithms

# ÖZ

## YÜKSEK LİSANS TEZİ

## GÖRÜNTÜ İŞLEME TEKNİKLERİ KULLANARAK ZEYTİN AĞAÇLARININ TESPİT EDİLMESİ, RESMEDİLMESİ VE SAYIMININ YAPILMASI

**Omar Ali Abbas AL-TEKREETI**

**ÇUKUROVA ÜNİVERSİTESİ**
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Danışman : Doç. Dr. Sami ARICA
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İHA'lar, uydu tabanlı uzaktan keşfi geliştirmek için hızla gelişmektedir ve artmaktadır. İHA (İnsansız Hava Aracı) uzaktan algılama ve düşük yükseklikten uzaktan algılama (DYUA) uygulamaları çevrede önemli bir rol oynamaktadır. Bu tez, bu çalışmada önerilen algoritmalar ile “zeytin ağaçlarının” tespiti ve sayılması için DYUA'ın tarımda kullanımını göstermektedir. RGB kamera tarafından elde edilen görüntü , algılama ve saymanın işlenmesi; Dijital Görüntü İşleme teknikleri ve Makine Öğrenimi algoritmaları kullanılarak yapılmıştır. Daha iyi sonuçlar elde etmek için çeşitli yöntemler önceden oluşturulmuş. İlk yöntemde zeytin ağaçlarını tespit etmek için Eşit Olmayan Aydınlatma Düzeltme, Gauss filtresi, Standart Sapma filtresi ve Dairesel Hough Dönüşümü (DHD) kullanılmıştır. İkinci yöntemde Histogram Eşitleme (HE), Ortalama, Medyan ve Wiener filtrelerini kullanılmıştır. Üç denetimsiz makine öğrenme algoritması (Kümeleme tekniği), K-ortalamaları, Bulanık C-ortalamaları (BCO) ve Beklenti Maksimizasyonu (BM) algoritmaları ve Morfolojik İşlemlerdir. Sonra Dairesel Hough Dönüşümü, üçüncü yöntemde ise Denetimli makine öğrenimi algoritmaları (Sınıflandırma) kullanılmıştır. K-En Yakın Komşu, Doğrusal Ayırım Analizi ve Destek Vektör Makinesi'dir.

**Anahtar Kelimeler**: İHA, Zeytin Ağaçları, Görüntü İşleme, Makine Öğrenimi

**EXTENDED ABSTRACT**

The financial significance of olive oil in the world is viewed as a positive investment in health identified with olive oil usage. To the extent, the estimation of an item, production, and evaluating of olive oil in the world market collectively higher than different vegetable fats and oils.

By calculating olive trees, we can evaluate the oil production yield. This procedure is of high importance to the growth of country's economy. Olive trees crown extraction has a vital impact on the agriculture and environment. In the environment, it is important in an improvement of usage, for instance, in the farm's management, urban zones fields management, and preventing harms generally in the agriculture. Besides, it tends to be conveniently used in counting, monitoring, and agribusiness. The tree crown extraction gives an approach for mapping vegetation distribution, biophysical parameters assessment (crown computations), and allow some tasks, for example, species grouping and estimation of the density of vegetation. In general, aerial imaging is an incredible and helpful means for estimating olive trees.

In this study, the technique which proposed performed to the 2D image of olive trees, with the size of 540 x 960 pixels of RGB color image, from Cukurova University Faculty of Agriculture, Adana, Turkey. The proposed algorithm implemented by MATLAB software with the Image Processing Toolbox.

The first proposed algorithm for detection and counting olive trees was by employing Digital Image Processing techniques. Uneven Illumination Correction performed to overcome unbalanced light distribution in the image, then converting the image to gray scale to make it easier to deal with. Gaussian filtering was used for noise reduction and smoothing, furthermore, Standard deviation filter implemented to obtain the edges. Circular Hough Transform utilized to extract the circular shapes to make the detection and counting of these circles to get finally the olive trees.

The second proposed algorithm for detection and counting olive trees was by employing Digital Image Processing techniques with Unsupervised Machine Learning algorithms. Several steps utilized for getting best results, firstly, image enhancement and preprocessing by Histogram Equalization for unbalanced distribution of the illumination and filtering procedure for noise removal. Secondly, Segmentation method to partition the image in order to separate the items from the background. Thirdly, Morphological operations to remove unwanted items and make the binary image more obvious. Fourthly, Circular Hough Transform for circle detection and then counting these circles.

In more details:

Firstly, the image which acquired from RGB camera containing inequitable or irregular lighting distribution in addition to noises. To defeat the illumination trouble, Histogram Equalization (HE) strategy implemented then converting the image to Gray scale and extracting G channel form Histogram Equalized color image.

In the Histogram Equalization step, three approaches performed. The first method “Approach 1” includes: dividing the image into four parts, computing the histogram of every part, obtaining the entropy of each histogram, choosing the part which contains the Maximum entropy value, using histogram matching of the other three parts with the selected histogram, and implement the histogram equalization for the whole image. The second method “Approach 2” includes: dividing the image into four parts, equalize the histogram of each part, computing the histogram of every part, obtaining the entropy of each histogram, choosing the part which contains the Maximum entropy value, using histogram matching of the other three parts with the selected histogram, and implement the histogram equalization for the whole image. The third method “Approach 3” includes: dividing the image into four parts, equalize the histogram of each part.

In the filtering step, three main types of filters utilized; Linear filters, Non-linear filters, and Adaptive filters. From each type just one filter was chosen, from linear filters Averaging/Mean filter selected, from Non-linear filters Median filter selected, and from Adaptive filters Wiener filter selected.

Secondly, Segmentation stage utilized Clustering technique, this stage involves three algorithms: k-means, Fuzzy c-means (FCM), and Expectation Maximization (EM). The common parameter between these three techniques to get better outcomes was the number of clusters which chosen were three clusters.

Thirdly, Morphological operations applied to exclude the undesired objects and make the binary image clearer for next stage.

Fourthly, Circular Hough Transform implemented to circular shapes detection and counting these circular shapes to finally get the olive trees.

Higher speed accomplished between the all filters was Wiener filter and among the segmentation algorithms k-means, which achieved a notable high speed among the three segmentation (clustering) algorithms.

The best results accomplished were EM algorithm with Wiener filter, K-means algorithm with both the Averaging and Wiener filter, and FCM algorithm with the all three filters.

EM algorithm with Wiener filter According to the first approach of histogram equalization “Approach 1”, were achieved 96.76% with G channel of the histogram equalized color image. K-means algorithm in general had a stable and good results with both Average and Wiener filter, but this algorithm based on “Approach 2” gave a highest percentage of detection with Median filter was about 97.73% with gray scale image. FCM algorithm generally accomplished approximately 96% with all filters according “Approach 1” and “Approach 2” and the best result was with Median filter with gray scale image with score 97.08%. Based on the parameter performance of the filters and according to the “Approach 1”, Median filter was the preferable filter because of achieving the Minimum Mean Square Error and the highest Peak Signal to Noise Ratio.

The third proposed algorithm for detection and counting olive trees was by employing Digital Image Processing techniques with Supervised Machine Learning algorithms. This method includes dividing the original image into sub images and then loading the data or sub images (sub blocks). The sub images divided into 2 groups or positive class and negative class that mean “olive tree” and “Non olive tree”. After that, feature extraction used like Histogram Orientation Gradient and Color histogram feature to get features for training stage. Three classification algorithms executed K-Nearest Neighbor, Linear Discriminant Analysis, and Support Vector Machine. We can get the input image then make a classifications on it according to Color histogram feature or the combination of Color histogram feature and Histograms Oriented Gradients feature to detect the “Olive trees” by “Sliding Window” and classify each window if it contains olive tree or not.

## GENIŞLETILMIŞ ÖZET

Dünyada zeytinyağının ekonomik önemi, zeytinyağı kullanarak sağlığa pozitif bir yatırım olarak görülmektedir. Bu kapsamda dünya pazarında zeytinyağı üretimi ve fiyatlandırması çeşitli bitkisel katı ve sıvı yağlardan daha fazladır.

Zeytin ağaçlarını hesaplayarak yağ üretimini tahmin edebiliriz ve bu yöntem ülke ekonomisinin büyümesinde büyük önem taşımaktadır. Zeytin ağaçlarının çıkarılması tarım ve çevre üzerinde efektif bir etkiye sahiptir. Çevrede, örneğin çiftlik yönetiminde, kentsel alan alanlarının yönetiminde ve genel olarak tarıma zararın önlenmesinde kullanımın geliştirilmesi önemlidir. Bunun yanı sıra, sayma, izleme ve tarım işleri kontrol etmek için kolayca kullanılabilir. Ağaç taç ekstraksiyonu, bitki örtüsü dağılımının haritalanması, biyofiziksel parametrelerin değerlendirilmesi (taç hesaplamaları) için bir yaklaşım sağlar ve örneğin tür gruplaması ve bitki örtüsünün yoğunluğunun tahmini gibi bazı görevlere izin verir. Genel olarak, havadan görüntüleme zeytin ağaçlarını tahmin etmek için yararlı bir araçtır.

Bu çalışmada, Türkiye, Adana, Çukurova Üniversitesi Ziraat Fakültesi'nden 540 x 960 piksel RGB renkli görüntü boyutundaki zeytin ağaçlarının 2D görüntüsüne önerilen teknik uygulanmıştır. önerilen algoritmanın MATLAB yazılımı tarafından Görüntü İşleme Araçları ile uygulanmıştır.

Zeytin ağaçlarını tespiti ve sayılması yapmak için önerilen ilk algoritma, Dijital Görüntü İşleme tekniklerinin kullanılmasıdır. Görüntüdeki dengesiz ışık dağılımının Aydınlatmaya Düzeltme uygulanmıştır, ardından kolaylık sağlamak için görüntüyü gri ölçeğe dönüştürülmüştür. Gauss filtreleme, gürültü azaltma ve yumuşatma için kullanılmıştır, ayrıca kenarları daha belirgin olması için standart sapma filtresi uygulanmıştır. dairesel şekilleri çıkarmak için Dairesel Hough Dönüşümü kullanıldı.son olarak zeytin ağaçlarını tespitini ve sayılmasını gerçekleştirilmektedir.

İkinci önerilen algoritma Zeytin ağaçlarının tanımlanması ve sayımı için önerilen algoritma, görüntü işleme teknikleri vasıtasıyla uygulanmış, algoritma, gözetim dışı tanımı öğretmiştir. En iyi sonuçları elde etmek için birkaç adım uygulanmıştır, ilk olarak, düzensiz ışık dağılımı için bir grafik denklemi ve gürültüyü ortadan kaldırmak için bir filtreleme prosedürü ile görüntüleri iyileştirme ve ön işleme tabi tutma. İkincisi, elemanları arka plandan ayırmak için görüntü fraksiyonlama yönteminin uygulaması. Üçüncüsü, istenmeyen unsurları kaldırmak ve grafik görüntüyü daha net hale getirmek için morfolojik süreci. Dördüncüsü, dairesel hough dönüşümüm daireleri tespit edip saymaktadır.

Daha fazla ayrıntı için:

İlk olarak (RGB) kameradan alınan görüntü parazite ek olarak düzensiz veya düzensiz ışık dağılımı içerir Aydınlatma problemini yok etmek için Histogram Eşitlemesi stratejisi uygulandıktan sonra görüntüyü gri düzeye dönüştürülmüştü ve G kanalını grafik olarak değiştirilip renkli görüntüden çıkartırılmıştır.

Histogram Eşitlemesi ile üç yaklaşım uygulanmıştır. Birinci yaklaşım "Yaklaşım 1" : görüntüyü dört parçaya bölüp, her parça için grafiği hesaplama, her grafik için entropi elde etme, en yüksek entropiyi içeren parçayı seçme, seçilen grafiğe sahip diğer üç parça için histogram bağlantısını kullanma ve her biri için grafik denklemini uygulama ve tüm resimler için grafik denklemi uygulanmaktadır. İkinci Yaklaşım "Yaklaşım 2" : görüntüyü dört parçaya bölüp her parça için grafik denklemi uygulayıp grafiği hesaplamak, her grafik için entropi elde etmek, en yüksek entropiyi içeren parçayı seçmek, seçilen grafiğe sahip diğer üç parça için histogram bağlantısını kullanmak, Ve tüm resimler için grafik denklemini uygulanmaktadır. Üçüncü Yaklaşım "Yaklaşım 3" : görüntüyü dört parçaya bölüp her parça için grafik denklemi uygulanmaktadır.

Filterlemekte ,üç ana çeşit filtre kullanmıştır, çizgisel, çizgisel olmayan ve adaptif filtreler. Her çeşitten sadece bir filtire seçilmiştir, çizgisel filtrelerden ortalama filtre seçilmiştir, çizgisel olmayan filtrelerden medyan filtre seçilmiştir, adaptif filtrelerden wiener filtre seçilmiştir.

İkinci olarak, segmantasyon aşamasında kümeleme tekniği kullanılmıştır, bu aşamada üç algoritma kullanılmaktadır, K-ortalamaları, Bulanık c-ortalamalar ve Beklenti Maksimızasyon, daha iyi sonuçlar elde etmek için bu üç tekninte üç küme olması gerekmektedir.

Üçüncü olarak, istenmeyen üsnsürler silmek için ve ikili görüntüleme daha net görünmesi için morfolojik operasyonu uygulanmıştır.

Dördüncü olarak, dairesel şekiller tespit edip saymak için dairesel hough dönüşümü uygulanmıştır böylece zeytin ağaçları tespit etmiş olunur.

Bu filterlerin arasında en hızlı alınan sonuç filtre wiener filtresidir ve algoritmalar arasında en hızlı alınan sonuç K-ortamaları.

Beklenti Maksimızasyon algoritması ile wiener filtresidir, K-ortalamalar ile ortalama filtre ve wiener filtre, Bulanık c-ortalamalar ve her üç filtre ile, En iyi sonuç elde edilmiştir.

Beklenti Maksimızasyon algoritması ile wiener filtre histogram eşiklem göre “Yaklaşım 1” 96.76% gerçekleştirdi G kanal ile renkli görüntü.Genelde K-ortalama algoritması ile wiener filtesi ve ortalama filtresi iyi sonuçlar elde ediyor ancak Medyan ile K-ortalama ve “Yaklaşım 2” yaklaşık olarak 97.73% gerçekleştirdi gri tonlama ile. “Yaklaşım 1” ve “Yaklaşım 2” ye göre Genellikle Bulanık c-ortalamalar her filtre ile 96% gerçekleştirdi ve en iyi sonuç Bulanık c-ortalamalar medyan filtresi ve gri tonlama ile 97.08% gerçekleştirdi, Filtrelerin parametre performansına ve “Yaklaşım 1” e göre, Minimum Ortalama Kare Hatası ve en yüksek Tepe Sinyal / Gürültü Oranına ulaşılması nedeniyle Medyan filtresi tercih edilen filtredir.

Zeytin ağaçlarını tespiti ve sayılması yapmak için önerilen üçüncü algoritma, Denetimli Makine Öğrenimi algoritmalarıyla Dijital Görüntü İşleme tekniklerini kullanılmaktadır. Bu yöntem orijinal görüntünün alt görüntülere bölünmesini ve ardından verilerin veya alt görüntülerin (alt bloklar) yüklenmesini içerir. Alt görüntüler 2 sınıfa ayrılır, pozitif sınıf “zeytin ağacı” . negatif sınıf. “zeytin dışı ağaç”. Bundan sonra, Histogram Oryantasyon Gradyanı ve Renk histogramı özelliği gibi eğitim aşamasından sonra üç sınıflandırma algoritması K-En Yakın Komşu doğrusal Ayırım Analizi ve Destek Vektör Makinesi'dir çalıştırılmıştır. Giriş görüntüsünü alıp, üzerine Renk histogram özelliği veya Renk histogram özelliği ve Dairesel Hough Dönüşümü özelliği kombinasyonuna göre bir sınıflandırma yaparak "Zeytin ağaçlarını" " Kayan Pencere" ile tespit edebilir ve her pencerenin zeytin ağacı olup olmadığını sınıfrlandırılabilir.

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**LIST OF ABBREVIATIONS**

| | |
|---|---|
| DIP | : Digital Image Processing |
| DSP | : Digital Signal Processing |
| UAV | : Unmanned Aerial Vehicle |
| LIDAR | : Light Detection and Ranging |
| VHR | : Very High Resolution |
| LARS | : Low Altitude Remote Sensing |
| HE | : Histogram Equalization |
| FCM | : Fuzzy C-Means. |
| EM | : Expectation-Maximization |
| HT | : Hough Transform |
| CHT | : Circular Hough Transform |
| MSE | : Mean Square Error |
| SVM | : Support Vector Machine |
| KNN | : K-Nearest Neighbor |
| LDA | : Linear Discriminant Analysis |

XXIII

# 1. INTRODUCTION

## 1.1. The Olive and Olive Oil

Olive oil is acquired from the olive tree (Olea Europaea); the product of olive oil has regularly been focused in the “Mediterranean Basin Countries” because of olive tree climatic necessities. [Spain, Italy, Greece, Tunisia, Turkey, and Morocco] are the most important producers of olive oil in the world. Recently, olive oil has been essential product of the Mediterranean eating regimen and expanding popularity of olive oil has been identified with its high content of monounsaturated fatty acids and its secondary ingredients. (Tuck & Hayball, 2002) (Visioli, Galli, & Chemistry, 1998) (Visioli, Galli, & nutrition, 2002)

The olive oil manufacturing businesses are in constant growth because of potential uses of olive oil in different fields. The production of the oil differs by region, cultivar, time of harvest, altitude, and extraction process. Olive oil is generally utilized in pharmaceuticals, cosmetics, fuel, and cooking. There have been numerous reports on planning, providing and processing of olive oil. (Najafian, Ghodsvali, Khodaparast, & Diosady, 2009)

Figure 1.1. Olive and Olive Oil (TMMOB, 2014)

The economic importance of olive oil in the world is considered a positive participation on health related to olive oil utilization. As far as the value of product, pricing and production of olive oil in the market of the world is altogether higher than other oils and vegetable fats. Indeed, the cost may vary relying on the year, category, and country of the oil. The production of olive oil has been increased in the Mediterranean basin countries: Spain, Italy, Greece, Portugal, Tunisia, Turkey, and Morocco. These seven nations represent about 90% of the production of the entire world. Increasing aim by many countries but mainly two significant generating nations are the main players of production of olive oil. In fact, the yields levels in “Spain” and “Italy” are greater than any other countries. This massive concentration of production o olive oil in these nations is illustrated by the requesting climatic requirements of the olive tree and the case that practically every olive tree is grown in the environment of Mediterranean-type weather. It ought to be likewise referenced that olive oil production in other nations like Australia and the United States of America is rising lately. (Grigg, 2001) (InternationalOliveCouncil, 2020)

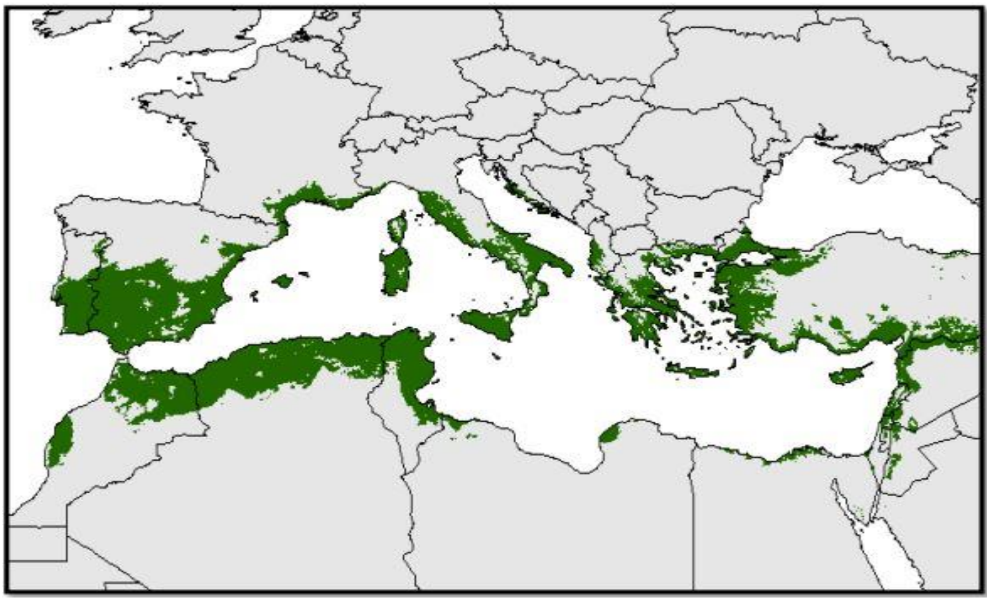

Figure 1.2. The ecological distribution of the olive tree (Moreno, 2014)

In Turkey, existing issues of olive oil and the olive sector in this country are grasped by policymakers. There have been some strategy efforts to develop the area and the sector since the start of 2000s. For this sector, in 2004, the minister for agriculture declared aims, to be achieved by the year 2014. These objectives were on the level of olive trees production. Furthermore, turkey has focused to be the second major producer after Spain by 2014. With these objectives, notable direct supports are given to expand the regions and the production of olives. Unfortunately, achievements in 2014 have been far underneath the objectives reported in 2004. The fundamental reason is the absence or the lack of sectoral policy that outlines the procedures and set policy toll to arrive at these objectives.

Currently, there are some conversations on sectoral aims for 2023 of various groups of sector leads without enunciation of sectoral policy. A few targets are infrequently reported by the government, a sectoral policy to eliminate and defeat the current problems to develop the productivity and quality of the olive and olive oil.

Turkey needs to enhance the productivity of the olive, quality and olive processing technology to become with leader's producer nations like Spain and Italy. Turkey can compete in the international markets and promote the chain of the global value. A sectoral policy can empower these developments by eliminating existing problems in this sector. In Turkey, a sectoral policy is needed because it would develop innovation in olive sector.

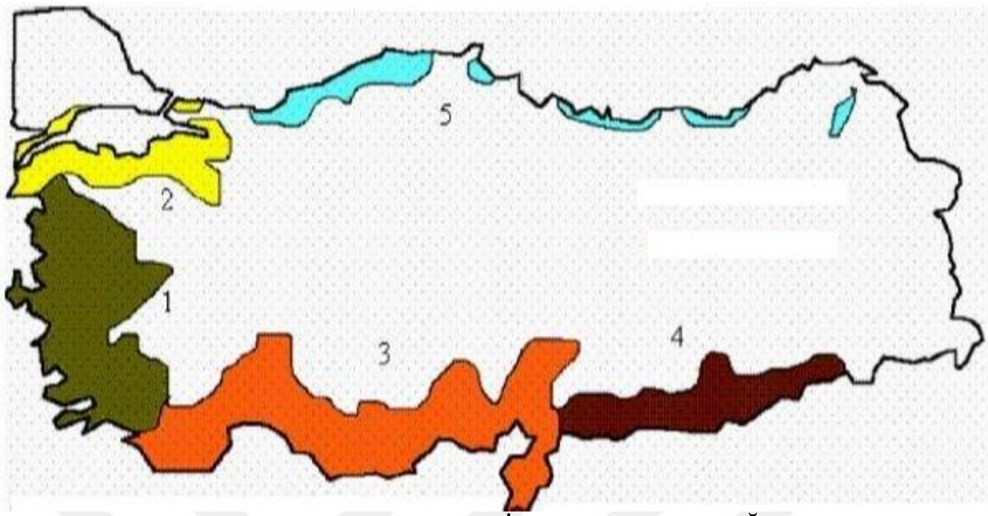

Figure 1.3. Olive tree regions in Turkey (TİCARETBAKANLIĞI, 2019)

The main regions in Turkey which contain olive production (Conexio, 2020):

1. Aegean region “Ege”
2. Marmara region
3. Mediterranean region “Akdeniz”
4. Southeastern Anatolia region “Güneydoğu Anadolu”
5. Black Sea region “Karadeniz”

The percentage of the production in Turkey is 53% in the Aegean region, 18% in the Marmara region, 23% in the Mediterranean region, 6% in the southeastern Anatolia region and 0.2% in the black Sea region.

In Turkey, in the period of 2018, the area of olive trees arrives to (864.428 ha) Hectare and the number of olive trees amount to (177,843) thousands of trees. From 2018 to 2019 the production of olive arrives to (423.6) thousand tons and (193.6) thousand tons of olive oil. In the same period, Turkey exports about (65) thousand tons of table olive and (55) thousand tons of olive oil. In the period between 2017 and 2018 the total amount which export of table olive and olive oil reached to (127,379,654 $) million dollars and (254,910,062 $) million dollars respectively. (TUIK, 2020) (TİCARETBAKANLIĞI, 2019)

### 1.2. Digital Image Processing

Digital image processing (DIP) belongs to the processing of 2-Dimentional image by a digital computer. The digital picture is an array of real numbers expressed by a limited number of bits. A picture given as a photograph or a slide is digitized and saved in computer memory as a matrix of binary digits. This digitized picture would then be prepared for processing and presented on a high-resolution monitor. (Ramesh, 2000)

Digital image processing comprises of the manipulation of pictures utilizing digital computers. Its utilizations have been expanding exponentially in the most recent decades. Its applications vary from medicine passing by remote sensing, and geological processing to entertainment. (Eduardo A.B. da Silva, 2005)

The regulation of digital image processing is huge, comprising digital signal processing (DSP) procedures just as strategies that are special to image. The image can be viewed as a function $f(x, y)$ of two continuous variables $x$ and $y$. To be digitally processed, it must be sampled and transformed into numbers in a matrix form. Since the computer describes the numbers utilizing limit or finite precision, these numbers must be quantized to be expressed digitally. Digital image processing comprises of the manipulation of those limited or finite precision numbers. The procedures or the processing of the digital images can be separated into a few categories:

- Image Enhancement
- Image Compression
- Image Analysis
- Image Restoration

In **image enhancement**, the image is often manipulated by heuristic methods; with the goal that human observer can obtain valuable data from it. A significant aspect of images is the gigantic amount of data required to express them, indeed, even a gray scale picture of the modest resolution. Therefore, to be effective to transmit and store digital images, there is requires to implement some kind of **image compression** which means decreasing the quantity of bits required in their description. **Image analysis** strategies allow that a picture is processed with the goal that data can be extracted automatically from it. Instances of image analysis are edge extraction, motion and texture analysis, and image segmentation. **Image restoration** methods try at processing damaged pictures from which there is a mathematical or statistical representation of the degradation with the goal that it very well may be returned. (Eduardo A.B. da Silva, 2005)

Types of an image (Umbaugh, 2005, p.45-54):

1) **Binary image**: every pixel has black "0" or white "1" (one of two gray levels).
2) **Gray scale image**: every pixel is given a gray level value from 0 to 255.
3) **Color image**: every pixel is mixture of three values (bands): Red, Green, and Blue.
4) **Multispectral image**: includes information outside normal human perceptual range, may contains ultraviolet, infrared, x-ray or other bands.

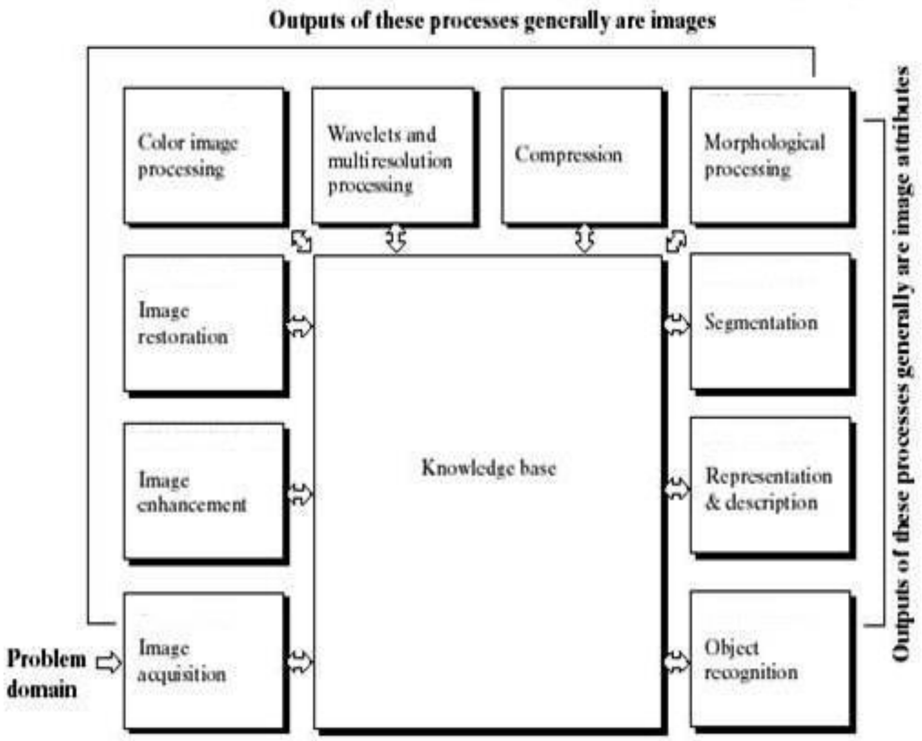


Figure 1.4. Essential procedures in digital image processing (Gonzales, 2008, p48)

Phrases or Essential procedures in digital image processing (Gonzales, 2008, p.47):

1) **Acquisition:** getting image which is in digital form, the principal task includes:
    a) **Scaling**
    b) **Color Conversion** (ex: RGB to Gray)
2) **Image Enhancement:** extract some hidden or useful details from the image.
3) **Image Restoration:** depends on probabilistic or mathematical of image degradation
4) **Color Image Processing:** there are many color models or spaces (such as RGB, HIS, and others)
5) **Wavelets and Multi Resolution Processing:** representing the pictures in different degrees of resolution.
6) **Image Compression:** deal with size or resolution of the image for lowering the storage required to keep the picture.
7) **Morphological Processing:** extracting image components which are valuable in the description and representation of shape.
8) **Segmentation Procedure:** it contains partitioning the picture into parts.
9) **Representation and Description:** it develops the output from the segmentation stage, keeping a representation of only the part of the solution of processed information.
10) **Object Detection and Recognition:** a procedure to make a recognition for individual objects which that allocate a label to an item or object depend on its descriptor

## 1.3. Previous Studies

The technologies of satellite imaging have become remarkably valuable instrument for gathering information for different agricultural applications (Li, 2014). Nonetheless, the significant constraints of utilizing the currently accessible satellite sensors are the significant expense, the absence of spatial resolution for description and identification of acceptable characteristic, the danger or the risk of the shady, vague or cloudy scenes of the main problems. Options dependent on manned airborne platforms have shown abilities for huge scope crop condition observing because of the high spectral and spatial resolutions of the sensors. Low-altitude and adjustable UAVs are significant, affordable instrument for accuracy agribusiness and they give a low cost and an easy way to deal with meet the basic and important prerequisites of spectral and spatial resolutions. UAVs can be utilized for executing autonomous duties using radio remote control device and auto-control system, which can be classified into a few sorts as indicated by the flight mode. Multispectral cameras, infrared thermal imagers, hyper spectral sensors, digital cameras and ranging (LIDAR) and light detection is generally used UAV sensors. The utilization of these sensors comprise visible imaging for canopy surface modeling, biomass estimation and crop height, visible-near-infrared spectroscopy to recognize physiological situation, thermal imaging for discovering water stress (Gonzalez-Dugo et al., 2013), LIDAR point cloud for estimating plant fine-scale geometric parameters with tremendous accuracy, and microwave images to measure soil moisture and canopy structure parameters by mixing various spectral bands. (Acevo-Herrera et al., 2010) (Gonzalez-Dugo et al., 2013) (Li, 2014) (Yang et al., 2017)

The “Olive” has a high agricultural importance, being a significant portion of the economy for countries, for example, Turkey, Greece, and Italy. Throughout the most recent 25 years, utilization of olive oil has expanded by 73%. The distribution and production of the crops which is economically important should be recorded and kept up for both economists and agriculturists. A manual gathering of information over huge zones is humanly time consuming, infeasible, and includes human error. Improvements in the field of “Image Processing” and the accessibility of the very high resolution “VHR” imagery has assisted for automating counting and detection. Automatic detection of “Olive Trees” has stayed a difficult subject for researchers. Different essential image preprocessing strategies containing image segmentation, blob detection, and template matching has been made for remote detection with high accuracy. Thus, complex procedures with artificial intelligence and classification-based systems has been suggested to produce precise detection results. (Waleed, Um, Khan, & Khan, 2020)

The extraction of the tree crown is significant in agriculture and ecology. In ecology it is helpful in a progression of utilizations, for example in forests management, parks management, vegetation in urban territories management, trees monitoring specially under power lines to restrict the harms in farming, for monitoring and counting trees in farms, planning of irrigation, estimation of yield (Malek et al., 2014), and detection of water stress. The extraction of a tree crown gives a way for vegetation distribution mapping, biophysical parameters measurement like crown dimensions and biomass, and provides executing tasks like vegetation changes monitoring, species classifications and vegetation density estimation. (Malek et al., 2014) (Kestur et al., 2018)

Generally, ground-based crown estimation includes sampling then statistical extrapolation which is expensive, inaccurate, tedious, and hard to acquire. Aerial imaging doing well for estimating tree crown. The detection of tree crown is implemented by a mix of high spectral resolution images and high spatial resolution LIDAR imagery which acquired utilizing a satellite remote sensing or manned aircraft (Alonzo, Bookhagen, & Roberts, 2014). Light detection and ranging (LIDAR) give precise tree height information. LIDAR is a promising information reference or source for extraction tree crown, nevertheless, the expense of LIDAR keeps on being a noteworthy cost component of the UAV platform. Moreover, the information which collected by aerial imagery is influenced by climate patterns and surface situations. LIDAR pulses are consumed by wet climate situations and in landscapes, with huge canopies and thickly populated trees, the information transmitted may not be precise. (Alonzo et al., 2014) (Man, Dong, Guo, Liu, & Shi, 2014)

Recently, very high-resolution imagery (VHR) with spatial resolution and unmanned aerial vehicles are likewise progressively being utilized as remote sensing platforms. Low altitude remote sensing (LARS) (Swain, 2010) is a remote sensing from UAVs, has numerous benefits when contrasted with conventional platforms. It costs less to manufacture and keep up smaller kilograms and can work without danger to human pilots. LARS is portrayed by image acquisition utilizing low priced cameras utilizing lightweight UAV platforms. LARS helps procedures at wanted time, for instance, to obtain imagery of a particular phenological stage and to work also with cloudy cover with high multi-temporal resolution. The permit mapping and observing small regions at a very fine scale. Nonetheless, imagery obtained from low price cameras worked from lightweight platforms dissimilar to the conventional satellite and manned aircraft platforms pretend additional difficulties in improving remote sensing products. (Swain, 2010) (Zarco-Tejada, Diaz-Varela, Angileri, & Loudjani, 2014) (Torresan, 2017)

Particular algorithms and techniques should be improved to examine the low spectral resolution and high spatial resolution imagery obtained from cameras, further extra for studies of tree crown. At present, this advancement is at an early stage and has produced encouraging avenues for experimentation. In 2012 (Hung, 2012) utilized just RGB vision band obtained from UAVs for identifying tree crowns. In this, shadow and geometry in addition to spectral (color) segmentation utilized in a “Template Matching” algorithm for recognizing and detecting tree crowns. In 2016 (Kang, 2016) investigated IR infrared imagery obtained by UAV for recognizing and identifying the planting zones of the Eucalyptus. Tree crown region is obtained by employing mathematical morphology, local spatial statistics, unsupervised segmentation, and iterative self-organizing data analysis technique algorithm (ISODATA). In 2014 (Malek et al., 2014) palm trees identified in vision spectrum (RGB) UAV pictures. By utilizing scale invariant feature transform (SIFT) key points extracted were investigated by performing ELM, a neural network classifier. Lastly, the texture is examined utilizing a local binary pattern (LBP) for detecting palm trees. Other studies utilized OBIA techniques and the other utilized Semi-Supervised Deep Learning Neural Networks. (Hung, 2012)

(Malek et al., 2014) (Kang, 2016) (Yurtseven, Akgul, Coban, & Gulci, 2019) (Weinstein, Marconi, Bohlman, Zare, & White, 2019) (Waleed et al., 2020)

An automated olive tree detection technique proposed (Bazi, Al-Sharari, & Melgani, 2009) to improve accuracy using supervised machine learning method for detecting olive trees. A "Gaussian process classifier" (GPC) with using of feature vector of the objects. Classification results may achieve high accuracy while the small quantity of training images sometimes not adequate for evaluation for the classifier execution precisely. An object-based classification strategy proposed (Peters, Van Coillie, Westra, & De Wulf, 2011) for detecting olive trees utilizing four-step model which contained image segmentation, feature extraction, classification, and result mapping with multispectral image. Other methods proposed by performing "Fuzzy logic", producing a fuzzy number and using "K-nearest neighbor" for detecting the olive trees. (Bazi et al., 2009) (Moreno-Garcia, 2010) (Peters et al., 2011) (Khan et al., 2018)

Olive trees detection in the ongoing years indicated the suggestion of different methods. Methods from basic image segmentation and blob detection to more complex strategies improved. These procedures used satellite image with aerially captured images with spectral information with RGB, gray scale or even multispectral bands. Higher accuracy achieved by using a public dataset which easily to deal with and contains a huge number of images with different categories. Generally, the algorithms demonstrated an improve in accuracy with an expansion in the information of spectral image. The goal of studies is automated method by using fewer images with decreasing the computational cost following with accurate detection for olive trees. (Karantzalos & Argialas, 2004) (González, Galindo, Arevalo, & Ambrosio, 2007) (Bazi et al., 2009) (Daliakopoulos, Grillakis, Koutroulis, Tsanis, & Sensing, 2009) (Moreno-Garcia, 2010) (Moreno-Garcia, 2010) (Peters et al., 2011) (Ramaniharan, Manoharan, & Swaminathan, 2016) (Chemin & Beck, 2017)

# 2. MATERIAL AND METHOD

## 2.1. Material

The proposed method applied to 2D image with the size of 540 x 960 pixels RGB color image from Cukurova University Faculty of Agriculture, Adana, Turkey. With MATLAB R2018a 64-bit software.

The proposed method performed by Windows 10 Home, with (12.0 GB) RAM, 64-bit Operating System and processor of Intel(R) Core (TM) i7-5500U CPU with 2.40 GHz.

## 2.2. Methods

### 1- Image processing Technique

In this approach, first of all, uneven illumination correction implemented for the input RGB image because of unbalanced light distribution, then converting the output image to gray scale. Cause of the noises, smoothing filtering was performed (Gaussian filter), in addition to Standard deviation filter to obtain the edges of the olive trees. Finally, Circular Hough Transform utilized to get the circular shapes to make the detection and counting of these (circles) olive trees.

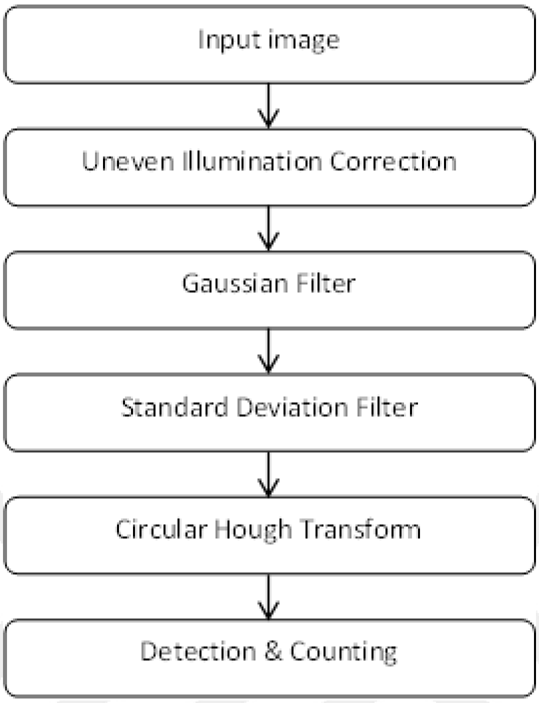


Figure 2.1. The proposed image processing algorithm

**2- Image Processing with Unsupervised Machine Learning Algorithms**

The proposed methods include many stages to count olive oil trees, starting to improve the illumination of the image, then applying filters. After that, implement segmentation technique. Thus, morphological operations to make the image clearer. Finally, Circular Hough Transform to detect the trees. The methods utilized in this study is summarized below. The stages which followed to get high accuracy are four stages:

1. ***Preprocessing and Image Enhancement***: this stage includes improving the illumination by “Histogram Equalization” strategy, after that, convert the image from “RGB” to “GRAY” scale and getting “G” channel and applying “Filtering” technique for noise removing.

For getting better results these three techniques were implemented for "Histogram Equalization":

1) Which I call it "Maximum Entropy + Histogram Equalization" or "Approach 1", includes Dividing the original image into 4 equal parts, then:
    i. Compute the "Histogram" of every part (segment).
    ii. Obtain the "Entropy" of each histogram.
    iii. Choosing the part which contains the "Maximum Entropy" value.
    iv. Using "Histogram Matching" of the other parts with the selected histogram.
    v. Implement "Histogram Equalization" for the whole image.
2) Which I call it "Histogram Equalization 4 parts + Maximum Entropy" or "Approach 2", includes Dividing the original image into 4 equal parts, then:
    i. Compute the "Histogram" of every part (segment).
    ii. Equalize the histogram of each part.
    iii. Obtain the "Entropy" of each histogram.
    iv. Choosing the part which contains the "Maximum Entropy" value.
    v. Using "Histogram Matching" of the other parts with the selected histogram.
    vi. Implement "Histogram Equalization" for the whole image.
3) Which I call it "Histogram Equalization 4 parts" or "Approach 3", includes Dividing the original image into 4 equal parts, then, applying histogram equalization for each part then gathering the 4 parts to become one image.

In “Filtering” technique, three filters utilized:

a) Linear Filter: Mean (Average) Filter

b) Non-Linear Filter: Median Filter

c) Adaptive Filter: Wiener Filter:

2. ***Image Segmentation***:

    a. K-Means algorithm.

    b. Fuzzy C-Means algorithm.

    c. Expectation-Maximization algorithm.

3. ***Morphological Operations***: to make the image suitable for detection and counting the objects.

4. ***Circular Hough Transform***: “CHT” utilized for circle identification and detection.

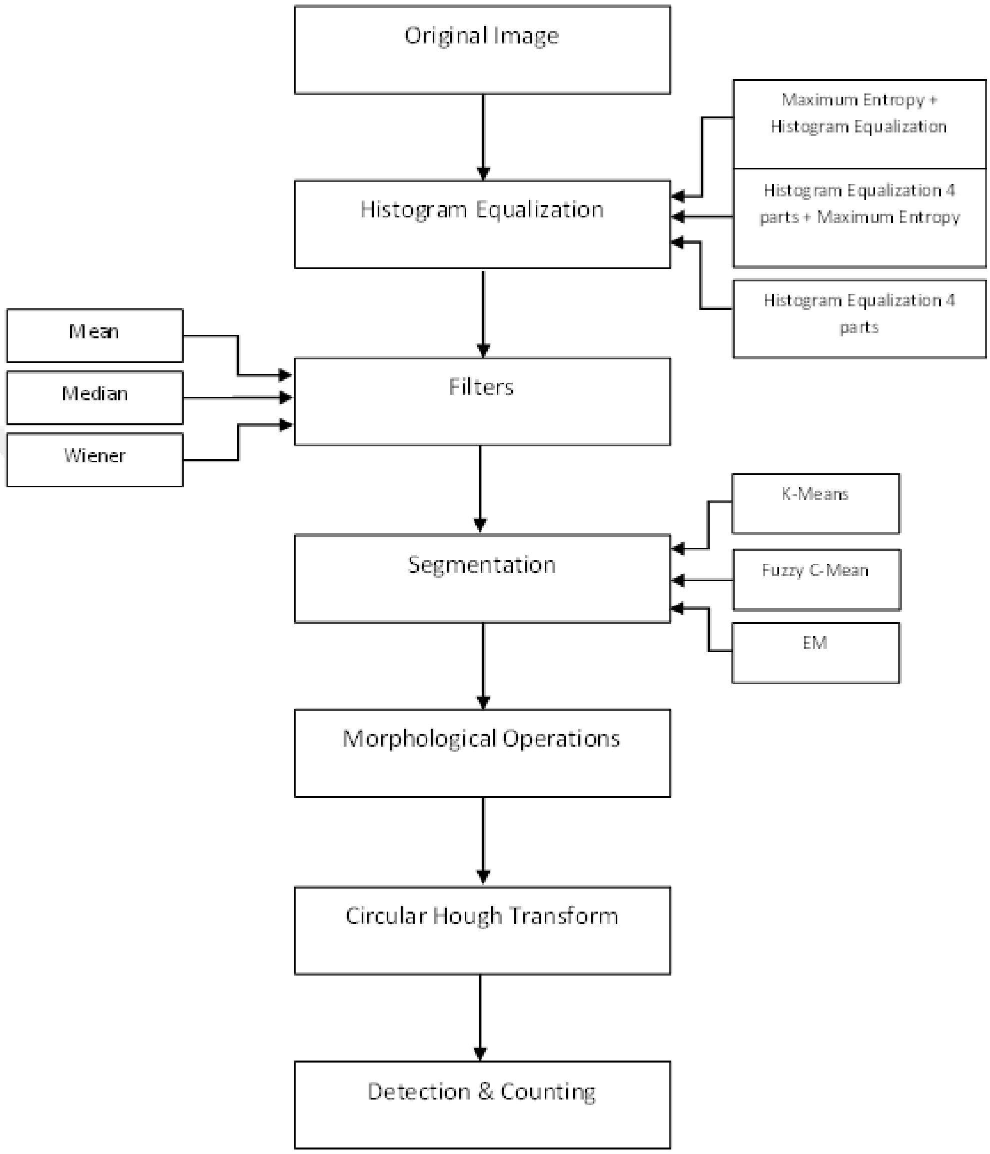


Figure 2.2. The proposed image processing with Unsupervised Machine Learning algorithms

**3- Image Processing with Supervised Machine Learning Algorithms**

This method include firstly loading the data or sub images (sub blocks),these sub blocks as a result of dividing the original image, these sub images basically divided into 2 groups or classes (1 and 0) which means positive class “1” which is “Olive tree” and negative class “0” means “Non olive tree”, each class contains “580” sub image,

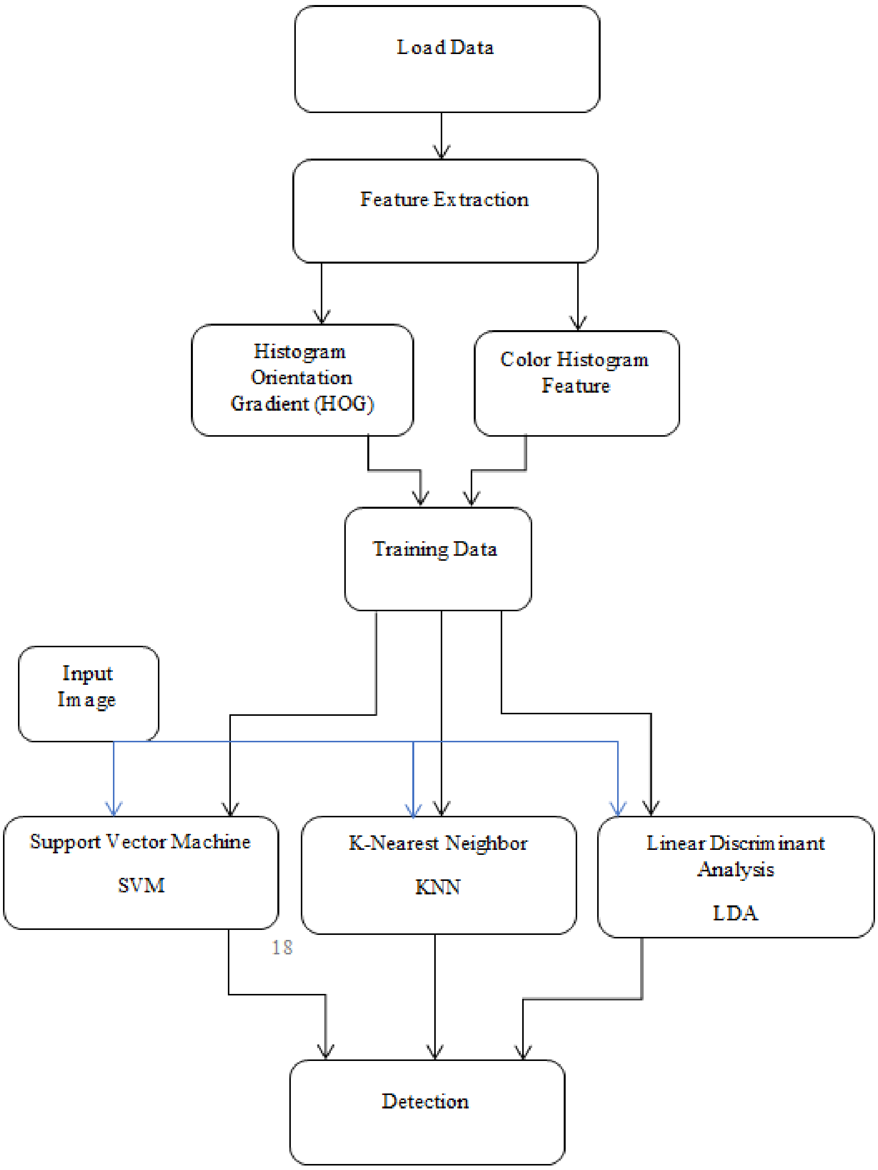


Figure 2.3. The proposed image processing with Supervised Machine Learning algorithms

### 2.3. Image Preprocessing and Enhancement

Image preprocessing is a general name for tasks or procedures with images. These pictures are of a similar kind as the first information caught by the sensor, with an intensity picture regularly described by a matrix of picture function values (brightness). The purpose of preprocessing is enhancement or improvement of the picture data that overcome unwilling distortions or improves some picture features significant for next additional processing. (Sonka, 1993, p.56)

The gained information is generally messy and originating from various sources. This information should be normalized and cleaned up. Preprocessing is utilized to improvements that will decrease the complexity and improve the accuracy of the implemented algorithm. (Elgendy, 2020)

We can't make an exceptional algorithm for every condition where a picture is taken, so when we acquire a picture, we will in general convert it into a structure that would enable a general algorithm to solve it. Data preprocessing strategies may involve: (Sonka, Hlavac, & Boyle, 1993) (Sonka, Hlavac, & Boyle, 1998) (Miljković, 2009) (Elgendy, 2020)

- Convert Color Image to Gray Scale
- Standardize Images
- Data Augmentation
- Remove Background Color
- Geometric Transformations (Scaling, Translation, Rotation)
- Image Cropping
- Intensity Adjustment
- Histogram Equalization
- Histogram Specification
- Filtering
- Increase/Decrease Brightness, Contrast and Alpha Correction
- Brightness Thresholding
- Detection Edges

### 2.3.1. Histogram Processing

A histogram is a graph that represents the frequency of anything. Regularly the histogram has bars that represent the frequency of happening or occurring of data in the whole data set. An image histogram is a chart to show what numbers of pixels are at each index or at each scale level for the indexed color image (Tan & Jiang, 2018). For a gray scale image, we can get a histogram by plotting pixels value distribution over the full gray scale range. (Tan & Jiang, 2018)

The digital image histogram with gray level in the range $[0, L-1]$ is a discrete function:

$$h( r_k) = n_k \tag{2.1}$$

where $r_k$ is the $k$th gray level and $n_k$ represents the pixel's number in the picture having gray level $r_k$ . It is a basic practice to order or normalize the histogram by separating each of its values by the whole number of pixels in the image indicated by $n$. $n$ it is the whole number of pixels in the picture $M \times N$ where $M$ picture rows and $N$ are picture columns. (Gonzales, 2008, p.142)
A normalized histogram is given by:

$$p(r_k) = n_k/n \text{ , for } k = 0,1,2,\dots,L-1 \tag{2.2}$$

$p(r_k)$ gives the probability estimation of the occurrence of the gray level $r_k$. Note that the total summation of all components of an ordered or a normalized histogram is equal to 1.

$$\sum p(r_k) = 1 \tag{2.3}$$

For various spatial domain processing methods and techniques, the histogram is the foundation. A histogram manipulation can be utilized successfully for image enhancement, also producing helpful image statistics in addition to other applications of image processing like image segmentation and image compression. (Gonzales, 2002, p.88)

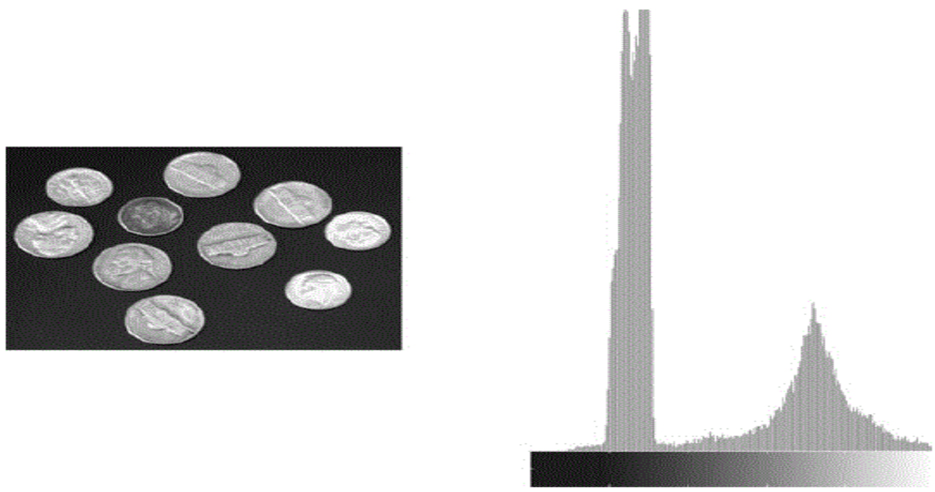

Figure 2.4. Sample image and corresponding image histogram (Solomon, 2011, p.64)

The figure above display a gray scale picture and corresponding picture histogram, the vertical axis represents the number of pixels and the horizontal axis represent scale level, the histogram can be created by basically counting the number of times each gray scale value from 0 to 255 happens inside the picture. Each “bin” inside the histogram is increased each time its value is found. In the figure, we can see two notable peaks in the histogram plot a high peak and lower peak, in the lower scope of pixel values the high tops or peaks related to the background intensity distribution of the picture and in the higher scope of pixel values the low peaks related to the foreground objects which are coins. (Solomon, 2011, p.64)

There are four essential intensity characteristics: (Gonzales, 2008, p.142-143)

- High Contrast
- Low Contrast
- Light
- Dark

The figure below shows four basic intensity characteristics, the left side shows the four images and the right side display the histograms of these pictures. The horizontal axis of every histogram plot identifies gray level values, $r_k$. The vertical axis identifies values of $h(r_k) = n_k$ or $p(r_k) = n_k/n$ if the values are normalized.

- In the dark image, we note that the histogram components are concentrated on the dark or low side of the gray scale.
- In the bright image, the histogram components are one-sided on the high side of the gray scale.
- In the low contrast image, the histogram of the image will be limited and be focused toward the center of the gray scale.
- In the high contrast image, the histogram of the image spread a wide range or scope of the gray scale. The distribution of the pixels isn't very far from the uniform.

#### 2.3.1.1. Histogram Processing Techniques

Image enhancement is a combination group of transformation techniques which aim to adjust and enhance the visual presentation of an image for study and analysis a specific region. The transformation or the processing technique is utilized to an input image then present the processed the output image. (H. Kaur & Sohi, 2017)

$$g(x, y) = T\ (f(x, y)) \tag{2.4}$$

Where $g(x, y)$ the processed output image, $T$ the transformation function, $f(x, y)$the input image.

There are many techniques for histogram processing (H. Kaur & Sohi, 2017):

- **Histogram Sliding**:
  It is a strategy where the total histogram of the image is just moved to leftwards or rightwards. By moving the histogram towards the left or the right a change is found in the brightness of the image. The brightness described as the intensity of light released by a specific light source. So, to increase the brightness of the image slides its histogram to the right or lighter (brighter) part.
- **Histogram Stretching**:
  It is a procedure of expanding the contrast of the image. The contrast describes the difference among the minimum and the maximum pixels intensity values in the image. So, to stretch the histogram of the image, the scope of intensity values is extended to cover the entire dynamic range of the histogram. Histogram of the image represents that the image having high or low contrast.
- **Histogram Equalization**:
  It is a method for getting better the contrast of the images by equalizing whole the pixels values of the image.it transform the image in the method that gives a uniform flatten histogram. Histogram equalization expands the

dynamic scope of pixel values and furthermore makes an equal count of pixels at each level, which creates a flat histogram with full dynamic scope and gives a high contrast image as a result.

Table 2.1. Comparison of histogram processing techniques (H. Kaur & Sohi, 2017)

| Processing techniques | Fully enhanced image | User interactive | Complex | Histogram shape affected | Full dynamic range | Characteristics affected |
|---|---|---|---|---|---|---|
| **Histogram sliding** | No | Yes | No | No | According user input | Brightness |
| **Histogram stretching** | Yes | Yes | No | No | According user input | Contrast |
| **Histogram equalization** | Yes | No | Yes | Yes | Yes | Contrast |

#### 2.3.1.2. Histogram Equalization (HE)

It is the strategy which expands the dynamic scope of the image. HE allocates the values of intensity of pixels in the input picture so the output picture includes a uniform spread or allocation of intensities. The aim and purpose of HE is to achieve a uniform histogram and improving the contrast. This method can be utilized on a portion of an image or entire image. (Bagade, Shandilya, & Practices, 2011)

The general working of HE performed on the image in three steps (Bagade et al., 2011):

1) Histogram formation
2) New intensity values count for every intensity level.
3) Substitute the new intensity values with the previous intensity values.

Deem continuous intensity amount and consign the variable $r$ indicate the intensities of a picture to be enhanced. Suppose that $r$ is in the scope of $[0, L-1]$. With $r = L-1$ illustration white and $r = 0$ illustrating black. (Gonzales, 2008, p.144)

$$s = T(r)\,, \quad 0 \le r \le L-1 \tag{2.5}$$

That make the output intensity level $s$ for each pixel in the input picture including intensity $r$.

The intensity level in the gray level in a picture might be seen as arbitrary variables in the interval [0, 1]. quite possibly the most major and basic descriptors of an arbitrary variable are probability density function (PDF). $p_r(r)$ and $p_s(s)$ indicate the probability density function of arbitrary variables $r$ and $s$ ,respectively, $p_r$ and $p_s$ are different functions. A basic outcome from probability theory is that if $p_r(r)$ and $T(r)$ are recognized and $T(r)$ is differentiable and continuous over the scope of values of interest. Thereafter the PDF of the transformed variables s can be acquired by this equation.

$$p_s(s) = p_r(r)\left|\frac{d_r}{d_s}\right| \tag{2.6}$$

The PDF of the producing intensity variable, $s$ is specified by the PDF of the input intensities by the chosen transformation function. The transformation function of specific significance in image processing comprise the format as follows:

$$s = T(r) = (L-1)\int_0^r p_r(w)dw \text{ , when } p_s(s) = \begin{cases} 1 & for\ 0 \le s \le 1 \\ 0 & otherwise \end{cases} \tag{2.7}$$

Where $w$ it is an integration dummy variable, the cumulative distribution function (CDF) of random variable $r$ in the right side of the equation.

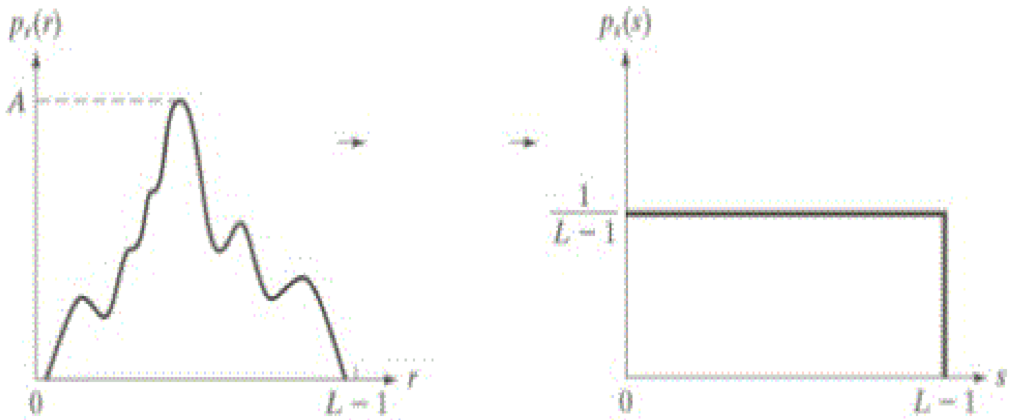


Figure 2.5. a) A random PDF. b) Output of effect the transformation to the whole intensity levels, s, have a regular PDF, r, the output intensities,. (Gonzales, 2008, p.146)

With discrete values, we deal with probabilities (values of histogram) and summations contrary to integrals and probability density functions. The probability of appearance or occurrence of density level $r_k$ in a digital image is:

$$p_r(r_k) = \frac{n_k}{MN} \qquad k = 0,1,2,\ldots,L-1 \tag{2.8}$$

Where $MN$ is the entire amount of pixels in the picture (numbers), $n_k$ is the amount of pixels that contain intensity $r_k$ and $L$ is the amount of possible intensity levels in the picture.

The discrete form of the transformation is:

$$s_k = T(r_k) = (L-1)\sum_{j=0}^{k} p_r(r_j) \tag{2.9}$$

$$= \frac{(L-1)}{MN}\sum_{j=0}^{k} n_j \qquad ,k=0,1,2,\ldots,L-1$$

Subsequently, the output or the processed image is acquired by mapping every pixel in the input image with intensity $r_k$ into a corresponding pixel with level $s_k$ in the output picture. The transformation $T(r_k)$ in this equation is called “Histogram linearization transformation” or “Histogram equalization”.

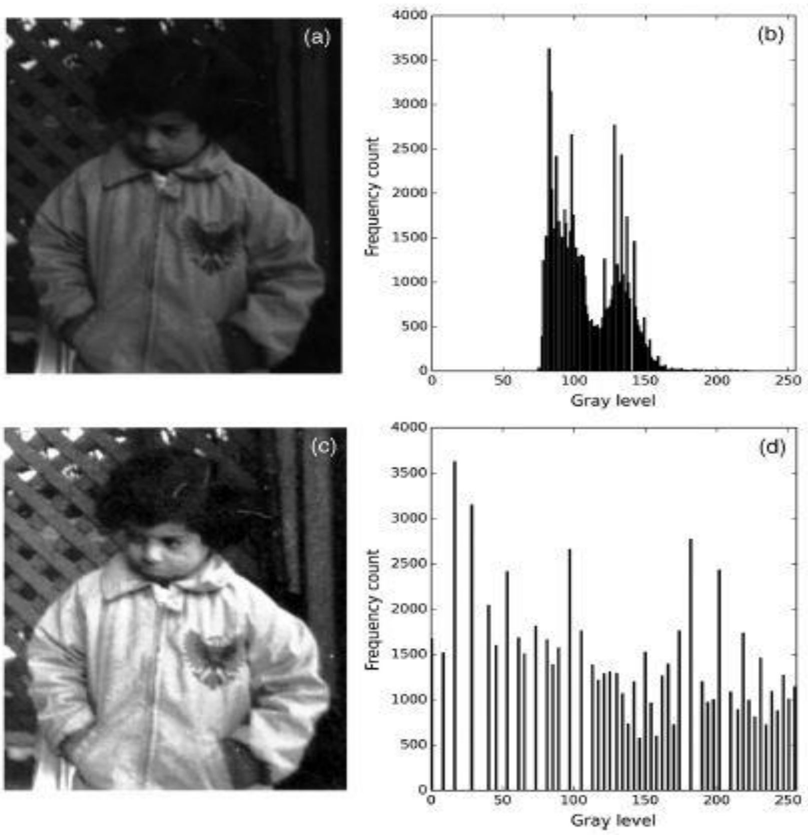


Figure 2.6. a) The input image. b) The histogram of the image. c) The image after histogram equalization. c) The equalized histogram. (Toet & Wu, 2014)

### 2.3.1.3. Entropy

Represent a statistical measure that utilized to describe, quantify, and distinguish the amount of information or the texture of the input image. Entropy helps to “Maximum Entropy” provides the maximum details present in the image.

Entropy is utilized widely as evaluation parameter for image. (Kansal, Purwar, & Tripathi, 2018)

The entropy of a picture when the picture is totally represented by just its grey level histogram when the grey level is $\{0, 1 \dots, L-1\}$:

$$H = -\sum_{i=0}^{L-1} p_i \ln p_i \qquad , i = 1,2, \dots , n \tag{2.10}$$

Where $p_i$ represent the probability of event occurrence $i$ and includes the normalized histogram counts returned from image histogram. (Kansal et al., 2018)

#### 2.3.1.4. Histogram matching (specification)

While the histogram transformation strategy is taking into account, numerous implementations required a desirable form of a histogram. We need to produce a processed picture that has the designated or specified desirable histogram called “Histogram matching” or “Histogram specification (HS)”. (Gonzales, 2008, p.150-156) (Wang & Ye, 2005)

For continuous intensities, let consider $r$ and $z$ are continuous random variables, let $p_r(r)$ and $p_z(z)$ indicate their corresponding continuous probability density functions. $r$ and $z$ indicate the intensity levels of the input and the processed or the output pictures, respectively. We can assessment $p_r(r)$ from the input picture, whereas $p_z(z)$ is the particular probability density function that we desire the output picture to have.

$$s = T(r) = (L-1) \int_0^r p_r(w)\ dw \tag{2.11}$$

Let $s$ be arbitrary variable with the property in the equation above, $w$ is a dummy variable of integration. This expression represents the continuous histogram equalization. Let we define an arbitrary variable $z$ with the property below.

$$G(z) = (L-1)\int_0^z p_z(t)\ dt = s \qquad (2.12)$$

Where $t$ represents a dummy variable of integration, then $G(z) = T(r)$ , thus $z$ must satisfy the condition

$$z = G^{-1}[T(r)] = G^{-1}(s) \qquad (2.13)$$

A picture whose the levels of intensity have a particular probability density function enable to acquire from a given picture by utilizing the following steps: (Gonzales, 2008, p.150-156)

- Acquire $p_r(r)$ from the input picture and acquire the values of $s$.
- Employ the specified PDF to acquire the transformation function $G(z)$.
- Obtain the inverse transformation $z = G^{-1}(s)$ this operation is mapping from $s$ to $z$.
- Obtain the processed or the output image by equalizing the input image, the values of the pixels in this picture are the $s$ values, for every pixel with value $s$ in the image which equalized, utilize the inverse mapping $z = G^{-1}(s)$ to acquire the corresponding pixel in the processed or the output image. When entire pixels have processed. PDF of the processed image will be similar or equal to particular or specified PDF.

The discrete formula of histogram matching or specification will clarify in the next equations:

$$s_k = T(r_k) = (L-1)\sum_{j=0}^{k} p_r(r_j) \tag{2.14}$$

$$= \frac{(L-1)}{MN}\sum_{j=0}^{k} n_j \quad , \qquad k = ,0,1,2,\ldots,L-1$$

Where $MN$ represents the entire pixels number in the picture, $n_j$ represents the pixels number that contain intensity value $r_j$ and $L$ is the entire number of potential intensity levels in the picture. So, given a particular or a specific value of $s_k$. The discrete formula includes computing the transformation function. (Gonzales, 2008, p.150-156)

$$G(z_q) = (L-1)\sum_{i=0}^{q} p_z(z_i) \tag{2.15}$$

For a value of $q$, so

$$G(z_q) = s_k \tag{2.16}$$

Where $p_z(z_i)$ is the $i$th value of the particular of specified histogram. The desired value $z_q$ by acquiring the inverse transformation:

$$z_q = G^{-1}(s_k) \tag{2.17}$$

This procedure gives a value of $z$ for every value of $s$, so it implements a mapping from $s$ to $z$. We deal with integer intensity levels (0-255), $q$=0, 1, 2…, L-1.

We can recap the histogram specification steps: (Gonzales, 2008, p.155)

- Acquire or compute the histogram $p_r(r)$ of the given picture. We can utilize it to find HE transformation.
- Compute entire values of $G$ transformation function, for $q = 0,1,2 \dots, L - 1$, while $p_z(z_i)$ represent the values of the particular or the specified histogram.
- For each value of $s_k$ , where $k = 0,1,2, \dots, L - 1$. Utilize the stored values of $G$ to detect the corresponding value of $z_q$. $G(z_q)$ is very close to $s_k$ , store these mapping from $s$ to $z$.
- Compose or form the image with specified histogram by histogram equalization the input picture and thus mapping each equalized pixel value, $s_k$, of this picture to the corresponding value $z_q$ in the image which has a specified histogram by utilizing the mapping $s$ to $z$.

**Application of histogram in image enhancement:** (H. Kaur & Sohi, 2017)

- Real time processing: the histogram is a well-known tool for the processing in real time and the histograms are easy for software calculations. Therefore, economic hardware applications.
- The histograms are utilized for image analyzing: by looking at the details of histogram, it is enable to expect the properties of the picture.
- Brightness purposes: histograms are utilized for brightness modification of a picture by owning the details of its histogram.
- Histograms are utilized to modify the image contrast: the image contrast is modifying by owning the details of gray level intensities or horizontal axis of the histograms.
- Image equalization: histograms are utilized for image equalization by extending the gray level intensities along the horizontal axis to create a high contrast image.
- Histograms are utilized in thresholding purposes.

- Histograms enhance the visual representation of a picture.
- We can determine the kind of picture transformation or which enhancement algorithm is applied by owning or knowing the input and the output histograms.
- The histogram describes the issues that start while image acquisition, for example, dynamic range of contrast, pixels and so on.
- Histograms indicate a wide scope of image compressing, gaps, saturation and spikes.
- The histogram shape predicts some information about contrast enhancement's possibilities.
- The input image can enhance by manipulating or adjusting the histogram such as histogram sliding, equalization and stretching.

#### 2.3.1.5. Color Histogram Feature

The histogram of a picture is a plot of the values or intensities of the gray level of a color channel versus the quantity of pixels at that value. The state of the histogram gives us data about the idea or characteristic of the picture, or sub-picture when we are thinking about an object inside the picture. For instance, a thin histogram infers a low picture contrast, a histogram slanted toward the very high end infers a light picture, and a histogram with two significant peaks, means an item that is in difference or contrast with the background of the picture.

The histogram features that we will treat are statistical based features, where the histogram is utilized as a probability distribution model of the levels of the intensity. These statistical features give us data about the properties of the intensity level allocation for the picture (Balke, 2011) (Sergyan, 2008)

#### 2.3.1.6. Histogram Oriented Gradients

It is a feature descriptor applied for distinguishing and detecting objects in image processing and computer vision. The HOG descriptor procedure calculates occurrences of gradient orientation in limited parts of a picture region of interest or window (Intel, 2021). Histograms of Oriented Gradients (HOGs) are picture descriptors invariant to 2 Dimensions rotation which utilized in various issues and tasks in computer vision like pedestrian detection. HOG descriptor effectively applied to face recognition issues. (Albiol, Monzo, Martin, Sastre, & Albiol, 2008; Baranda, Jeanne, & Braspenning, 2008; Chuang, Huang, Fu, & Hsiao, 2008; Kobayashi, Hidaka, & Kurita, 2007) (Déniz, Bueno, Salido, & De la Torre, 2011; Watanabe, Ito, & Yokoi, 2009) (Intel, 2021)

Execution of the HOG descriptor algorithm is as per the following:

- Make a division of the picture into small associated areas "cells", and for every cell calculate the histogram of gradient edge orientations or directions for the pixels inside the cell.
- Discretize every cell into angular bins as indicated by the gradient orientation.
- Every cell's pixel gives a weighted gradient to its analogous angular bin.
- Assortments of neighboring cells are considered as spatial areas "blocks". The gathering of cells into a block is the foundation for the gathering and normalization of histograms.
- The normalized assortment of histograms describes the block histogram. The collection of these block histogram describes the descriptor.

The gradient of an image should calculate the horizontal $G_H$ and vertical $G_V$ by filtering image with $[-1\ 0\ 1\ ]$ then calculate the orientation and the norm of the gradient .After that splitting the picture into cells the calculate histogram for each cell and make a normalization for the whole histograms inside the block of the cell and finally the last descriptor is acquired by gathering the whole normalized histograms into a single vector. (Dalal & Triggs, 2005) (Bertozzi et al., 2007)

Norm and gradient orientation equations as follows: (Bertozzi et al., 2007)

$$N_G(x,y) = \sqrt{G_H(x,y)^2 + G_V(x,y)^2} \tag{2.18}$$

$$O_G(x,y) = \operatorname{atan}\left(\frac{G_H(x,y)}{G_V(x,y)}\right) \tag{2.19}$$

**2.3.2. Filtering**

Filtering is a method or technique for modifying and enhancing the picture. For instance, we can filter a picture to indicate and maintain specific features or to eliminate and exclude other features. Methods in image processing performed with filtering comprise edge enhancement, sharpening and smoothing. (MathWorksFiltering, 2020)

Filtering is a neighborhood operation, where the amount of any pixel in the yield picture is defined by employing some computation or algorithm to the value of the neighborhood pixels of the identical or the corresponding pixel (input). The pixel's neighborhood is several pixels collection, determined by their areas (positions) corresponding to that pixel. (MathWorksFiltering, 2020)

One of the essential uses and applications of the filtering in image enhancement is for removing noises. The application of various filters to remove noises such as Gaussian noises, additive 'salt and pepper' noises (Solomon, 2011, p.90)

Image is frequently oblique by unequal, infrequent diversity in intensity values " noise". Several kinds of noise are impulse noise, Gaussian noise, and salt and pepper noise. Salt and pepper noise contain arbitrary events of white and black intensity values. Meanwhile impulse noise consists of just arbitrary events of white intensity values. Gaussian noise contains varieties in intensity that is drawn from normal distribution or a Gaussian and is an excellent model for several sorts of sensor noise, for example, the noise because of camera electronics. (Jain, 1995)

Some operations of neighborhood work with the estimations or the values of the pixels of the picture in the neighborhood and the identical or the corresponding values of the "sub-image" that has identical dimensions from the neighborhood. The "sub-image" known as a "Mask", "Kernel", "Window", template or "Filter". The assess in a window or the kernel are assigned to as coefficients instead of pixels. (Gonzales, 2002, p.116)

The idea of "Filtering" comprise its sources in the utilization of the "Fourier Transform" for "Signal Processing" in the "Frequency Domain" processing (Gonzales, 2002, p.116), where "Filtering" points out to passing (accepting) or refusing specific frequency component, as an instance, a mask which accept or pass low frequencies "Low pass Filter", an influence created via low pass filtering is to "Smooth" or "Blur" an image. (Gonzales, 2002, p.116) (Gonzales, 2008, p.167)

Noise is undesirable, mutilates or damages that may decrease the quality of the image. Noise has been created in the image because of transmission. Therefore, the main cause of image de-noising is "Image Digitalization". In the image processing, noise presents a picture that may comprise of odd lines, distortion in the pixels, blurred objects, etc. images are damaged because of different kinds of noises such as photo electronic, Gaussian and impulse noise. (G. Kaur, Kumar, Kainth, & Engineering, 2016) (Kalpana & Technology, 2015)

**Noise sources**: (Arya & Semwal, 2017) (Kumar, 2010) (Sontakke, Kulkarni, & Science, 2015)

- Image Transmission
- Image Acquisition
- Image Storage
- Image Retrieval
- Sensors
- Circuitry of a Digital Camera

"Digital Noise" may appear from different sorts of provenance, for example, "Charge Coupled Device (CCD)" and "Complementary Metal Oxide Semiconductor (CMOS)" sensors. "Points Spreading Function (PSF)" and "Modulation Transfer Function" utilized for total investigation and noise models study. Histogram and "Probability Density Function (PDF)" is likewise utilized to characterize or design the models of noises. (Sontakke et al., 2015) (Boyat & Joshi, 2015)

**Noise models:** (Boyat & Joshi, 2015) (Sontakke et al., 2015)

- Periodic Noise
- Erlang (Gamma) Noise
- Photon Noise (Poisson Noise)
- Quantization Noise
- Rayleigh Noise
- Structured Noise
- Gaussian Noise
- Speckle Noise
- Exponential Noise
- White Noise
- Impulse (Salt and Pepper) Noise
- Brownian Noise (Fractal Noise)
- Poisson-Gaussian Noise
- Uniform Noise

Image de-noising or noise reduction is a significant duty in “Image Processing” for the examination and picture analysis. However, the superior one ought to eliminate noises entirely from a picture while saving the specifics. De-noising techniques can be “Linear” in addition to “Non-Linear” (Verma, Ali, & engineering, 2013). Linear techniques are sufficiently quick; however, they don’t save the details of the picture, though the non-linear strategies save the specifics of the picture. There are various sorts of linear and non-linear filters, generally, de-noising filters can be classified or categorized in: Averaging filter, ordering statistics filter, and Adaptive filter. (Verma et al., 2013) (Sontakke et al., 2015) (G. Kaur et al., 2016)

**Linear Filters**: utilized for eliminating specific sort of noises. Average or Gaussian filters are appropriate for this objective. These filters likewise perform for blurring sharp edges and damage fine specifics and the lines of a picture. Linear filter is basically the average of pixels comprise in a neighborhood of a kernel or the filter, these filters also called ”Averaging Filters” and they likewise are referred to low pass filters (Gonzales, 2008, p.174). A linear filter is performed utilizing the weighted sum of the pixels in successive windows, the same example or pattern of weights is utilized in every window. The linear filters can be executed utilizing a convolution mask. (Kasturi, 1995) (Gonzales, 2008, p.174) (Verma et al., 2013)

**Non-Linear Filters**: an assortment of non-linear median type filters, for example, relax median, rank selection, rank conditioned and weighted median have been created and improved to defeat the weakness of linear filter. Any filter that isn’t a weighted sum of pixels is a non-linear filter. (Kasturi, 1995)

**Adaptive Filters**: this method changes the conduct of the picture. It is more selective than a similar linear filter. It stores the high frequency parts (such as edges) of the picture. This strategy mostly utilizes wiener filter; however, wiener filter takes more time in the computations more than the linear filtering. (Kamboj & Rani, 2013) (G. Kaur et al., 2016)

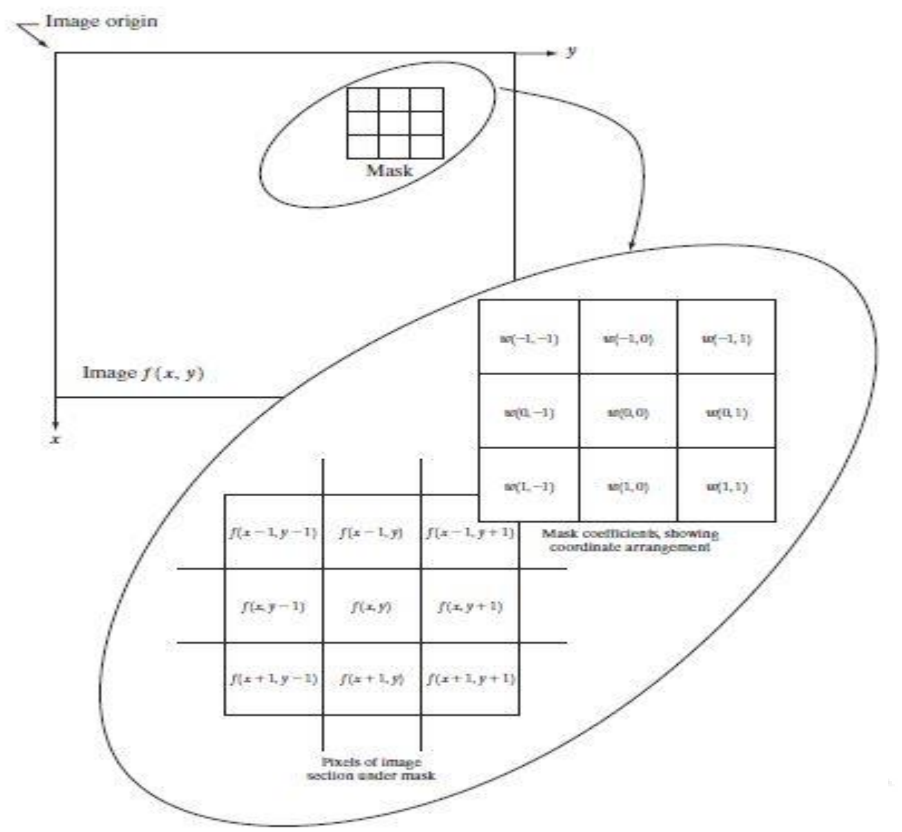


Figure 2.7. The technique of "linear spatial filtering" using 3 x 3 "filter mask" (Gonzales, 2008, p.168)

The figure above shows the technique of linear filtering utilizing "3 x 3" neighborhoods. At any point $(x, y)$ in the picture, the response $g(x, y)$ of the filter is the total or the sum of products of the "coefficients" of the kernel and the picture pixels surrounded by the kernel (Gonzales, 2008, p.167-168):

$$\begin{aligned} g(x, y) = {} & w(-1,-1)f(x-1, y-1) + w(-1,0)f(x-1, y) \\ & + \cdots + w(0,0)f(x, y) + \cdots \\ & + w(1,1)f(x+1, y+1) \end{aligned} \tag{2.20}$$

The center coefficient of the kernel $w(0,0)$, stands with the pixel at position $(x, y)$. The "linear spatial filtering" of an image of size $M\ X\ N$ with a filter of size $m\ X\ n$ where ( $m = 2a + 1, n = 2b + 1$ ) is given by the formula:

$$g(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x+s, y+t) \tag{2.21}$$

Where $x$ and $y$ are changed, thus each pixel in $w$ visits each pixel in $f$, $a$ and $b$ are positive integers, where $a = (m-1)/2$ and $b = (n-1)/2$

#### 2.3.2.1. Averaging Filter

One of the least complex (simplest) "linear filters" is performed by a local averaging process where the assess of every pixel is substituted by the average of whole amounts in a local neighborhood.

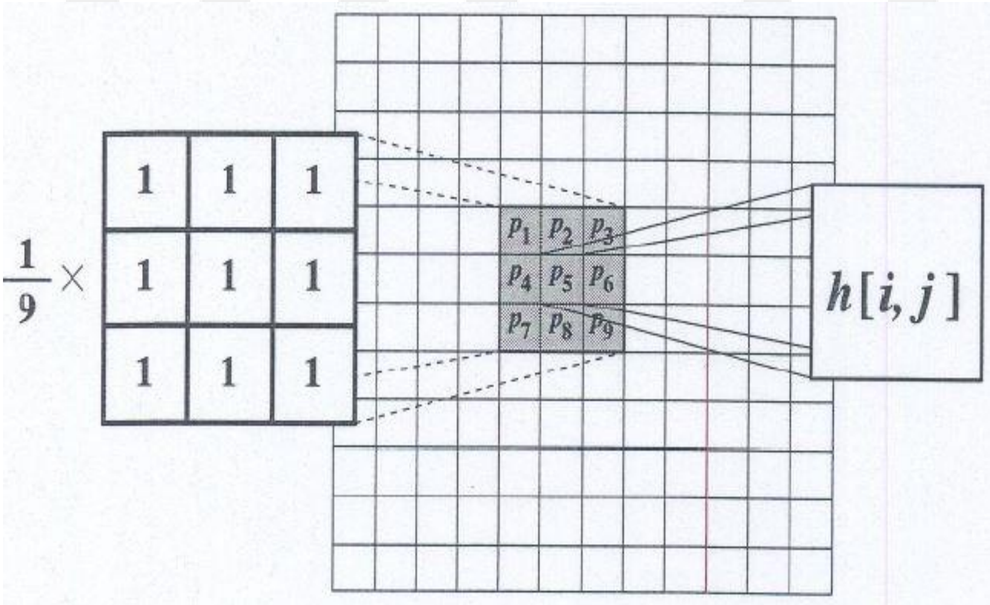


Figure 2.8. An example illustrating the mean filter using a 3 x 3 neighborhood (Kasturi, 1995, p.120-122)

$$h(x, y) = f(x, y) * g(x, y) \tag{2.22}$$

where $h$ and $f$ are images, $h(x, y)$ and $f(x, y)$ are the input and output images, the output $h(x, y)$ is the convolution of $f(x, y)$ with the impulse response $g(x, y)$
For discrete function:

$$h[i, j] = \frac{1}{M} \sum_{(k,l)\in N} f[k, l] \tag{2.23}$$

Where $M$ is the entire number of pixels in the neighborhood $N$. For instance, taking a 3 x 3 neighborhood about $[i, j]$ yields:

$$h[i, j] = \frac{1}{9} \sum_{k=i-1}^{i+1} \sum_{l=j-1}^{j+1} f[k, l] \tag{2.24}$$

Where $h$ and $f$ are images, $g[i, j]$ is referred to as a convolution mask, if $g[i, j] = 1/9$ for every $[i, j]$ in the convolution mask, the convolution process lessens to the local averaging process. The outcome determines that a mean filter can be performed as a convolution process with equal weights in the "convolution mask".

The size of neighborhood $N$ controls the measure of filtering. A bigger neighborhood, corresponding to a bigger "convolution mask" and will the outcome become in a greater degree of filtering, thus, the noise reduction become greater, but larger filters likewise result in a loss in the details of the image. (Kasturi, 1995, p.120-122)

Table 2.2. Unfiltered Values (G. Kaur et al., 2016)

| Unfiltered Values | | |
|---|---|---|
| 8 | 4 | 7 |
| 2 | 1 | 9 |
| 5 | 3 | 6 |

8+4+7+2+1+9+5+3+6=45

45 / 9 = 5

Table 2.3. Mean Values (G. Kaur et al., 2016)

| Mean Values | | |
|---|---|---|
| * | * | * |
| * | 5 | * |
| * | * | * |

The “**Arithmetic Mean**” filter is very simple one; there are several forms of “mean filters” with somewhat diversified behavior: (Gonzales, 2008, p.344-345)

- **Geometric Mean**: accomplishes alike smoothing to the “Arithmetic mean”, however, tends to loss low picture detail
- **Harmonic Mean**: operates properly for “Salt” noises, still fails for “Pepper” noises
- **Contra harmonic Mean**: adjusting its value changes the filter’s behavior (eliminate pepper noise, eliminate salt noise, adjust the order of the filter)

**Strength**: (Kamboj & Rani, 2013)

- ✓ Simple to execute
- ✓ Eliminate the “impulse” noise

**Weaknesses**:

- Does not maintain details of a picture

#### 2.3.2.2. Median filter

The "median filter" is the best "order static", "non-linear" filter, which response depends on the positioning or the ranking of values of pixel included in the mask area. The "median filter" is very well known for diminishing particular sorts of noise. The center value of the pixel is substitute by the "median" of the pixel values under kernel area. "Median filter" is a simple, strong and important "non-linear" filter that is depends on "order statistics". It is effortless and simple to perform the procedure of smoothing images. The median filter is utilized for decreasing the quantity of intensity diversity between one pixel and the other pixel. (Hwang & Haddad, 1995)

In the median filter, we don't substitute the pixel value of the picture with the "mean" of whole adjoining pixel values; instead of that, we institute it by the "median" value. At this point, the median is determined by first sorting whole the pixel values into climbing order and afterward displace the pixel being determined with the middle pixel value. In the event that the neighboring pixel of the picture which is to consider carry or include an even number of pixels, the middle or the average of the two center or middle pixel values is utilized to displace. Note that when the amount of impulse noise expanded or extended the median filter does not give the best outcome. The median filter is useful for "salt and pepper" noise. These filters are generally utilized as smoothers for "Image Processing", just as in "Signal Processing". A significant benefit of the median filter over the "linear" filters, the median filter enable to exclude the impact of the values of input noise with remarkably huge magnitude. (Sontakke et al., 2015)

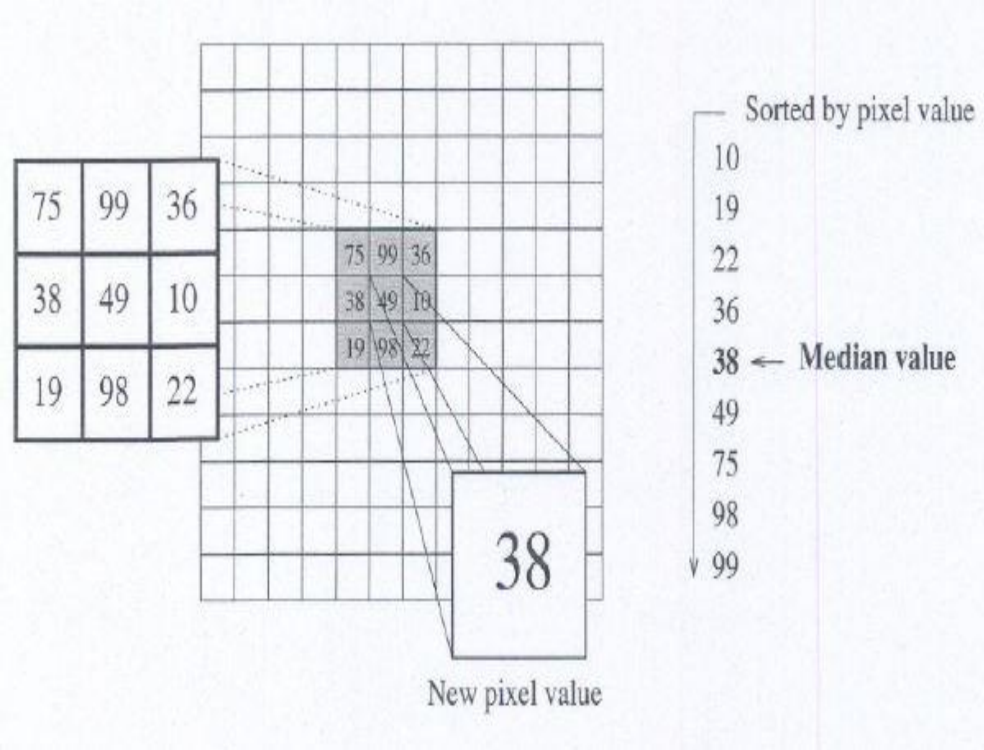


Figure 2.9. An example illustrating the median filter using a 3 x 3 neighborhood (Kasturi, 1995, p.124)

The problem with local averaging processes is that they in general perform for blurring sharp discontinuities in an image intensity values. A substitution method is to substitute each pixel with the "median" of the gray values in the local neighborhood. The filters which utilizing this procedure are "Median filters". Median filters are so efficient in eliminating impulse and "salt and pepper" noise while preserving the specifics of the image since they don't rely on values which essentially unlike from regular and normal amounts in the neighborhood. "Median" filters work in serial image windows in a manner like "linear" filters. Nevertheless, this procedure is not a weighted sum. As an instance, take 3 x 3 window then measure the "median" of the pixels in every window centered about $[i, j]$ : (Kasturi, 1995, p.122-123)

1) Arrange the pixels into climbing or “ascending” order by gray level.
2) Pick out the assess of the center or middle pixel as a new assess for pixel $[i, j]$.

In general, an odd-size neighborhood is utilized for computing the median. Nevertheless, if the quantity of pixels is even, the median is taken as the middle or the average of the middle two pixels after ordering or sorting. (Kasturi, 1995, p.122-123)

**Strength**: (Kamboj & Rani, 2013)

- ✓ Easy to implement
- ✓ Used to denoise several types of noises

**Weaknesses**:

- o Remove the details of the image while reducing the noises
- o Is not satisfactory for signal dependent noises, various variations of median filter improved for better outcomes.

#### 2.3.2.3. Wiener Filter

Wiener filter is established on considering noise an images as arbitrary procedures and the goals are to discover or find a gauge or an estimate of the uncorrupted picture such that the “Mean Square Error (MSE)” between them is limited or diminished. Wiener filter can be recognized as a linear estimating technique. (Arya & Semwal, 2017)

Wiener filter was proposed by “Norbert Wiener” in 1940s and distributed in 1949 (Wiener, 1949) the discrete time equivalent of the works of wiener was determined individually by “Andrey Kolmogorov” and distributed in 1941. Subsequently, the hypothesis is regularly called “Wiener-Kolmogorov filtering theory". Wiener filter was the initial statistically designed filter to be proposed and, in this manner, offered to ascend to numerous others including the "Kalman" filter.

The reason for the wiener filter is to absent the noise which destroyed or damaged a signal. The wiener filter is depending on a statistical process. This filter has alternative view to deal with filtering the image. The objective of the wiener filter is to lessen or decrease the "Mean Square Error" as much as possible. The wiener filter is able to decrease the noise and degrading function. One technique that we expect we know about the spectral property of the original signal and the noise. (Kumar, 2010) (Kamboj & Rani, 2013)

The wiener filter characteristics are: (Kumar, 2010) (Kamboj & Rani, 2013)

a) Assumption: additive noise and the signal are stationary linear-random technique with known their spectral attributes.
b) Demand: the wiener filter should be realizable physically or causal.
c) Implementation criterion: Minimum "Mean Square Error (MSE)".

The fact that utilized which is the product of a complex volume or quantity with the conjugate of itself is equivalent to the squared magnitude of the complex quantity. This outcome is "Wiener Filter". After N. Wiener (in 1942), who initially proposed the idea in that year. Is generally related to as the "least square error filter" or the "minimum mean square error filter". (Gonzales, 2008, p.374-376)

The technique is established on thinking about images and noise as arbitrary variables and the goal is to discover or find an estimate $\hat{f}$ of the uncorrupted image $f$ such that the "Mean Square Error" between them is limited or minimized. This error measure is characterized as:

Where $E\{.\}$ It is the expected value of the argument. Assume that the image and the noise are uncorrelated. The mean square error can be near to in terms of a summation involving the main and reconditioned pictures:

$$\text{MSE} = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[f(x,y) - \hat{f}(x,y)]^2 \tag{2.25}$$

The wiener filter and the minimum of the error function are given in the "Frequency Domain" by the expression:

$$\hat{F}(u,v) = \left[\frac{H^*(u,v)S_f(u,v)}{S_f(u,v)|H(u,v)|^2 + S_\eta(u,v)}\right]G(u,v) \tag{2.26}$$

$$= \left[\frac{H^*(u,v)}{|H(u,v)|^2 + S_\eta(u,v)/S_f(u,v)}\right]G(u,v)$$

$$= \left[\frac{1}{H(u,v)}\,\frac{|H(u,v)|^2}{|H(u,v)|^2 + S_\eta(u,v)/S_f(u,v)}\right]G(u,v)$$

Where:

$H(u,v)$ = degradation function

$H^*(u,v)$ = complex conjugate of $H(u,v)$

$|H(u,v)|^2 = H^*(u,v)H(u,v)$

$S_\eta(u,v) = |N(u,v)|^2$ = power spectrum of the noise

$S_f(u,v) = |F(u,v)|^2$ = power spectrum of the undegraded image

$H(u,v)$ it is the transform of the degradation function, $G(u,v)$ demonstrates the transform of the degraded image. In the "Spatial Domain", the restored image is presented or given by the "Inverse Fourier Transform" of the "Frequency Domain" estimate $\hat{F}(u, v)$. In the case of noise is zero, thus the "power spectrum" of the noise fades and the filter "Wiener Filter" minify to the inverse filter. (Gonzales, 2008, p.374-376)

Various valuable measures depend on the "power spectra" of the undegraded image and the noise. Quite possibly the most significant is the "signal-to-noise ratio", approximated utilizing "Frequency Domain" measures:

$$\mathrm{SNR} = \frac{\sum_{u=0}^{M-1} \sum_{v=0}^{N-1} |F(u, v)|^2}{\sum_{u=0}^{M-1} \sum_{v=0}^{N-1} |N(u, v)|^2} \tag{2.27}$$

This proportion gives a gauge of the level of data bearing "signal power" of the original, undegraded picture to the level of "noise power". The picture with least noise would lead to have a top "SNR", then, a similar picture with more significant level of noise would have a least "SNR". This proportion is a significant measure utilized in representing and describing the restoration techniques execution.

In the event that one recognizes picture to be signal and the distinction between this picture and the main to be noise, the "signal-to-noise ratio" in the "Spatial Domain" as:

$$\mathrm{SNR} = \frac{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \hat{f}(x, y)^2}{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [f(x, y) - \hat{f}(x, y)]^2} \tag{2.28}$$

The nearest $f$ and $\hat{f}$ are, the larger this proportion will be. The square root of the preceding two measures sometimes is utilized rather, they are mentioned to as the "Root-Mean-Square-Error" and the "Root-mean-square-signal-to-noise ratio", respectively. (Gonzales, 2008, p.374-376)

The "Peak Signal-to-Noise Ratio (PSNR)" and the "Signal-to-Noise Ratio (SNR)" are helpful in evaluating the contrast of the image; PSNR is more valuable when we deal with the part of contrast adjustment. PSNR is favored to be utilized because of weakly characterizing of SNR for homogenous images. PSNR is characterized as comparative with peak dynamic range (255) for the picture. PSNR is utilized for estimating the quality of the picture after the reconstruction where higher a PSNR shows a decent reconstruction, consequently, guaranteeing a high image enhancement. In general, PSNR is given in dB and expressed by:

$$PSNR = 10\ \log_{10}\left[\frac{L^2}{MSE}\right] \tag{2.29}$$

Where $MSE$ represent Mean Square Error and $L$ is the pixel intensities dynamic range. (Isa, Sulaiman, Mustapha, & Darus, 2015)

**Applications**: (Boulfelfel, Rangayyan, Hahn, & Kloiber, 1994) (Waterschoot, 2020)

- ✓ Noise Reduction
- ✓ Time Alignment of Multichannel Sensor Signal
- ✓ Channel Equalization
- ✓ De-Convolution

**Strength**: (Evans, 2020)

- ✓ Controls output error
- ✓ Straightforward to design

**Weaknesses**:

- o Results often too blurred

#### 2.3.2.4. Standard Deviation Filter

For each assortment of pixels in the input data, map or image, a standard deviation filter measures the standard deviation and allocates this amount to the center pixel in the yield map or image. (SpatialAanalyst, 2021)

The assessment of each yield pixel is the "standard deviation" of the neighborhood around the conforming or the relating input pixel. (MathWorksStdfilt, 2020)

The texture is a significant feature for the analysis of numerous sorts of pictures and furthermore has a fundamental function in numerous image processing and computer vision applications by including a wealthy source of visual data. Texture analysis related to the description of areas or locales in a picture by the content of the texture. Texture analysis tries to quantify and estimate natural characteristics expressed by texture terms, for example, smoothness, bumpiness, silky, or roughness as a duty of the spatial variability in the intensities of pixel. The bumpiness or roughness related to varieties in gray levels or intensity values. The texture analysis needs identification of those texture properties which can be utilized for classification, shape computation, pattern recognition, or segmentation and the advancement of computational methods for achieving these tasks. Texture filtering such as standard deviation filtering measures the local standard deviation of an input picture. (Dash, Jena, & technology, 2017; Rajalakshmi & Subashini, 2014)

The equation or the formula to compute the standard deviation is: (SpatialAanalyst, 2021)

$$stddev = \sqrt{\frac{\sum(x_i - \bar{x})^2}{r * c - 1}} \tag{2.30}$$

Where:

$x_i$ The individual assess of the pixels of the input map or image considered by the filter

$\bar{x}$ The mean of the values of the pixels considered by the filter

$r$ The filter size in rows

$c$ The filter size in columns

**2.3.2.5. Gaussian Filter**

In image processing applications, signal noise can be brought into the picture during the steps of transmission, compression, and acquisition. Noise reduction step is utilized for eliminating the noise and guaranteeing the general image processing performance. Gaussian filter is a specific filter utilized for noise reduction and blurring. In addition, the Gaussian filter can be joined or mixed with the edge detector to accomplish the stage perfection of digital image processing without unreasonably make a distortion to the original picture. (Hsiao, Chou, & Huang, 2007)

In computer vision, the input data is frequently corrupted by noise. Quite possibly the most widely recognized operations performed on pictures are to smooth the brightness values of the picture to decrease the noise. Image smoothing can be improved in order to ideally set the resolution at which picture features (texture and edge) will be found, this focusing on a change of spatial scales in the second goal for picture smoothing. (ANDONIE, 1992)

$$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \qquad \frac{1}{273}\begin{bmatrix} 1 & 4 & 7 & 4 & 1 \\ 4 & 16 & 26 & 16 & 4 \\ 7 & 26 & 41 & 26 & 7 \\ 4 & 16 & 26 & 16 & 4 \\ 1 & 4 & 7 & 4 & 1 \end{bmatrix}$$

Figure 2.10. Discrete approximation of the Gaussian kernel 3x3, 5x5 (Shipitko & Grigoryev, 2018)

Smoothing by convolution with a Gaussian-like kernel is identical to implementing a low-pass filter to the picture. The size of the kernel is controlled by the scale parameter $\sigma$, denoting the standard deviation of the Gaussian filter. While the scale increases, the smoothing degree increases without lack of information.

Gaussian filters are likewise valuable in the combination of high-pass and band-pass channels. The "Laplacian" applied to the "Gaussian" is a famous band-pass channel. The "Gaussian function" is also renowned in probability and statistics as the normal density function. (Wells & Intelligence, 1986) (ANDONIE, 1992)

One dimensional Gaussian function is: (ProgrammerSought, 2021)

$$G(x) = \frac{1}{\sqrt{2\pi}\sigma}\, e^{-\frac{x^2}{2\sigma^2}} \tag{2.31}$$

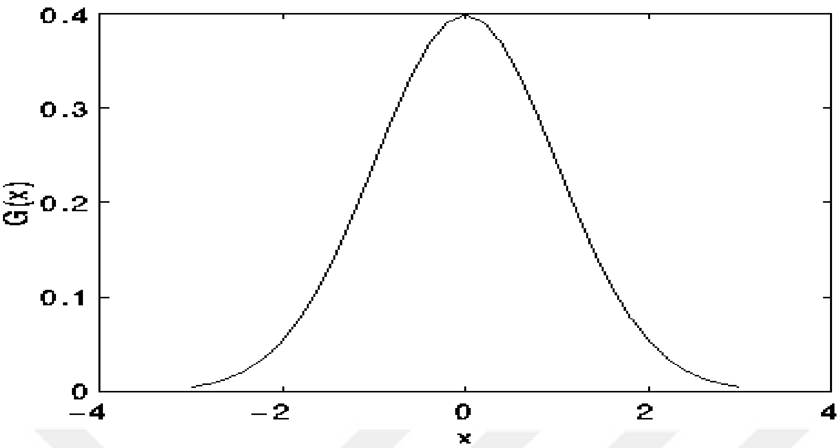


Figure 2.11. 1-D “Gaussian” distribution at $\sigma$ =1 and mean 0 (ProgrammerSought, 2021; R. Fisher, 2003 ; UCF, 2015)

Two dimensional equation of Gaussian function is: (ANDONIE, 1992; Wells & Intelligence, 1986)

$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2}\, e^{\left(-\frac{x^2+y^2}{2\sigma^2}\right)} \tag{2.32}$$

$G(x,y,\sigma)$ Is Gaussian kernel, $\sigma$ the standard deviation of the Gaussian filter, this function might be detached into a function of $x$ multiplied or “convolved” by a function of $y$.

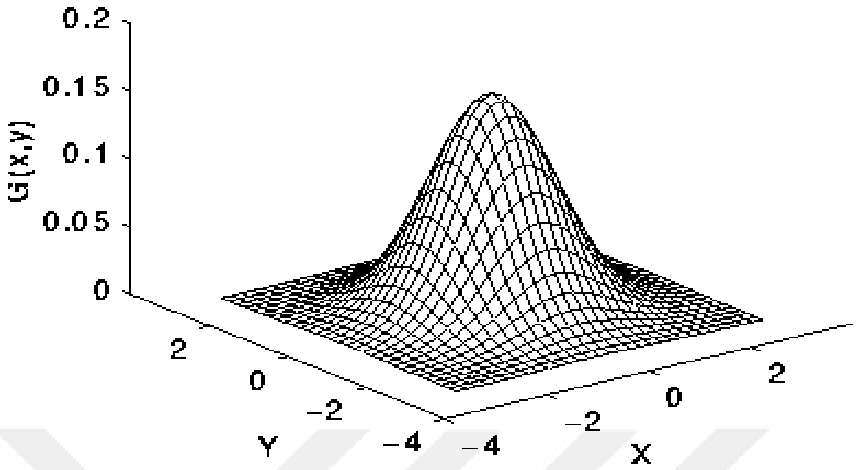


Figure 2.12. 2-D “Gaussian” distribution at $\sigma$ =1 and mean (0, 0)

## 2.4. Unsupervised Machine Learning (Clustering for Segmentation)

### 2.4.1. Introduction to the Clustering

It is a kind of “unsupervised machine learning” technique. An unsupervised machine learning technique is a strategy where we draw references from datasets comprising of input information without labeled responses. Frequently it is utilized as a procedure to discover significant structure, obstetric features and groupings in a lot of models or examples.

Clustering is isolating, separating or partitioning data or objects in groups, so that data or objects in the same group “Cluster” are like or similar to each other than to another different groups. (M. Kaur, Kaur, & Computing, 2013)

Rather than “Classification” which predefined the classes is offered. In the “clustering” strategy, objects of the supplied or the given dataset are gathered into groups as to the likeness of them. Clustering has moreover been utilized for a wide assortment of tasks in image analysis in remote sensing filed, for example, feature extraction, data visualization, dimensionality reduction, preprocessing and segmentation. One of the most generally utilized groups of clustering algorithms which involve iterative partitioning techniques is “k-means” and its augmentations like “k-mediods” and “Fuzzy c-means”. These techniques aim to iteratively minimize the error. Clustering based method is oncoming from image segmentation which plan to utilize the concept of data partitioning or grouping procedures for pattern recognition. (R. O. Duda, Hart, & Stork, 2001) (R. O. Duda, Hart, & Stork, 2012)

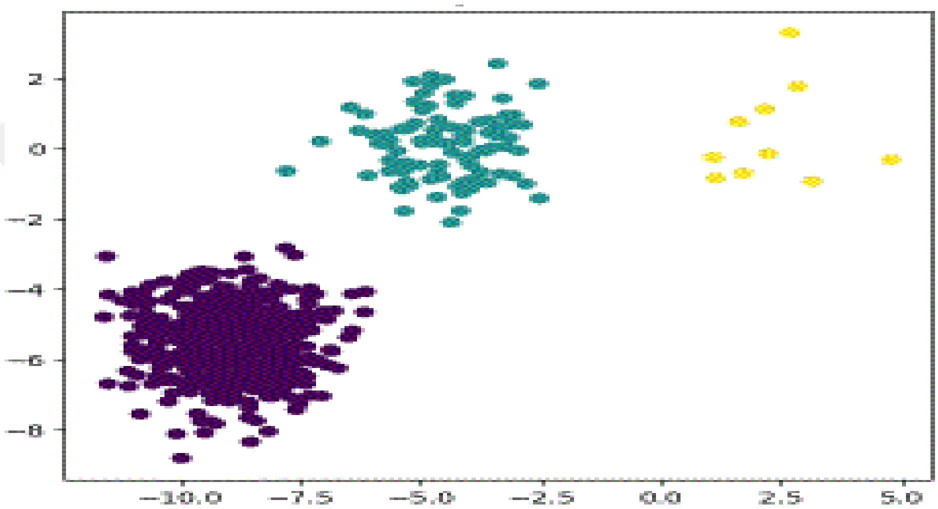


Figure 2.13. Clustering technique (example of k-means with k=3) (Scikitlearn, 2020)

**Clustering Techniques**: (Jain, Murty, & Flynn, 1999) (Xu & Wunsch, 2008)

- Hierarchical Clustering
  - “Agglomerative hierarchical” clustering (bottom-up)
  - “Divisive hierarchical” clustering (top-down)
- Partitional Clustering
  - “K-means”
  - “Mixture Density-Based” clustering (Expectation Maximization algorithm “EM”)
  - “Fuzzy” clustering (Fuzzy c-means “FCM”)

    - “Graph Theory-Based” clustering
- Artificial Neural Network-Based Clustering (ANNs)
    - “Self-Organizing Map (SOM)”
    - “Learning Vector Quantization (LVQ)”
    - “Adaptive Resonance Theory (ART)” models
    - “Hard Competitive Learning” clustering
    - “Soft Competitive Learning” clustering
- Kernel-Based Clustering
    - Kernel “Principal Component Analysis (PCA)”
    - “Squared-Error –Based” clustering with “kernel functions”
- Sequential Data Clustering
    - “Indirect Sequence” clustering
    - “Model-Based Sequence” clustering
- Large Scale Data Clustering
    - “Random sampling” methods
    - “Condensation-Based” methods
    - “Density Based” methods,” DBSCAN”,” OPTICS”
    - Grid-based methods,” STING”,” CLIQUE”, “wave cluster”
    - “Divide and Conquer”
    - “Incremental” clustering
- Data Visualization and High-Dimensional Data Clustering
    - “Linear Projection” algorithms
    - “Nonlinear Projection” algorithms
    - “Projected and Subspace” clustering

**Applications:** (Xu & Wunsch, 2008) (Everitt, 2011, p.9-12)

✓ Engineering:

Machine Learning, Artificial Intelligence, Pattern Recognition, Electrical Engineering, Mechanical Engineering. Common applications of clustering in the field of engineering are biometric recognition, speech recognition, radar signal analysis, noise removal, and information compression.

- ✓ Computer Sciences:

  Web mining, textual document collection, spatial database analysis, and image segmentation.
- ✓ Medical Sciences:

  Microbiology, biology, genetic, pathology, clinic, paleontology, psychiatry, and phylogeny. There are significant applications like disease diagnosis and treatment, taxonomy definition, protein and gene function identification.
- ✓ Astronomy and Earth Science:

  Remote sensing, geography and geology. Clustering can be utilized to identify or classify planets and stars, study mountain and river, examine land formation and segment or partition regions and urban areas.
- ✓ Social Science:

  Psychology, sociology, anthropology, archeology and education. Include applications such as relation and connection identification between various societies, social network analysis, behavior pattern analysis, development of transformative history of languages, artifacts classifications in archeological science and criminal psychology studies.
- ✓ Economics:

Business and marketing. Applications in buying pattern recognition and client attributes, a grouping of companies and trend analysis of stock market.

### 2.4.2. K-means

Clustering based techniques segment the picture into portions, groups or partitions having pixels with identical or comparable properties. The partition-based techniques use improvement or optimization strategies iteratively for minimizing the objective function. There are many types of clustering specially "Hard clustering" and "Soft clustering". (Dehariya, Shrivastava, & Jain, 2010)

Hard clustering is a basic clustering technique that partition the picture into a lot of groups or bunches with aim to one pixel can just relate to one group or cluster. Every pixel belongs to precisely one cluster. These strategies employ membership functions having values 0 or 1. For example one specific pixel can belong to a specific group or not. The renowned instances of a "Hard clustering" method is "k-means". In this method firstly the centers are calculated then every pixel is assigned to the closest center. (D. Kaur, Kaur, & Computing, 2014)

"K-means" utilized by "James MacQueen" in 1967 (MacQueen, 1967), the idea returns to "Hugo Steinhaus" in 1956 (Steinhaus, 1956). Firstly, the standard algorithm propose by "Stuart Lloyd" in "1957" as a method for pulse-code modulation, however was not distributed as a journal article until "1982" (Lloyd, 1982). "Edward W. Forgy" distributed basically a similar strategy in "1965", which is the reason it is at times referred to as "Lloyd-Forgy" (Forgy, 1965).

K-means is an effective clustering procedure. In view of initial centroids of the group or cluster it is utilized to isolate comparative information or data into groups. According to k-means algorithm, firstly it picks K data value and consider it as initials cluster center then detect of find the distance between each centers of the groups and every data value and appoint it to the closest bunch, for every cluster make updating the averages, repeat this procedure until a model or a criterion doesn't match. A K-means clustering algorithm plan to separate the information or the data into K bunches and every data value belongs to the group with the nearest mean. (Shinde, Tidke, & Networks, 2014)

K-means algorithm represent every group's center is expressed by the mean value of objects in the bunch (Shafeeq & Hareesha, 2012)

$$\boldsymbol{J} = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| \boldsymbol{x}_i^{(j)} - \boldsymbol{c}_j \right\|^2 \qquad (2.33)$$

Where $\left\| \boldsymbol{x}_i^{(j)} - \boldsymbol{c}_j \right\|^2$ is a chosen distance measurement among a data point $\boldsymbol{x}_i^{(j)}$ and the center of cluster $\boldsymbol{c}_j$ (such as Euclidean distance), suppose we get a data set $\{\boldsymbol{x1}, \ldots, \boldsymbol{x}_n\}$ contains $\boldsymbol{n}$ observations of arbitrary D-dimensional Euclidean variable $\boldsymbol{x}$, $\boldsymbol{k}$ number of clusters where $\boldsymbol{k} = \boldsymbol{1}, \boldsymbol{2}, \ldots \boldsymbol{K}$ , the distance term is utilized to calculate the minimum distance between the centroids of the cluster. (Bishop, 2006, p.424-425) (Shafeeq & Hareesha, 2012)

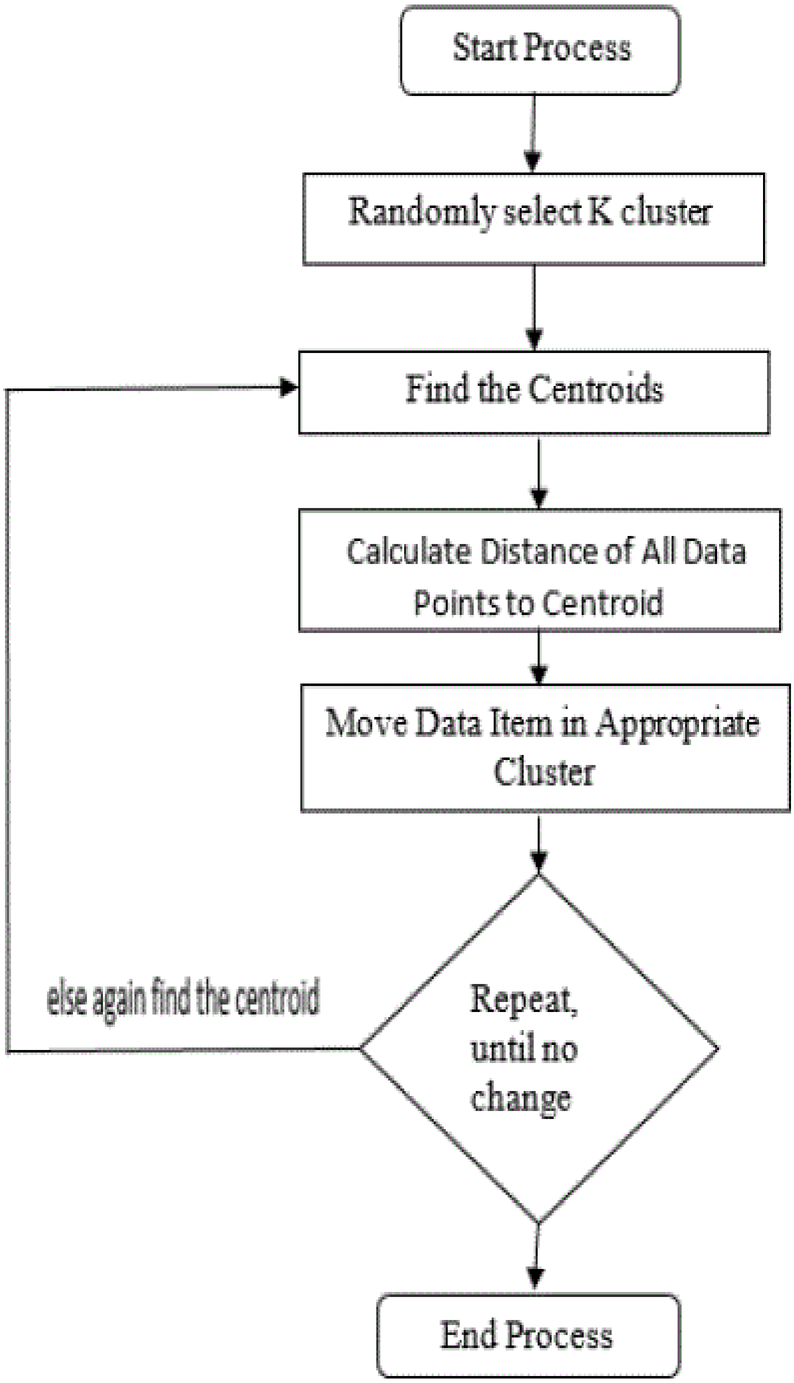


Figure 2.14. K-means algorithm process (Panwar, Gopal, & Kumar, 2016)

"K-means" Algorithm

We expect that: (Han, 2006)

Input: K represents number of clusters

Output: a lot of K clusters

Method:

- Arbitrary opt K objects from D (data set) as first cluster centers
- Repeat
- Reassign every object to the group "cluster" to which the item is the most like, premised on the mean assess of the objects in the "cluster" group.
- Update the means of clusters. Computing the mean assess of the objects for every group.
- No change

We can explain the figure above of "k-means algorithm" by:

- Initialization: is the initial step which number of groups "clusters" and the centroids are named for each group. Specify number of "k" clusters.
- Classification: is the step in which the distance is specified for every data point from the centroid having least or minimum distance from the centroid of a cluster is assigned to specific cluster.
- Centroid re-measures: the clusters or bunches are created in the initialization step, in this step the centroids recalculated.
- Convergence: all the steps will keep iterating until this step, this step has conditions to stop:
    - When the iterations numbers are reached.
    - When there is no trade of information or data point between clusters
    - When the threshold value is accomplished.

This part demonstrates the advantages and disadvantages of K-means:Strengths: (K-means, 2020)

- ✓ Simple: easy to understand and implement
- ✓ Efficient
- ✓ Scales to large data sets.
- ✓ Adapt to new examples easily.

Weaknesses:

- o The user needs to specify the number of clusters manually “k”.
- o Dependent on initial values.
- o Only applicable only if the mean is defined.
- o Sensitive to the outliers (are data points very far from each other).

### 2.4.3. Fuzzy c-means

“Soft clustering” is a common sort of clustering because definite division often is not possible cause of the noise in real applications. Therefore, soft clustering procedures are generally helpful for segmentation the image in which partition is not strict. The famous example of “Soft clustering” method is “Fuzzy c-means”. Based on partial membership, pixels are divided or partitioned into groups. For example, one pixel can belong to one or more than one groups and this belonging is expressed as membership values. Soft clustering is more adaptable than other strategies. (Yambal, Gupta, & Engineering, 2013)

“Fuzzy c-means” clustering algorithm is an “unsupervised machine learning” technique. In 1973, this algorithm was presented (Dunn, 1973). After that this algorithm was improved (Bezdek, 2013) to solve the problem of hard clustering. In this algorithm “FCM”, membership degree function is utilized to demonstrate the extent or the degree to which every data point has a place with each cluster, and this data is additionally used to refresh or update the values of the centers of the clusters (Dunn, 1973) (Bezdek, 2013) (Wikaisuksakul, 2014)

FCM algorithm works by distributing membership to every data point matching with each group or cluster center based on the distance among the group or the cluster and the data point. The more the data is close to the group center more is its membership towards the specific group or cluster. The summation of the membership of every data point ought to be equal to one. FCM algorithm depends on the minimization of the objective function.

An ideal c partition is performed iteratively by limiting or minimizing the weighted inside or within group total of squared error objective function:

$$\boldsymbol{J} = \sum_{i=1}^{n}\sum_{j=1}^{c}(\boldsymbol{u}_{ij})^{m}\, \boldsymbol{d}^{2}(\boldsymbol{y}_{i}, \boldsymbol{c}_{j}) \tag{2.34}$$

Where $\boldsymbol{Y} = [\boldsymbol{y}_1, \boldsymbol{y}_2, \dots, \boldsymbol{y}_n]$ is the data set in a d-dimensional vector space, $\boldsymbol{n}$ is the number of data terms, $\boldsymbol{c}$ is the number of clusters that identified by the user where $\boldsymbol{2} \leq \boldsymbol{c} \leq \boldsymbol{n}$, $\boldsymbol{u}_{ij}$ is the degree of membership of $\boldsymbol{y}_i$ in the $\boldsymbol{j}$th cluster, $\boldsymbol{m}$ is a weighted index or type on each fuzzy membership, $\boldsymbol{c}_j$ represents the center of cluster $\boldsymbol{j}$, $\boldsymbol{d}^2(\boldsymbol{y}_i, \boldsymbol{c}_j)$ is a square distance measure between the object ($\boldsymbol{y}_i$) and the center ($\boldsymbol{c}_j$).

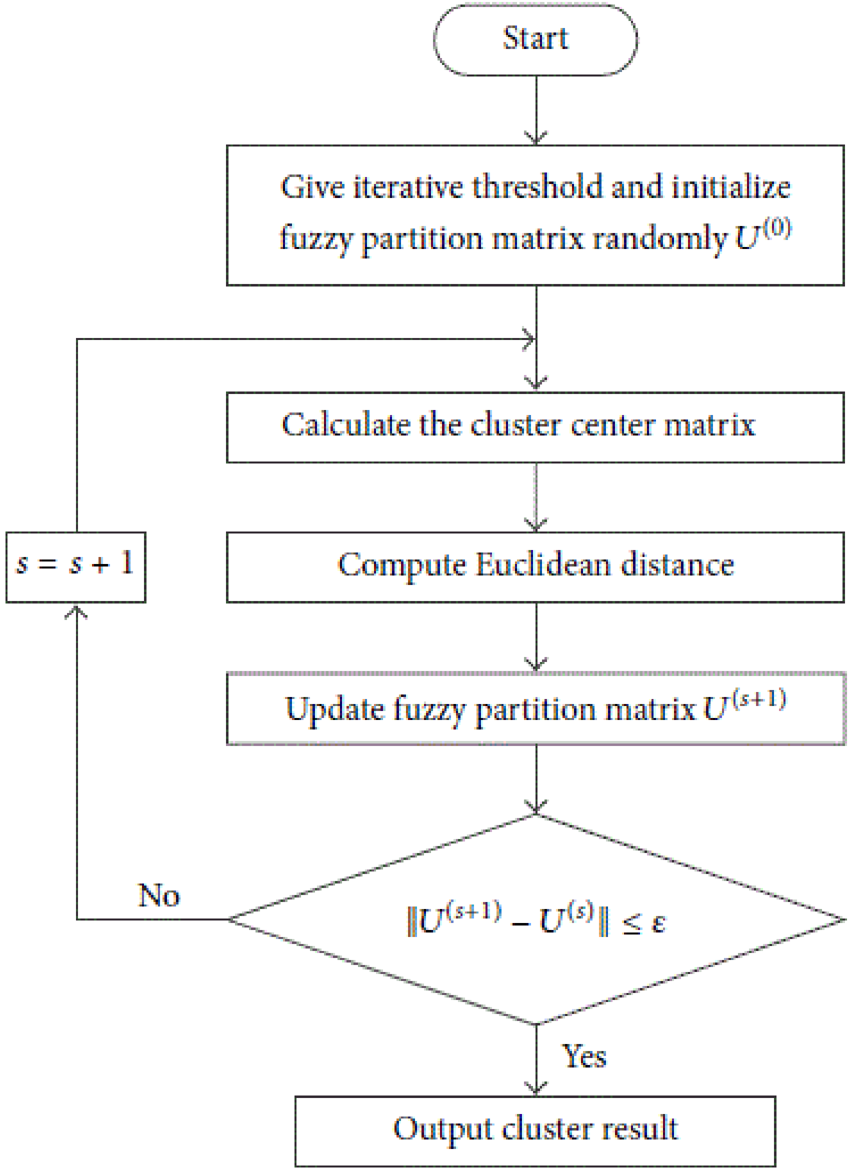


Figure 2.15. Fuzzy c-means algorithm (Wang, 2015)

"Fuzzy C-Means" Algorithm

The obvious solution with c partition can be achieved by an iterative procedure: (Ludwig & cybernetics, 2015)

- Firstly, the matrix of fuzzy partition is commenced.
- Within a reiterated loop next step are performed: the centers of the clusters are updated.
- The membership matrix is updated.
- The loop still repeated until reaching to the threshold value.

Input: $\boldsymbol{c}$: centroid matrix

$\boldsymbol{m}$: weighted exponent of fuzzy membership

$\in$: threshold value utilized as stopping criterion

$\boldsymbol{Y}$: data, where $\boldsymbol{Y} = [\boldsymbol{y_1}, \boldsymbol{y_2}, \dots, \boldsymbol{y_n}]$

Output: $\boldsymbol{c}$: updated centroid matrix

The process:

- begin the fuzzy partition matrix randomly

$$\boldsymbol{U} = [\boldsymbol{u_{ij}^k}]$$

- Repeat
  - Calculate the cluster centers with $\boldsymbol{U^k}$:

$$\boldsymbol{c_j} = \frac{\sum_{i=1}^{n} (\boldsymbol{u_{ij}^k})^{\boldsymbol{m}} \boldsymbol{y_i}}{\sum_{i=1}^{n} (\boldsymbol{u_{ij}^k})^{\boldsymbol{m}}}$$

  - Update the membership matrix $\boldsymbol{U^{k+1}}$:

$$\boldsymbol{u_{ij}^{k+1}} = \frac{\mathbf{1}}{\sum_{k=1}^{c} (\frac{\boldsymbol{d_{ij}}}{\boldsymbol{d_{kj}}})^{\frac{2}{(m-1)}}}$$

$$\boldsymbol{d_{ij}} = \left\| \boldsymbol{y_i} - \boldsymbol{c_j} \right\|^2$$

- Until

$$\boldsymbol{max_{ij}} \left\| \boldsymbol{u_{ij}^k} - \boldsymbol{u_{ij}^{k+1}} \right\| < \in$$

- Return $\boldsymbol{c}$

In light of the idea of fuzzy c-means, “FCM” clustering algorithm utilized effectively in a vast assortment of **applications**:

- ✓ Fault Diagnoses (Xu, 2011) (Li, 2011)
- ✓ Thermal System Monitoring (Zhao, Wang, Qian, Su, & Peng, 2011)
- ✓ Data Mining (Omkar, Suresh, Raghavendra, & Mani, 2002)
- ✓ Image Segmentation (Cai, Chen, & Zhang, 2007)
- ✓ Image Recognition (Höppner, Klawonn, Kruse, & Runkler, 1999)
- ✓ Data Analysis (Kannan, Ramathilagam, Devi, Hines, & Software, 2012)
- ✓ Pattern Recognition (Bezdek, 2013)
- ✓ Signal Processing (Omkar et al., 2002) (Svečko, Hančič, Kusić, & Grum, 2014)

This part demonstrates the advantages and disadvantages of fuzzy c-means: (Suganya, Shanthi, & Publications, 2012) (Cai et al., 2007)
Strengths:

- ✓ Unsupervised
- ✓ Converges
- ✓ For overlapped data set gives best results better than k-means.

Weaknesses:

- o Long computational time.
- o Sensitivity to noise.
- o Specification of the number of clusters.

### 2.4.4. Expectation Maximization

The EM algorithm is a general strategy to measure or compute maximum likelihood (Minka, 1998) estimates if the detected information can be viewed as "incomplete". (Lagendijk, Biemond, Boekee, & Processing, 1990)

EM algorithm is an iterative optimization technique to assess some obscure or unknown parameters. However, we are not given "hidden" nuisance variables, which require to be integrated out. Specifically, we need to maximize the posterior probability of the parameters. (Dellaert, 2002)

The EM algorithm is utilized for finding maximum likelihood parameter estimates when there is absent or incomplete data. (Carson, Belongie, Greenspan, Malik, & intelligence, 2002)

Generally, an expectation-maximization algorithm is a system that approaches maximum likelihood or maximum posteriori assessments for parameters in mathematical (Dempster, Laird, & Rubin) models. With regards to fuzzy or probabilistic model-based clustering, the expectation maximization algorithm begins with initial arrangement or assortment of parameters and repeats until the bunching or the clustering can't be improved until the converges of the clustering or the change is adequately little (according a preset threshold). Every repetition comprised of two steps: the expectation step and the maximization step. (Han, 2011, p.505)

One of the most initial papers on EM is (Hartley, 1958), however the original reference that formalized EM and gave a proof of convergence which is "DLR" paper in 1977 .The EM algorithm was found and utilized by many researchers until (Dempster et al., 1977) produced their thoughts, proved convergence and established the expression "EM algorithm". Since that fundamental work, several EM papers utilized the algorithm in numerous sections have been published. Comparable and related algorithms have developed, for example, (Musicus & Lim, 1979) (M. Segal & Weinstein, 1988). A recent book dedicates completely to EM and the applications is (McKachlan & Krishnan, 1997), while (Tanner, 1996) is another famous and valuable reference. One of the strongest clarifications and descriptions of EM, that gives a more profound understanding of its operation than the instinct or the intuition of alternative between variables, in view of lower bound maximization (Minka, 1998) (Neal & Hinton, 1998). The E-step can be explained as creating a local lower-bound to the posterior distribution, while the M-step upgrades or optimizes the bound, that way improving the assessment for the unknown. (Dellaert, 2002)

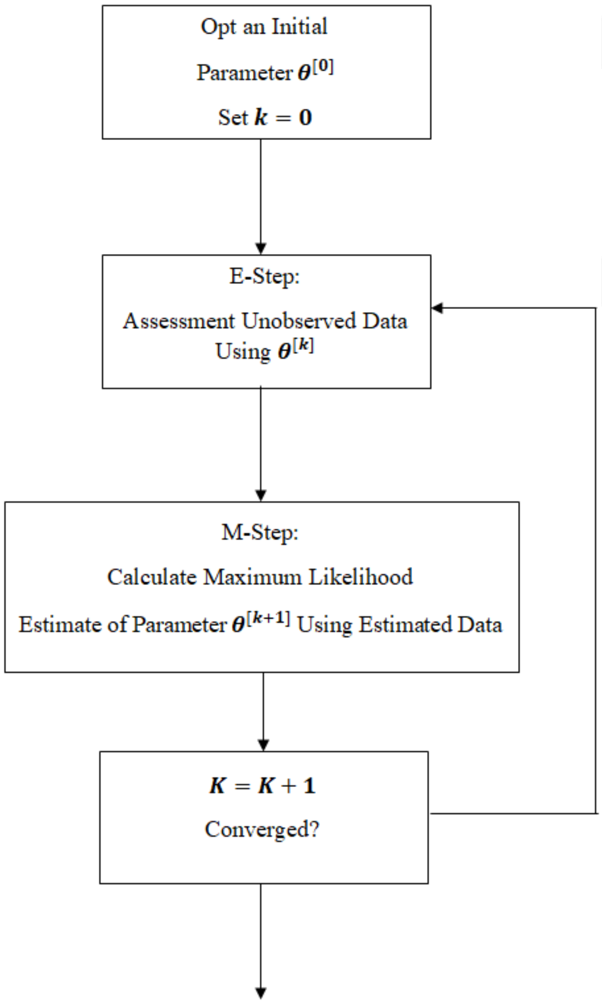


Figure 2.16. “Expectation Maximization” algorithm (Moon, 1996)

The "Expectation Maximization" algorithm begins with an initial collection of parameters and repeats until the grouping or the clustering can't be updates, that is until the grouping or the clustering converges or the changes is enough small and less than the threshold which preset. Every cycle or iteration includes two steps: (Han, 2011, p.505)

- Expectation step: this step specifies the items to clusters according to the current parameters of probabilistic clusters.
- Maximization step: this step obtains or finds the new clustering or parameters that amplify or maximize the expected likelihood in probabilistic model-based clustering.

**The general EM algorithm**: (Bishop, 2006, p.440-441)

Given a joint distribution $\boldsymbol{p(X, Z|\theta)}$ over observed variables $\boldsymbol{X}$ and latent variables $\boldsymbol{Z}$, governed by parameters $\boldsymbol{\theta}$, the goal is to maximize the likelihood function $\boldsymbol{p(X|\theta)}$ with respect to $\boldsymbol{\theta}$.

1. Choose an initial setting for the parameters $\boldsymbol{\theta^{old}}$.
2. E-Step: Evaluate $\boldsymbol{p\left(X \middle| Z, \theta^{old}\right)}$.
3. M-Step: Evaluate $\boldsymbol{\theta^{new}}$ given by:

$$\boldsymbol{\theta^{new} = arg_{\theta} \max\ Q(\theta, \theta^{old})} \tag{2.35}$$

Where

$$\boldsymbol{Q\left(\theta, \theta^{old}\right) = \sum_{Z} p\left(Z \middle| X, \theta^{old}\right) \ln p(X, Z|\theta)} \tag{2.36}$$

**4.** Check for convergence of either the log likelihood or the parameter values. If the convergence criterion is not satisfied, then let

$$\boldsymbol{\theta}^{old} \leftarrow \boldsymbol{\theta}^{new}$$

And return to step 2.

"E-step" represent the expectation, "M-step" maximize this expectation. If the current assessment for the parameters is indicated $\boldsymbol{\theta}^{old}$, then a pair of sequential E and M steps confer an increase or a rise to a revised assessment $\boldsymbol{\theta}^{new}$. The EM algorithm initialized by choosing some starting value for the parameters $\boldsymbol{\theta}_0$. The employ of the expectation might seem somewhat random. Every cycle of EM will rise or increase the incomplete-data log likelihood.

In E step, we utilize the current parameter value $\boldsymbol{\theta}^{old}$ for finding the posterior distribution of the hidden or the latent variables given by $\boldsymbol{p}(\boldsymbol{X}|\boldsymbol{Z}, \boldsymbol{\theta}^{old})$. Thereafter we utilize this posterior distribution for finding the expectation of the complete-data log likelihood estimated or evaluated for some public or general parameter value $\boldsymbol{\theta}$. This expectation, indicated $\boldsymbol{Q}(\boldsymbol{\theta}, \boldsymbol{\theta}^{old})$.

In M step, we define the revised parameter assessment $\boldsymbol{\theta}^{new}$ by maximizing the function $\boldsymbol{arg}_{\boldsymbol{\theta}} \max \boldsymbol{Q}(\boldsymbol{\theta}, \boldsymbol{\theta}^{old})$ , in the definition of $\boldsymbol{Q}(\boldsymbol{\theta}, \boldsymbol{\theta}^{old})$ the logarithm directly acts on the join distribution $\boldsymbol{p}(\boldsymbol{X}, \boldsymbol{Z}|\boldsymbol{\theta})$ and so the corresponding M-step will.

**EM for Gaussian Mixtures**: (Bishop, 2006, p.438-439)

Given a Gaussian Mixture Model, the aim is to maximize the likelihood function with respect to the parameters (including the means, covariance of the components and the mixing coefficients).

**1)** Initialize the means $\boldsymbol{\mu}_k$, covariance $\boldsymbol{\Sigma}_{\boldsymbol{\kappa}}$ and mixing coefficients $\boldsymbol{\pi}_k$, and evaluate the initial value of the log likelihood.

**2)** E-Step: Evaluate the responsibilities using the current parameter values

$$\boldsymbol{\gamma(z_{nk}) = \frac{\pi_k \mathcal{N}(x_n|\mu_k\,, \Sigma_k\,)}{\sum_{j=1}^{k} \pi_j \mathcal{N}\left(x_n|\mu_j\,, \Sigma_j\,\right)}} \tag{2.37}$$

**3)** M-Step: re-estimate the parameters using the current responsibilities

**4)**

$$\boldsymbol{\mu_k{}^{new} \ = \ \frac{1}{N_k}\sum_{n=1}^{N} \gamma(z_{nk})x_n} \tag{2.38}$$

$$\boldsymbol{\Sigma_k^{new} \ = \ \frac{1}{N_k}\sum_{n=1}^{N} \gamma(z_{nk})(x_n - \ \mu_k{}^{new})(x_n - \ \mu_k{}^{new})^T} \tag{2.39}$$

$$\boldsymbol{\pi_k^{new} \ = \ \frac{N_k}{N}} \tag{2.40}$$

Where

$$\boldsymbol{N_k = \sum_{n=1}^{N} \gamma(z_{nk})} \tag{2.41}$$

**5)** Evaluate the log likelihood

$$\ln p(X|\mu, \Sigma, \pi) \ = \ \sum_{n=1}^{N} \ln\left\{\sum_{k=1}^{K} \pi_k \mathcal{N}(x_n|\mu_k\,, \Sigma_k)\right\} \tag{2.42}$$

And check for convergence of either the parameters or the log likelihood. If the convergence criterion is not satisfied return to step 2.

EM algorithm takes a lot more iterations to reach (approximate) convergence when we compare EM with k-means algorithm, each cycle requires more calculation, thus its normal to run k-means algorithm to locate an appropriate initialization for a Gaussian Mixture Model and subsequently that is adjusted using EM. The covariance can be initialized conveniently to the individual covariance of the bunches or the clusters found by k-means method, what's more, the mixing coefficients can be set to the portions or fractions of data points distributed or assigned to the particular clusters. Techniques must be utilized for avoiding singularities or to maintain a strategic distance from singularities of the likelihood function where a Gaussian component gives onto a specific data point. It ought to be indicated that there will frequently or generally be multiple local maxima of the log likelihood function, and that EM isn't insured to locate or find the largest these maxima. Since the EM technique for Gaussian mixtures plays significant role.

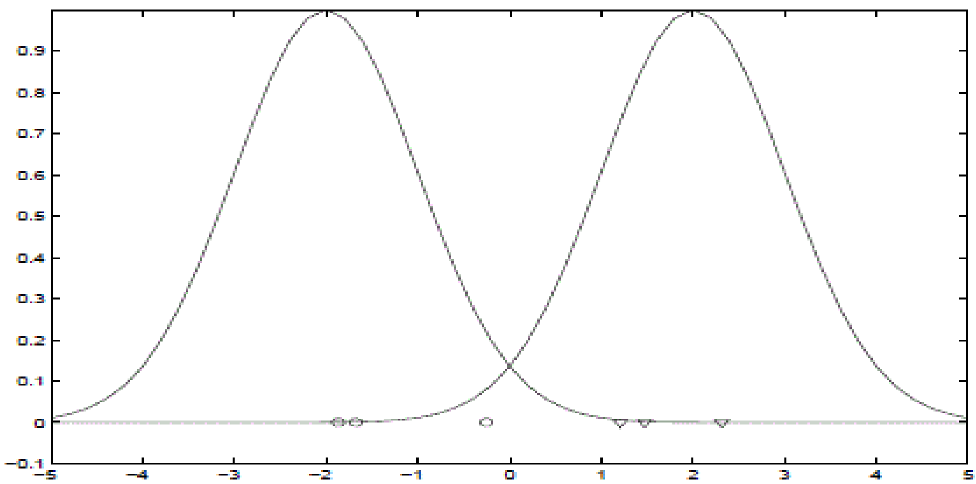


Figure 2.17. Gaussian Mixture component (Dellaert, 2002)

This part demonstrates the advantages and disadvantages of Expectation Maximization algorithm: (Pierre-Julien Trombe, 2011)

Strength:

- ✓ Likelihood is ensured to increment for every iteration
- ✓ Is a derivative-free optimizer

Weaknesses:

- Requires both forward and backward probabilities
- Convergence may be slow

**Applications:**

(Schmee & Hahn, 1979) (Shepp, 1982) (Little & Rubin, 1983) (Redner & Walker, 1984) (M. Segal, & Weinstein, E. , 1987) (Rabiner, 1989) (Zabin, 1991) (Jiang, Pan, & Gu, 1994)

- ✓ In genetics: the genotype
- ✓ Econometric, clinical and sociological: when that have unknown factors affecting the outcomes
- ✓ Statistical methods
- ✓ Image recognition
- ✓ Pattern recognition and neural network training
- ✓ Speech recognition and Hidden Markov Model
- ✓ Parameter estimation
- ✓ Direction finding
- ✓ ARMA modeling
- ✓ Simultaneous detection and estimation
- ✓ Noise suppression
- ✓ Signal and sequence detection
- ✓ Multiprocessing algorithm development
- ✓ Spectroscopy
- ✓ In information theory to compute channel capacity and rate distortion function
- ✓ Specialized developments of EM algorithm itself such as “The Cascade EM algorithm”
- ✓ Estimating parameters of mixture distributions

## 2.5. Supervised Machine Learning (Classification)

### 2.5.1. Introduction to supervised machine learning (classification)

Classification algorithms give a way that can be utilized to develop or make data models on the training set utilizing a given collection of variables. Classification assists to assessing objective class for a given data examples and is quite possibly the most generally utilized techniques for data mining in the field of medical.

Classification algorithms have two stages:

Training stage: it is likewise called “learning stage” where the classification model is created utilizing training instances.

Testing stage: is called “classification stage” where the model is utilized for prediction unseen data, and classifying the system yields or the outputs is called “labeling”.

Classification algorithms are a kind of supervised machine learning algorithms, an example data set which is human-determined is utilized for learning the structure of training data set same as the relationship between the instructor and student, afterward the algorithm attempt for classifying hidden or unseen data. (Aggarwal, 2015; Paluszek & Thomas, 2017) After that, test data is utilized for measuring the accuracy of the model, and afterward, we keep on applying the model on new data whether the accuracy is adequate or note. (Charu, 2015; Annasaheb, 2016; Paluszek, 2017)

### 2.5.2. Accuracy calculation

Accuracy is a need to estimate or gauge the performance of an algorithm and determines or obtains the missed data or percentage of effectively assessed. Accuracy which calculates the classification can be represented below and the summation of whole these four quantities give the total number of cases to classify: (Baldi, Brunak, Chauvin, Andersen, & Nielsen, 2000; Galdi, Tagliaferri, & Biology, 2018)

- **TP** or true positive, the number of correctly classified positive data
- **TN** or true negative, the number of correctly classified negative data
- **FP** or false positive, the number of missed classified positive data
- **FN** or false positive, the number of missed classified negative data

**Confusion Matrix** can be shown in a picture or table which is 2x2 matrix utilizing to measure Accuracy, Specificity, Precision, and Recall to evaluate the performance of the classifiers.

**Accuracy** demonstrates how well the algorithm or classifier can figure or calculate the unseen data.

**Recall** demonstrates the correctly recognized positive cases.

**Precision** is the appropriate response of which proportion of classified or distinguished positive data is really correct.

**Error rate** is the estimation or computation of the number of wrong prediction divided by the whole number of a data set.

| | Predicted YES | Predicted NO |
|---|---|---|
| Actual YES | TP | FN |
| Actual NO | FP | TN |

Figure 2.18. Confusion Matrix

$$Accuuracy = \frac{NumberOfCorrectedPredictions}{TotalNumberOfPredictions}$$

$$Accuuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2.43)$$

$$ErrorRate = \frac{NumberOfIncorrectPredictions}{TotalNumberOfPrediction}$$

$$ErrorRate = \frac{FP + FN}{TP + TN + FP + FN} \tag{2.44}$$

$$specificity = Precision = \frac{TP}{TP + FP} \tag{2.45}$$

$$Sensitivity = Recall = \frac{TP}{TP + FN} \tag{2.46}$$

### 2.5.3. Support Vector Machine

SVM is supervised learning method that is trained in order to make classification for various categories of data from different fields. SVMs were at first proposed by Vapnik (1995) to solve the regression and classification problems SVMs utilized for classification problems with two-class and are suitable and applicable to both non-linear and linear data classification duties. SVM makes a hyper plane or various hyper planes in a high-dimensional space, and the better hyper plane between them is the one that perfectly splits data into various classes with the biggest disconnection or separation between the classes. A non-linear classifier utilizes different kernel function to determine the margins. The fundamental goal of these kernel functions (i.e., sigmoid, radial basis, polynomial, and linear) is to maximize margins among hyper-planes. As of late, numerous exceptionally encouraging applications have been created by analysts as a result of the expanding interest in SVMs. SVM has been broadly utilized in pattern recognition and image processing applications. (Ahmad, 2018)

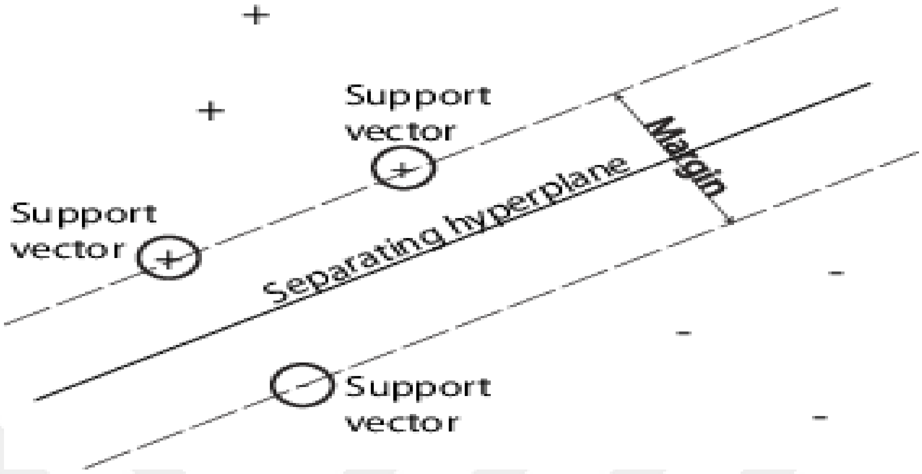


Figure 2.19. Example of Support Vector Machine seperation (MathWorksSVM, 2020)

Given a collection of training data points with $m$ properties for each of them and a related class label, SVM struggles to divide or separate these points utilizing $(m-1)$ dimentional hyperplane. $x_i \in \mathbb{R}^m, i = 1, \ldots, n$ are $n$ training data examples in two unique or various classes, and $y_i \in \{-1, +1\}, i = 1, \ldots, n,$ are their class labels. The Linear Support Vector Machine tries to create a hyper plane:

$$w^T x + b = 0 \tag{2.47}$$

in the $m$ dimentional data space $\mathbb{R}^m$ that has the biggest distance to the most related or akin training data examples of each class. The margin which is the distance between hyper planes that we want to maximize is given as:

$$\frac{2}{||\vec{w}||} \tag{2.48}$$

The optimization equation written as:

$$min_{w,b,\xi}\ \frac{1}{2}w^T w + C\sum_{i=1}^{n}\xi_i \tag{2.49}$$

Subject to:

$$y_i(w^T x_i + b) \geq 1 - \xi_i\ , \xi_i \geq 0, i = 1, \dots, n \tag{2.50}$$

$\xi_i$ is slack or error variable, $i = 1,2, \dots, n$, Whereas $C$ is user-alterable parameter to measure and control the margin maximizing or providing of separating every training data examples. (Ma, 2017; Ahmad, 2018; Mostafa, 2021)

The followings are significant notions in SVM: (PointSVM, 2021)

**Support Vectors**: Data points which are nearest to the hyper plane. The dividing or separating line will be recognized with the assistance of these data points.

**Hyper plane**: a decision plane (space) which is split between bunches of elements having various classes.

**Edge**: depict as the gap among two lines on the closet information points or data of various groups “classes”. A perpendicular distance from the support vectors to the line. A big or huge margin is deemed as a decent margin and a tiny margin is deemed as a bad margin.

The principle objective of SVM is to isolate the datasets into classes to obtain a maximum marginal hyper plane and it very well may be done in the accompanying two stages −

- SVM will create hyper planes in iterative way that divides, or separates the groups “classes” in the most ideal manner.
- It will select effectively the hyper plane that divides the groups “classes”.

**Applications:**

A support vector machine (SVM) technique broadly utilized in a vast of application areas and purposes: (Cortes, 1995; Ma, 2017)

- ✓ Text Analysis (Tong & Koller, 2001)
- ✓ Computer Vision (Osuna, Freund, & Girosit, 1997)
- ✓ Bioinformatics (Furey et al., 2000; Hasenauer et al., 2012)
- ✓ Images Retrieval (Tao, Tang, Li, Wu, & intelligence, 2006)
- ✓ Fault Diagnosis (Tian, Fu, & Wu, 2015)
- ✓ Text Detection (Shin, Kim, Park, & Kim, 2000)
- ✓ Regression Problems (Hemmati-Sarapardeh et al., 2014)

**Strength**: (PointSVM, 2021)

- ✓ SVM classifiers offer incredible accuracy
- ✓ Work excellently with high dimensional space
- ✓ SVM classifiers essentially utilize a subset of training subsequently in outcome
- ✓ Use almost no memory.

**Weaknesses**:

- o They have high training time
- o Not suitable for enormous datasets
- o Do not work properly with overlapping classes.

### 2.5.4. K Nearest Neighbor

K nearest neighbor algorithm is quite possibly the most famous classification algorithm. It was first found in 1950s and became common at 1960s (Sharma & Suryawanshi, 2016). It is particularly utilized in optical character recognition, facial recognition, and pattern recognition. KNN technique is amazingly powerful, effective, and simple strategy. Given an unlabeled test data, KNN discovers k closest records in the training dataset and afterward allocate them the most appropriate label. Generally, KNN allocates label to data point from its neighbors regarding about the nearest neighbor points.

The KNN algorithm aims to utilize a database in which the data points are divided or separated into several classes for making a prediction for the classification of description of another new examples or sample point. There are some issues might be occur we should consider such as may time consuming and it may needs a huge memory for storing all data. (Segaran, 2007) (Hamzah, 2018)

The distance calculations utilized to figure out which of the K example or instance in the data are generally like the new input data. We can pick the best distance metric based on the properties of the data. KNN creates a model by considering the larger part vote of neighboring data points of a specific or given data point. There are many distance measurement which utilized with KNN algorithm such as Manhattan, Minkowski, and Euclidean distance which is the most popular. (Hamzah, 2018; MERAL, 2019)

**The K-NN algorithm can be explained**: (javaKnn, 2018; pointKnn, 2020)

1 Opt the neighbors number “K”
2 Compute the “Euclidean distance” of “K”
3 Pick the “K” nearest neighbors as per the calculated “Euclidean distance”.
4 Between these “k” neighbors, enumerate the number of the data points in each group.
5 Allocate the new data points to that group for which the number of the neighbor is maximum.

**Strength:** (AugmentedStartups, 2017)

- ✓ It is extremely straightforward algorithm to grasp and interpret
- ✓ It is beneficial for nonlinear data

- ✓ It is flexible and versatile algorithm as we can utilize it for regression and classification
- ✓ It has generally high accuracy
- ✓ Effective if training data is large
- ✓ No training phase

**Weaknesses:**

- o Needs to decide the estimation of the value parameter k
- o Low computational efficiency with high dimensional data
- o The calculation cost is high as a result of measuring the distance between the data points for the whole samples of training

**Applications of KNN:** (AugmentedStartups, 2017)

- ✓ Politics: We can classify a potential voter into various classes like “Will Vote”, “Will not Vote
- ✓ Image Recognition
- ✓ Money laundering analyses
- ✓ Video Recognition.
- ✓ Bank customer profiling
- ✓ Handwriting Detection
- ✓ Speech Recognition
- ✓ Text mining
- ✓ Currency exchange rate
- ✓ Text categorization
- ✓ Trading futures
- ✓ Climate forecasting
- ✓ Loan management
- ✓ identify risk factors of such as prostate cancer
- ✓ Understanding and managing financial risk

### 2.5.5. Discriminant Analysis

In traditional machine learning, discriminant analysis relates to determination of an assortment of practical or functional hyper planes which make classes separation. The discriminant analysis is a famous strategy in statistical classification that utilizations training data to evaluate the parameters of discriminant roles of functions of the predictor variables. Discriminant functions decide boundaries of limits in the predictor space between different classes. The subsequent classifier separates among the classes in view of predictor data. (Cao, Sanders, Engineering, & Computing, 1996; Fukunaga, 2013)

Dimensionality reduction strategies are significant in numerous applications identified with machine learning, the main objective of the dimensionality reduction strategies is to diminish the dimensions by eliminating redundant and dependent features by changing or transforming these characteristics (features) from a higher dimensional space to lower dimensional space. There are two significant methodologies of the dimensionality reduction procedures, in particular, supervised and unsupervised methods. In the unsupervised approach, there is no requirement for labeling classes of the data, there are numerous unsupervised dimensionality reduction strategies, and the most popular procedure of the unsupervised methodology is the Principal Component Analysis (PCA). The supervised approach has numerous methods; the most remarkable procedure of this methodology is the Linear Discriminant Analysis (Acevo-Herrera et al.).

The LDA strategy is created to change or transform the features into a lower dimensional space; the objective of the LDA method is to project the initial data matrix onto a lower dimensional space, to accomplish this objective, three stages should have been performed the initial step is to compute the distinctness between various classes which is known as the between-class matrix or between-class variance, the subsequent step is to compute the distance between the samples of each class and the mean, which is known as the within-class matrix or within-class variance. The third step is to build the lower dimensional space which minimizes the within class variance and maximizes the between-class variance.(Tharwat, Gaber, Ibrahim, & Hassanien, 2017)

**Applications in:** (Tharwat et al., 2017)

- ✓ Agriculture applications
- ✓ Medical applications
- ✓ Biometrics applications
- ✓ Data mining
- ✓ Bioinformatics
- ✓ Information retrieval
- ✓ Chemistry

### 2.6. Morphological Operations

It is a set of operations of image processing that process images dependent on shapes. In a "Morphological Operation" every pixel in the picture is modified dependent on the value of others in its neighborhood. By determining the shape and size of the neighborhood, we build a morphological operation that is delicate or sensible to special shapes in the input picture. (Morphology, 2020)

We can consider mathematical morphology as a mean to extract image elements or parts that are valuable in the description of region shapes, for example, skeletons, convex hull, and boundaries. Likewise, there are morphological techniques for preprocessing and post processing, for example, morphological thinning, pruning, and filtering. (Gonzales, 2008, p.649)

In the field of image processing, we utilize mathematical morphology as a way to recognize and extract important and meaningful picture descriptors dependent on properties of structure or shape inside the picture. morphology includes an incredible and significant group of strategies that can be accurately treated mathematically inside the structure of set theory. Morphological operations can be implemented to different types of images, however the essential use for morphology is to process binary images and the key and the most famous morphological operators are almost basic ones called erosion and dilation. (Solomon, 2011, p.197)

Structuring element is important factor and is a key element for any procedure contains morphological operations. The structuring element is the element that decide precisely which picture pixels encircling the given foreground or background pixel should be put into consideration for making the choice to change its value or not. The specific decision of structuring element is the central to morphological processing. Structuring element is comprised on pixels in a rectangular array including values 1 or 0. (Solomon, 2011, p.198)

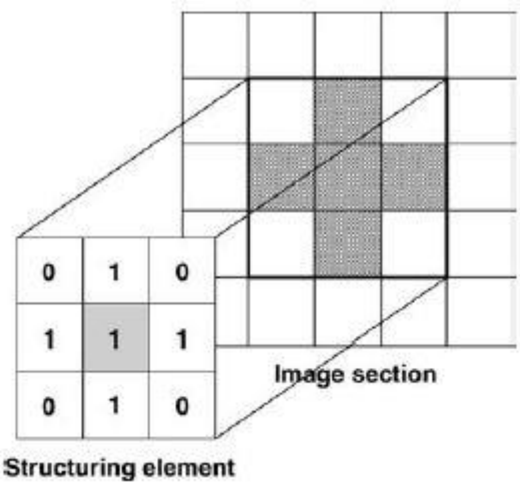


Figure 2.20. The local neighborhood defines by a structuring element by those shaded pixels in the image which lie beneath the pixels of value 1 in the structuring element (Solomon, 2011, p.199)

The mechanics of the erosion and dilation work in fundamentally the same as behavior to the convolution kernels utilized in spatial filtering. The "Structuring Element" slides over the picture so its middle (center) pixel lies on top of every background pixel or foreground pixel as fitting successively. The new value of every picture pixel at that point relies upon the values of the pixels in the neighborhood characterized by the structuring element. (Solomon, 2011, p.200)

### 2.6.1. Erosion

To implement erosion of a binary image, we place the middle (center) pixel of the structuring element on each pixel (foreground) of value 1 successively. In the event that any of the neighborhood pixels are pixels of (background) of value 0, at that point, the pixel of foreground is turned to background. Officially, the erosion of image $A$ by structuring element $B$ is mean: (Solomon, 2011, p.200)

$$A \ominus B \tag{2.51}$$

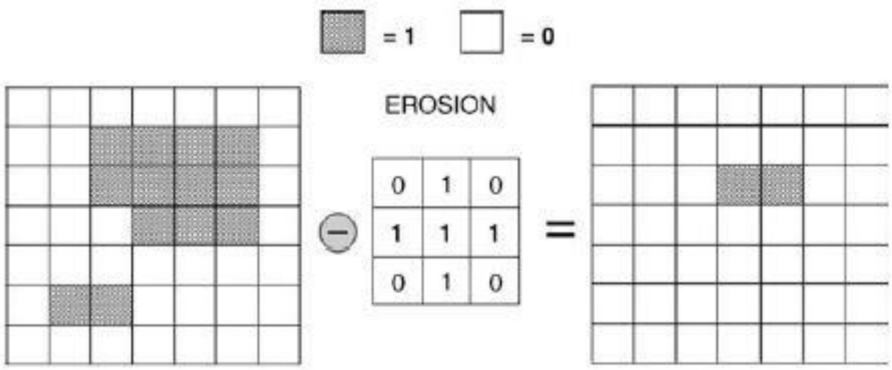


Figure 2.21. Erosion (Solomon, 2011, p.200)

### 2.6.2. Dilation

To implement dilation of a binary image, we place the middle (center) pixel of the structuring element on each background pixel. In the event that any of the neighborhood pixels are pixels of (foreground) of value 1, at that point, the pixel of background is turned to foreground. Officially, the dilation of image $A$ by structuring element $B$ is mean: (Solomon, 2011, p.200)

$$A \oplus B \tag{2.52}$$

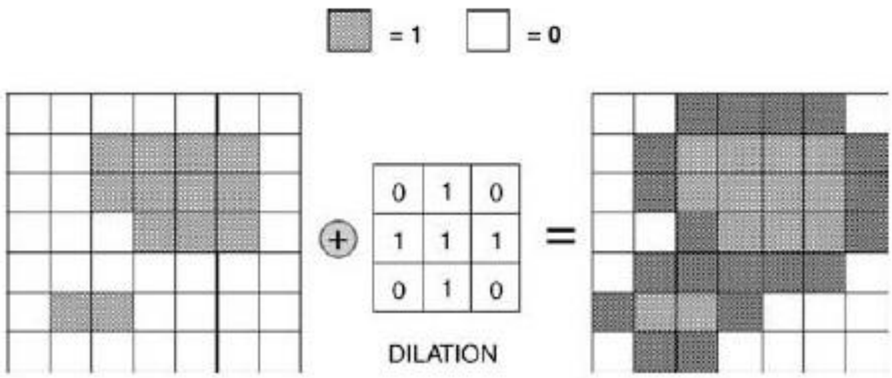


Figure 2.22. Dilation (Solomon, 2011, p.200)

### 2.6.3. Opening

It is about morphological operation including "Erosion" followed by "Dilation" with the equivalent structuring element, which means:

$$A \circ B = (A \ominus B) \oplus B \tag{2.53}$$

The general effect of opening is to exclude small or detached objects from the image foreground, then setting them in the background. It will in general breaks joining (narrow) areas and smooth the contours in a binary object. (Gonzales, 2008, p.657-658) (Solomon, 2011, p.209)

### 2.6.4. Closing

It is about morphological operation including "Dilation" followed by "Erosion" with the equivalent structuring element, which means:

$$A \bullet B = (A \oplus B) \ominus B \tag{2.54}$$

The general effect of closing is to exclude small holes in the image foreground, then setting small areas of the background into foreground. It will in general join (narrow) areas or between binary objects. (Gonzales, 2008, p.657-658) (Solomon, 2011, p.209)

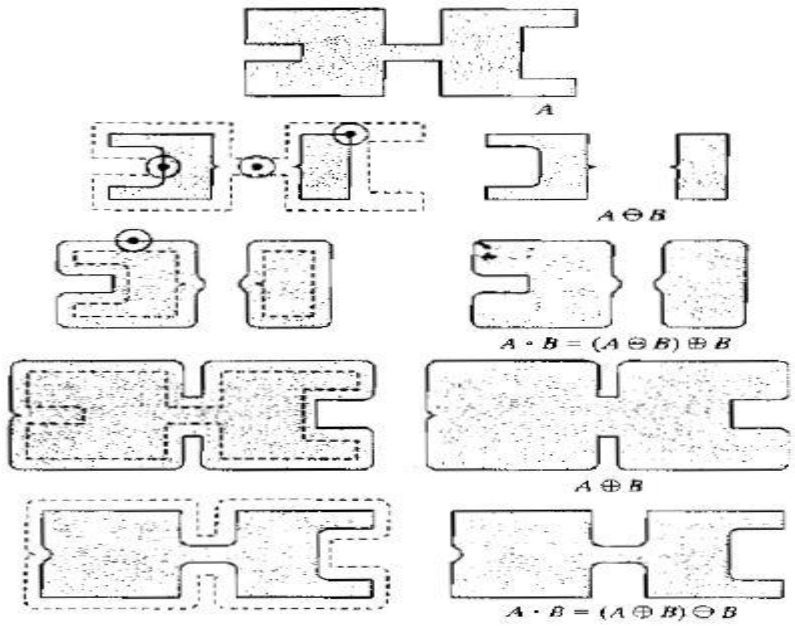


Figure 2.23. Morphological opening and closing (Gonzales, 2008, p.659)

**2.6.5. Hole Filling**

Hole might be characterized as a background area surrounded or enclosed by a connected border of frontal areas pixels. This algorithm dependent on set of complementation, intersection, and dilation to fill holes in a picture.

Let $A$ indicate a set of whose elements are 8 connected boundaries with every boundary including a (hole) background area. Given a point in each gap, the goal is to fill all the gaps or holes with foreground elements. we start by forming an array $X_0$ of zeros which is the same size of $A$ (the picture including $A$), aside from at areas $X_0$ that correspond or relate to pixels that are known to be gap, which we set to 1. At that point the next method or procedure to fill all the gaps with ones;

note that the dilation of image $X$ by$B$ is the dilation of the elements of foreground of $X$ by:

$$X_k = (X_{k-1} \oplus B) \cap A^2 , \qquad K = 1,2,3, \dots \tag{2.55}$$

Where $B$ it is the structuring element (symmetric), the algorithm finish at iteration step $K$ if $X_k = X_{k-1}$ , thus, $X_k$ includes all the filled gaps. The set union of $X_k$ and $A$ includes all the filled gaps and holes. (Gonzales, 2008, p.665)

**Morphological Operations Applications:** (Ravi, 2013) (Kowalczyk, 2008)

- ✓ Boundary Extraction
- ✓ Extract Connected Components
- ✓ Hole Filling
- ✓ Thinning
- ✓ Thickening
- ✓ In Segmentation
- ✓ Extracting Edges
- ✓ Detecting Characteristic Objects
- ✓ Detecting Defects

### 2.7. Circular Hough Transform (CHT)

It is an essential feature extraction procedure utilized in digital image processing for to detect circles in images. It is a particularism of “Hough Transform (HT)”. Circular Hough transform method based on the circle candidates are provided by “Voting” in the Hough parameter space, thereafter select local maxima in an accumulator matrix. The Hough Transform (HT) and various adjusted variants have been identified as strong procedure for curve identification or detection. This strategy can identify and detect an object even contaminated by noise. (Rizon, 2005) The CHT was described by (R. O. Duda, & Hart, P. E., 1972) the CHT is one the altered variants of the HT. the CHT try to discover circular patterns inside a picture. (R. O. Duda, & Hart, P. E., 1972) (Kimme, 1975) (Yuen, 1990) (Borovicka, 2003) (Rizon, 2005)

CHT is utilized to transform a lot of feature points in the image space into a lot of accumulated votes in the parameter space. At that point, for each feature point, votes are aggregated in an accumulator array for all parameter sequences. The array components or elements that include the highest number of votes shows the presence of the shape. (Rizon, 2005)

A Most basic method for circle detection which is utilized by scientific community is "Circular Hough Transform" and its variations. The Hough Transform can be expressed as a transformation to the parameter space from $x, y$ (Pedersen, 2007) plane, the equation of the circle mathematically given by: (Pedersen, 2007) (Yadav, 2014)

$$r^2 = (x-a)^2 - (y-b)^2 \tag{2.56}$$

Where $r$ it is the circle radius, $a, b$ are the center coordinates of the circle, and the parametric representation of the circle:

$$x = a + r \cos \Theta \tag{2.57}$$

$$y = b + r \sin \Theta \tag{2.58}$$

Circular Hough Transform theory: (Rhody, 2005)

- Search with fixed radius R
- Multiple circles with known radius R
- Voting and Accumulator matrix

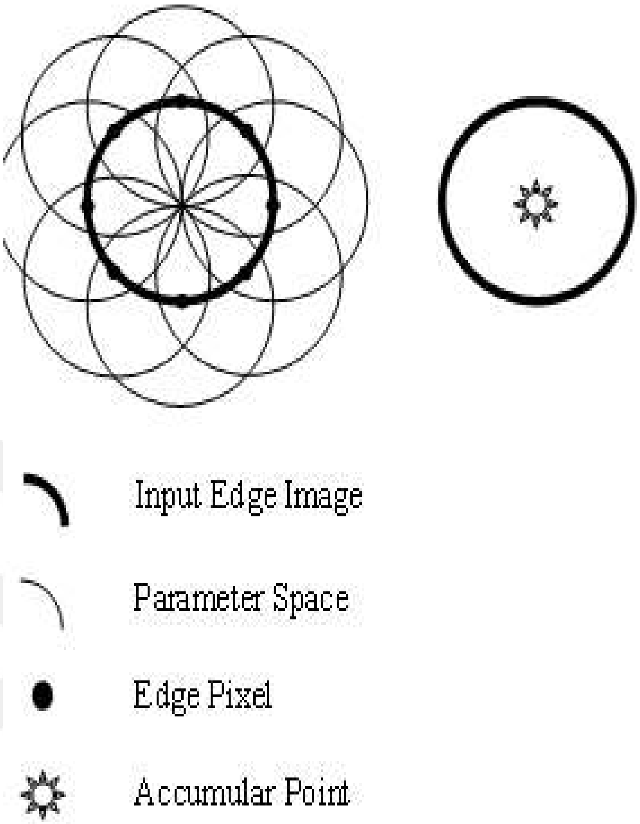


Figure 2.24. The edge point's contribution to the accumulator space (Raheja, 2012)

The black circle show set edge points within the picture. Each edge point provides or contributes a circle of radius R to yield accumulator space showed by the grey circles. The yield accumulator space has a crown or peak where these contributed circles overlap at the core or the center of the original circle. Adjustment to the CHT has been generally performed to decrease computational complexity or increase the detection rate. (Rizon, 2005)

**Applications**:

- ✓ Object Counting (Liu, 2010)
- ✓ Brain Aneurysm Detection (Mitra, 2013)
- ✓ Detection Fingertips Position (Rizon, 2005)

- ✓ Automatic Ball Recognition (D'Orazio, 2004)
- ✓ Iris Detection for Face Detection (Kawaguchi, 2005)
- ✓ Industrial Circle Detection Hardware (Jen, 2006)

**2.8. Uneven Illumination Correction**

The strategy depends on the presumption that the uneven illumination is an additional signal with low-frequency. Hence, low pass filtering can be utilized to extract it from a picture. This filtering might be accomplished by convolving a Gaussian kernel with the image. The impact of the Gaussian function is to delimit the spatial frequencies in a picture, producing the loss of edges and intensity value averaging, the Gaussian function determined by: (Leong, Brady, & McGee, 2003)

$$G(x,y)=\frac{1}{2\pi\sigma^2}\exp[-(x^2+y^2)/2\sigma^2\,] \tag{2.59}$$

Where the $G(x,y)$ is Gaussian function, the $\sigma$ is effective spread of the function, the bigger value of $\sigma$ the more smoothing effect.

So the final result image is [restored image = image - blurred image with Gaussian filtering]

**2.9. Regional Maxima**

In gray image, the regional maxima are associated of pixels with a constant value of intensity enclosed by pixels with a lower value. Generally, morphological reconstruction utilizing for creating a background picture, which can be deducted from the original picture for separating bright characteristics (regional maxima). (Regionalmaxima, 2020) (FilteringRegionalMaxima, 2021)

The regions of low and high intensity in a picture, valleys and peaks can be significant morphological characteristics since they frequently mark important and relevant picture objects. For instance, in a picture of a few spiral items, points of big intensity could describe the highest points of the items. Utilizing morphological processing, these maxima can be utilized to distinguish object in a picture. (izmiran, 2021)

### 2.10. Greenness Identification

Greenness identification from the pictures contain a crop taken outdoors is a significant step for crop observing. The regularly utilized techniques for greenness identification depend on visible spectral-index, for example, the vegetative index, the excess green minus excess red index, the combined index, the color index of vegetation extraction, and the excess green index. All these depend on strategies are working with respect to the presumption that plants show an obvious high level or degree of greenness, and the soil is the background component. İn deed, the contrast and brightness of a picture coming from outdoors conditions and environment are influenced by the captured time and the climate conditions. The shade, color, and intensity of the plant ranges from light or bright green to dull or dark green.

Greenness identification outcomes are genuinely influenced by the yield picture quality, the quality of the picture caught outside id affected by different elements like background, leaf color, and illumination. The background is complex and confused. The normalized color, r, g, b in RGB color space are characterized as follows, where R,G,B are color elements or components of the input picture. (Yang, 2015)

$$\boldsymbol{r} = \frac{\boldsymbol{R}}{\boldsymbol{R}+\boldsymbol{G}+\boldsymbol{B}}, \quad \boldsymbol{g} = \frac{\boldsymbol{G}}{\boldsymbol{R}+\boldsymbol{G}+\boldsymbol{B}}, \quad \boldsymbol{b} = \frac{\boldsymbol{B}}{\boldsymbol{R}+\boldsymbol{G}+\boldsymbol{B}} \tag{2.60}$$

# 3. RESULTS AND DISCUSSIONS

## 3.1. Image Processing Technique

In this method, the input is RGB color image, uneven illumination correction performed because of unbalanced light distribution, converting the output image to gray scale. After that, Gaussian filtering was used for smoothing and noise reduction with standard deviation of 4 (sigma=4), in addition to Standard deviation filter (with 9 neighborhood) to obtain the edges of the olive trees. Circular Hough Transform utilized to get the circular shapes to make the detection and counting of these circles (with the range between 6 and 20) to get finally the olive trees. When applying regional maxima and greenness identification, the number of detection decreased. The actual number of the olive trees in the input (original) picture is "618", the detection number by this method is "621" olive tree with gray scale image, meanwhile "627"olive tree with G channel.

Figure 3.1. Input image

Figure 3.2. After Uneven Illumination Correction

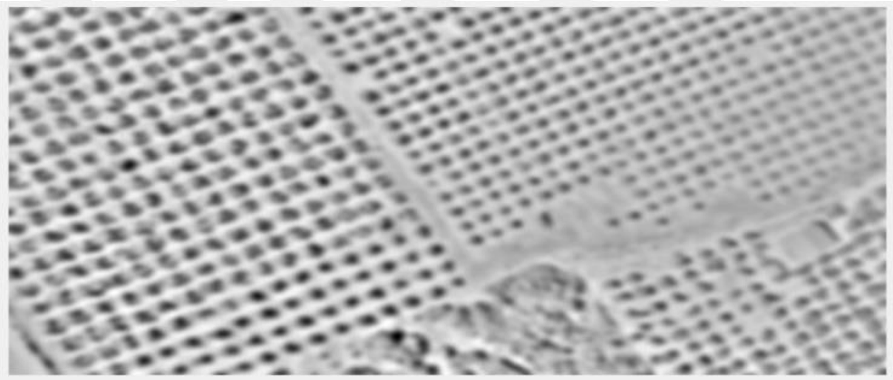

Figure 3.3. Gray scale image and after Gaussian filter (Standard Deviation=4)

Figure 3.4. After Standard Deviation filter (9 neighborhoods)

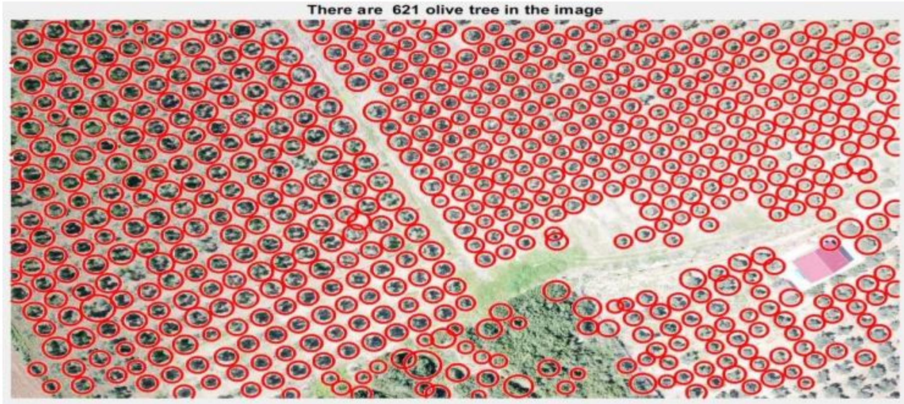


Figure 3.5. After Circular Hough Transform, detection, and counting

### 3.2. Image Processing with Unsupervised Machine Learning algorithms

The original RGB image (.jpg) including (618 olive tree) acquired for detecting and counting olive trees in it, several stages implemented to get high accuracy of detection and counting, firstly improve the unbalanced illumination of the image using three strategies: “Approach 1”, “Approach 2”, and “Approach 3”, after that convert the image to gray scale and getting the G channel and applying three types of filter: “Averaging Filter”, “Median Filter”, and “Wiener Filter”. By unsupervised machine learning algorithms, three of clustering techniques utilized for segmentation purpose which are: “EM”,” FCM”, and “K-means”. Morphological operations were very important to make the binary image clearer and to be ready for circle detecting and counting by “CHT”.

All the functions utilized in this study was by MATLAB built in functions except the EM segmentation algorithm was from MathWorks website (File Exchange) posted by prof. “Jose Vicente Manjon-Herrera” in 2006 under the title “EM image segmentation”.

In this study, the “**Filters**” were important to get better result and the filter neighborhood size parameter was:

- Wiener filter with parameter size [5, 5] of neighborhood.
- Median filter with parameter size [3, 3] of neighborhood.
- Averaging filter with parameter size [3, 3] of neighborhood.

The "**Morphological Operations**" were important for removing very small areas and some other procedures:

After **EM** algorithm the morphological operations utilized were:

1) Remove small areas under 10 pixels
2) Hole filling
3) Image close, with structuring element "disk" with "1" pixel
4) Hole filling
5) Image open, with structuring element "disk" with "1" pixel
6) Keeping the objects between range of areas [30 1000]

After **FCM, K-means** algorithms the morphological operations utilized were:

1) Remove small areas under 40 pixels
2) Hole filling
3) Image open, with structuring element "disk" with "1" pixel
4) Keeping the objects between range of areas [30 1000]

The "**CHT"** for the Maximum radius [20] and Minimum radius [5] for the whole algorithms.

All the **Segmentation** techniques in this study select "3 Clusters". For "**Automatic**" choosing the suitable cluster there is a condition in this image, the number of white/ black pixels in one of the three clusters:

-in **FCM,** should be greater than (>350,000) pixels.

-in **K-means,** should be:

In "Approach 1":

(>350,000) pixels for G channel and gray scale with Wiener filter

(>350,000) pixels for gray scale and (>360,000) pixels for G channel with Average filter

In "Approach 2":

(>351,000) pixels for G channel with Wiener filter

(>350,000) pixels for gray scale with Median filter

(>350,000) pixels for gray scale and (>360,000) pixels for G channel with Average filter

In "Approach 3":

(>350,000) pixels for G channel with Wiener filter

(>350,000) pixels for gray scale and G channel with Median filter

(>350,000) pixels for gray scale and (>360,000) pixels for G channel with Average filter

All "Time Consuming" based on time calculation in "Approach 1" with "G" channel and "Average Filter"

Table 3.1. Time consuming of the three filters

| Average | Median | Wiener |
|---|---|---|
| 0.07 | 0.11 | 0.05 |

Table 3.2. Time consuming of the whole algorithm including the function of segmentation

| The Algorithm + EM | EM | The Algorithm + K-means | K-means | The Algorithm + FCM | FCM |
|---|---|---|---|---|---|
| 22.15 | 10.34 | 12.25 | 0.43 | 24.47 | 10.63 |

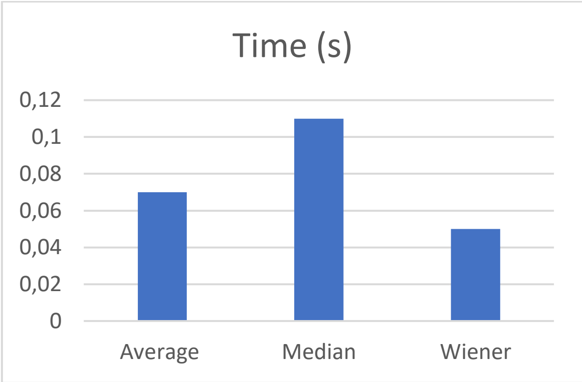


Figure 3.6. Time consuming of the three filters

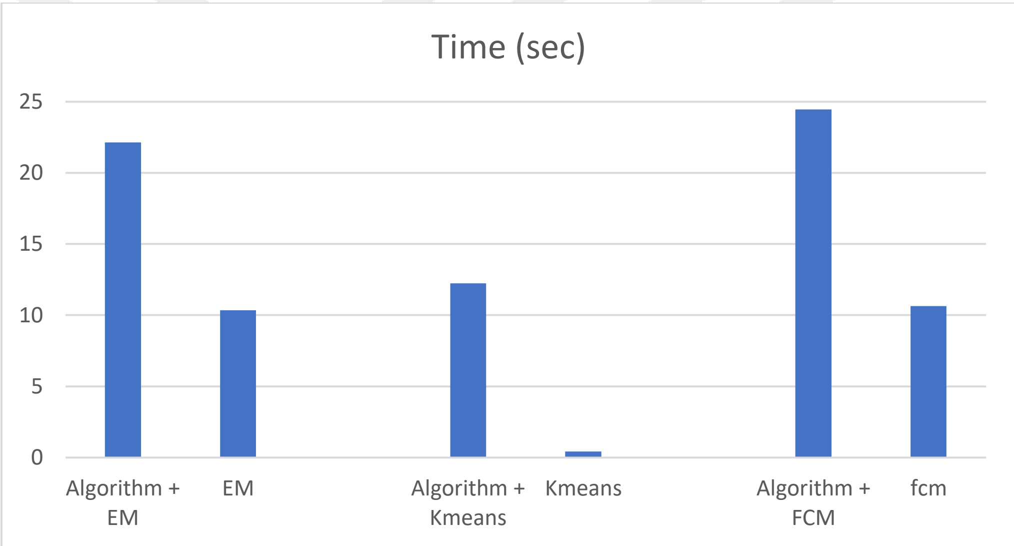


Figure 3.7. Time consuming of the whole algorithm including the function of segmentation

In the upcoming figures, I choose just 3 results to show, which are:

- “EM” with “Wiener Filter”
- “FCM” with “Median Filter”
- “K-means” with “Averaging Filter”

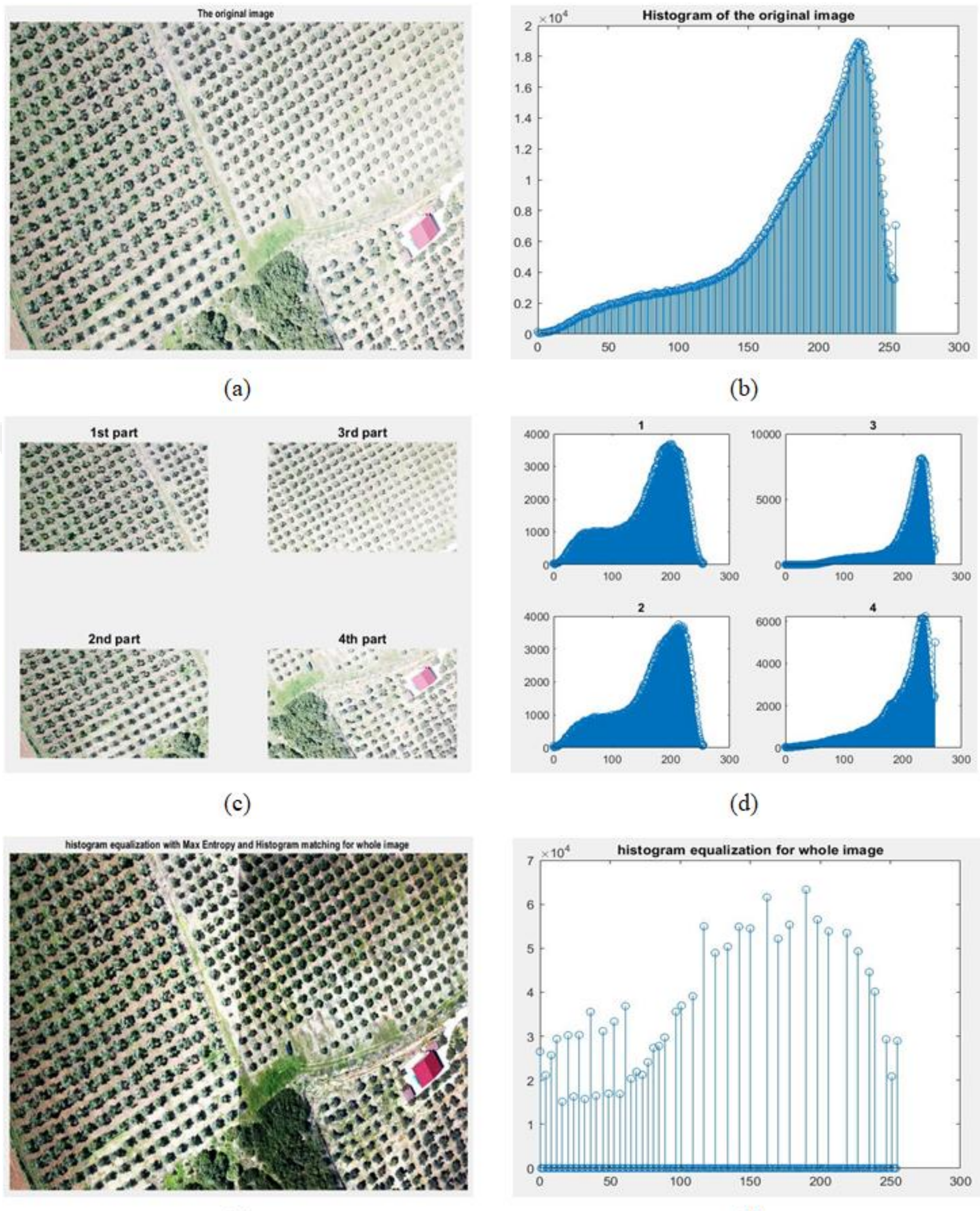


Figure 3.8. a) the original image b) the histogram of the original image c) dividing the image 4 equal parts d) the histogram of each part e) the histogram equalization for whole image after choosing maximum entropy f) the histogram after equalization of the image


Figure 3.9. EM segmentation after Wiener filter

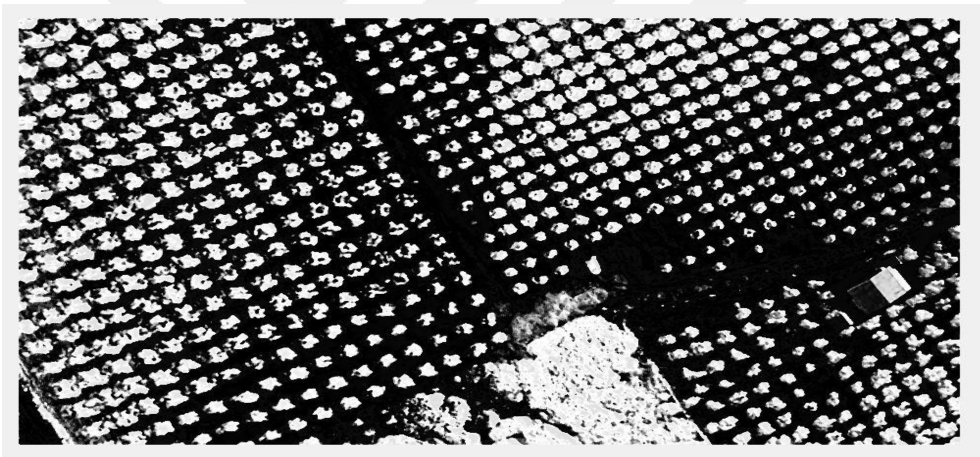

Figure 3.10. FCM segmentation after Median filter

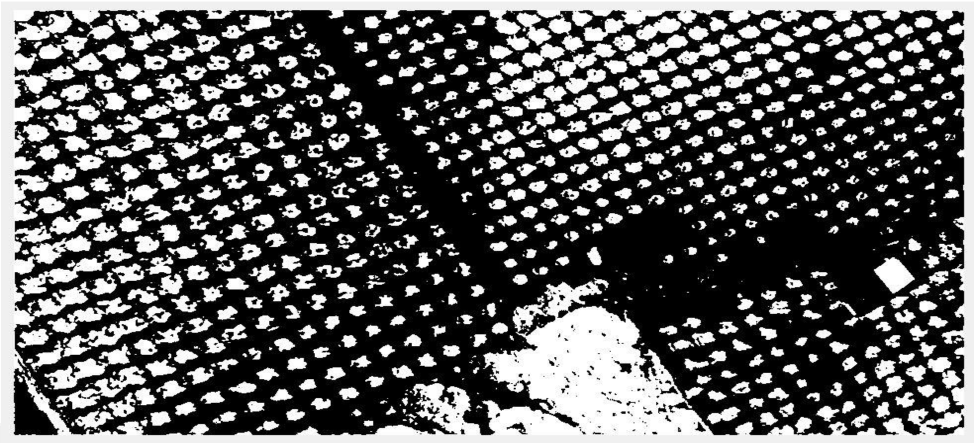

Figure 3.11. K-means segmentation after Average filter

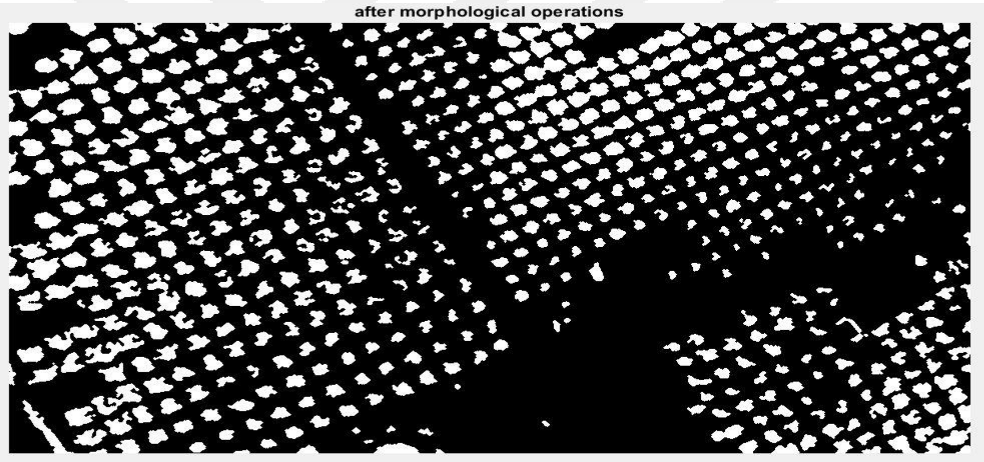


Figure 3.12. EM after Morphological operations

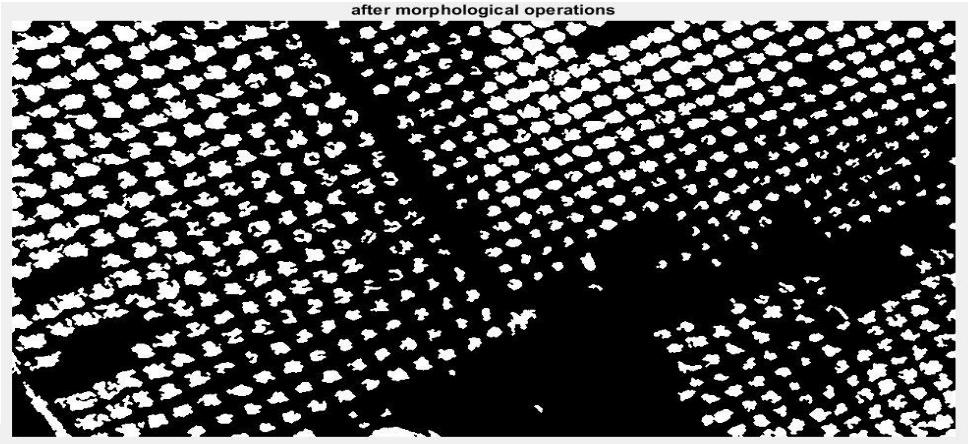


Figure 3.13. FCM after Morphological operations

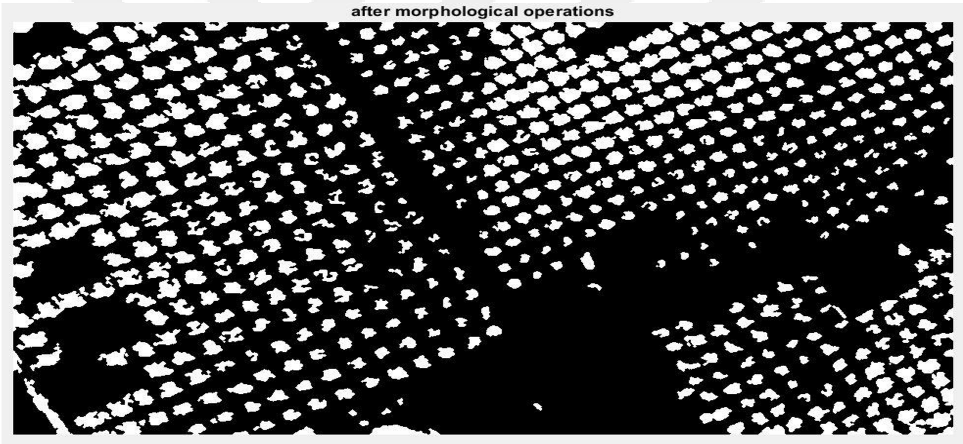


Figure 3.14. K-means after Morphological operations

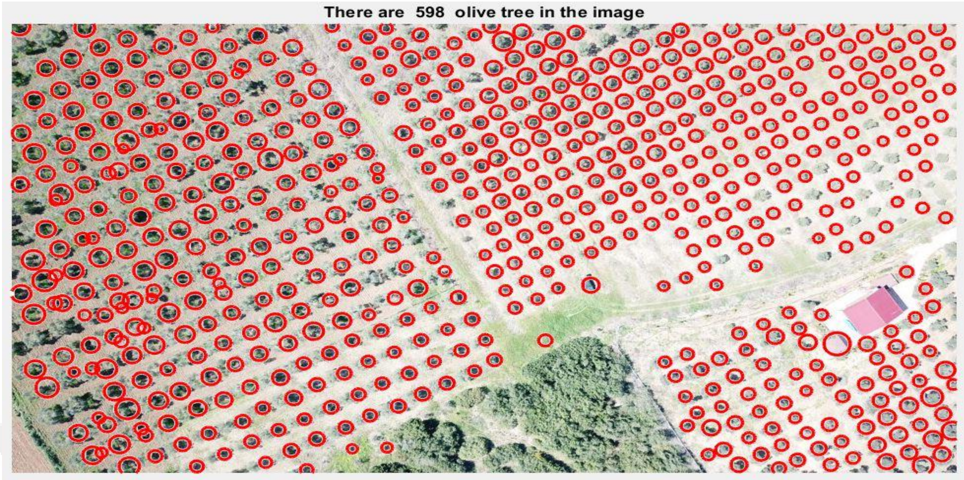


Figure 3.15. The result of detection by CHT and counting of EM algorithm with Wiener filter


Figure 3.16. The result of detection by CHT and counting of FCM algorithm with Median filter


Figure 3.17. The result of detection by CHT and counting of K-means algorithm with Averaging filter. The original image contains (618) olive trees

Table 3.3. The results of counting number of olive trees with different filters and EM algorithm. (The original image contains 618 trees)

| EM | Average | Median | Wiener |
|---|---|---|---|
| "Approach 1" + G | 563 | 568 | 598 |
| "Approach 1" + Gray | 584 | 575 | 590 |
| "Approach 2" + G | 562 | 549 | 589 |
| "Approach 2" + Gray | 589 | 562 | 592 |
| "Approach 3" + G | 554 | 515 | 584 |
| "Approach 3" + Gray | 580 | 554 | 586 |

Table 3.4. The results of counting number of olive trees with different filters and K-means algorithm. (The original image contains 618 trees)

| K-means | Average | Median | Wiener |
|---|---|---|---|
| "Approach 1" + G | 586 | - | 592 |
| "Approach 1" + Gray | 592 | - | 591 |
| "Approach 2" + G | 592 | - | 594 |
| "Approach 2" + Gray | 593 | 604 | - |
| "Approach 3" + G | 587 | 567 | 575 |
| "Approach 3" + Gray | 584 | 592 | - |

Table 3.5. The result of counting the number of trees with different filters and FCM segmentation algorithm. (The original image contains 618 trees)

| Fuzzy c-means | Average | Median | Wiener |
|---|---|---|---|
| "Approach 1" + G | 597 | 595 | 594 |
| "Approach 1" + Gray | 594 | 600 | 591 |
| "Approach 2" + G | 592 | 591 | 594 |
| "Approach 2" + Gray | 596 | 600 | 589 |
| "Approach 3" + G | 582 | 584 | 575 |
| "Approach 3" + Gray | 592 | 592 | 587 |

Table 3.6. The percentage (%) result of counting the number of trees with different filters and EM segmentation algorithm. (The original image contains 618 trees)

| EM | Average | Median | Wiener |
|---|---|---|---|
| "Approach 1" + G | 91.1 | 91.9 | 96.76 |
| "Approach 1" + Gray | 94.49 | 93.04 | 95.46 |
| "Approach 2" + G | 90.93 | 88.83 | 95.3 |
| "Approach 2" + Gray | 95.3 | 90.93 | 95.79 |
| "Approach 3" + G | 89.64 | 83.33 | 94.49 |
| "Approach 3" + Gray | 93.85 | 89.64 | 94.82 |

Table 3.7. The percentage (%) result of counting the number of trees with different filters and K-means segmentation algorithm. (The original image contains 618 trees)

| K-means | Average | Median | Wiener |
|---|---|---|---|
| "Approach 1" + G | 94.82 | - | 95.79 |
| "Approach 1" + Gray | 95.79 | - | 95.63 |
| "Approach 2" + G | 95.79 | - | 96.11 |
| "Approach 2" + Gray | 95.95 | 97.73 | - |
| "Approach 3" + G | 94.98 | 91.74 | 93.04 |
| "Approach 3" + Gray | 94.49 | 95.79 | - |

Table 3.8. The percentage (%) result of counting the number of trees with different filters and FCM segmentation algorithm. (The original image contains 618 trees)

| Fuzzy c-means | Average | Median | Wiener |
|---|---|---|---|
| "Approach 1" + G | 96.60 | 96.27 | 96.11 |
| "Approach 1" + Gray | 96.11 | 97.08 | 95.63 |
| "Approach 2" + G | 95.79 | 95.63 | 96.11 |
| "Approach 2" + Gray | 96.44 | 97.08 | 95.3 |
| "Approach 3" + G | 94.17 | 94.49 | 93.04 |
| "Approach 3" + Gray | 95.79 | 95.79 | 94.98 |

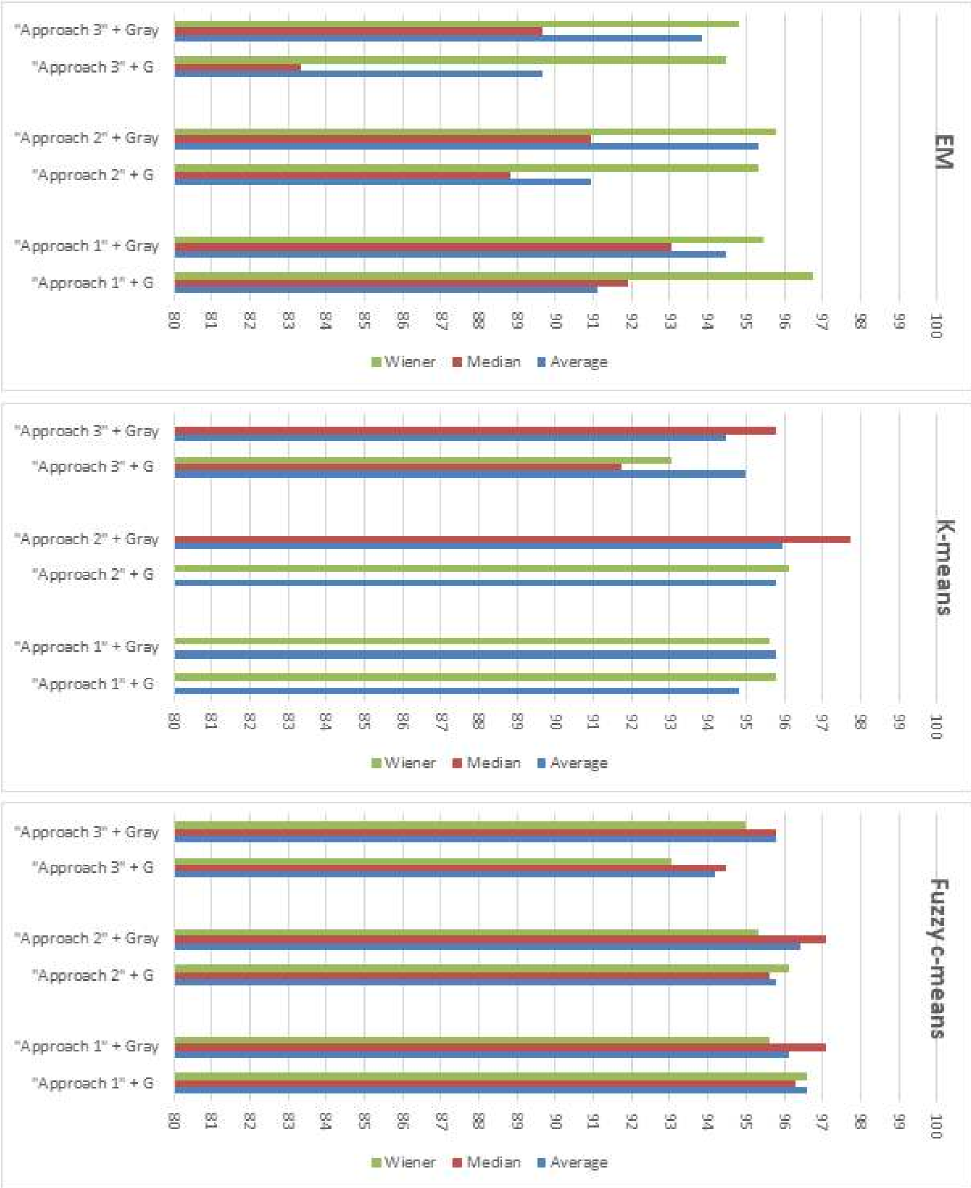


Figure 3.18. The results of the segmentation techniques with filters

Table 3.9. Performance parameters with Peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio (SNR), and Mean Square Error (MSE), in this case, Median filter shows desirable outcome with higher PSNR and the lowest MSE. (This comparison according "Approach 1" with "Gray scale" image)

| | Averaging | Median | Wiener |
|---|---|---|---|
| PSNR | 20.65 | 21.28 | 21.04 |
| SNR | 16.11 | 16.74 | 16.50 |
| MSE | 559.5 | 484 | 511.2 |

Table 3.10. Sensitivity, Percentage of detection and Positive Prediction Value of the first method which using image processing and the second method which use image processing with unsupervised machine learning algorithms

| Method | algorithm | Approach | Image | Filter | Percentage of detection (%) | Sensitivity (%) | Positive Prediction Value (%) |
|---|---|---|---|---|---|---|---|
| Method 1 "Image Processing" | - | - | Gray scale | Gaussian-Standard Deviation | 100.48 | 94.01 | 93.55 |
| | - | - | G-channel | Gaussian-Standard Deviation | 101.45 | 95.3 | 93.93 |
| Method 2 "Unsupervised" | EM | 1 | G | Wiener | 96.76 | 92.71 | 95.65 |
| | | 1 | Gray | Median | 93.04 | 89.48 | 96.5 |
| | | 2 | Gray | Average (Mean) | 95.3 | 91.9 | 96.43 |
| | K-means | 2 | G | Wiener | 96.11 | 91.58 | 95.28 |
| | | 2 | Gray | Median | 97.73 | 93.2 | 95.36 |
| | | 2 | Gray | Average (Mean) | 95.95 | 91.9 | 95.78 |
| | FCM | 1 | G | Wiener | 96.11 | 92.39 | 96.12 |
| | | 1 | Gray | Median | 97.08 | 93.04 | 95.83 |
| | | 1 | G | Average (Mean) | 96.60 | 91.9 | 95.14 |

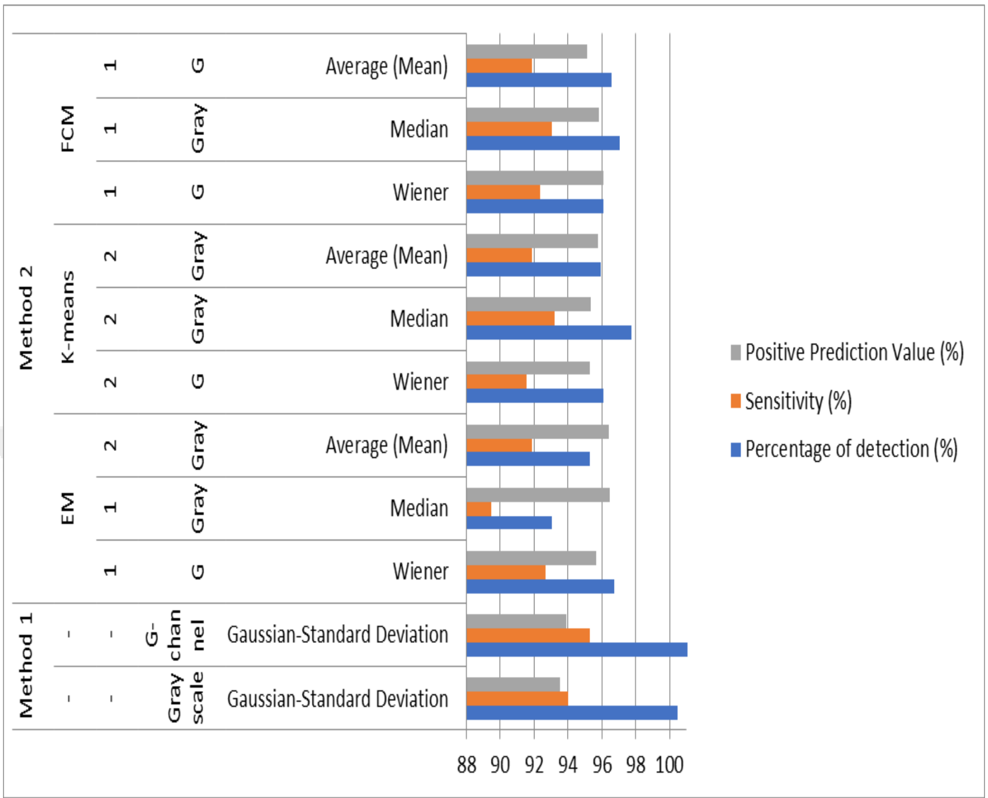


Figure 3.19. Sensitivity, Percentage of detection and Positive Prediction Value between the first method which using image processing and the second method which use image processing with unsupervised machine learning algorithm

### 3.3. Image Processing with Supervised Machine Learning algorithms

This method include firstly loading the data or sub images (sub blocks),these sub blocks as a result of dividing the original image, each block has a size of “21” rows and “21” that implies the block size is “21x21”, these sub images basically divided into 2 groups or classes (1 and 0) which means positive class “1” which is “Olive tree” and negative class “0” means “Non olive tree”, each class contains “580” sub image. After that, feature extraction implemented like Histogram Orientation Gradient and Color histogram feature to get features for training stage and save these results as a “.mat” files. Three classification algorithms executed K-Nearest Neighbor, Linear Discriminant Analysis, and Support Vector Machine. We can get the input image then make a classifications on it according Color histogram feature or the combination of Color histogram feature and HOG feature to detect the “Olive trees” by “Sliding Window” and classify each window contains is it olive tree or not, the window size is “21x21” with the stride of “10”, the final result image contains a black background and a colored objects which means “Olive trees”. This method shows weak results because of the small number of training images or sub images, the light of the divided image was contains shadows and illumination problems ,and some areas was merged.

The Accuracy of the training data increased when Color histogram features merged with Hog features, the results of the Accuracies of the classifiers on the training data when depending on Color histogram features were “72%”, “52%”, and “60%” for KNN, LDA, and SVM respectively. When Color histogram features combined with HOG features the results were “72%”, “82%”, and “79%” for KNN, LDA, and SVM respectively.

KNN used the number of neighbors “4” with the distance “Euclidean distance”. LDA and SVM used the default Matlab function’s parameters for classification.

Table 3.11. Confusion Matrix of KNN with Color Histogram Feature

| **KNN** | **Predicted** Olive Tree | **Predicted** Non Olive Tree |
|---|---|---|
| **Actual** Olive Tree | 212 | 4 |
| **Actual** Non Olive Tree | 78 | 8 |

Table 3.12. Confusion Matrix of LDA with Color Histogram Feature

| **LDA** | **Predicted** Olive Tree | **Predicted** Non Olive Tree |
|---|---|---|
| **Actual** Olive Tree | 171 | 5 |
| **Actual** Non Olive Tree | 119 | 7 |

Table 3.13. Confusion Matrix of SVM with Color Histogram Feature

| **SVM** | **Predicted** Olive Tree | **Predicted** Non Olive Tree |
|---|---|---|
| **Actual** Olive Tree | 176 | 5 |
| **Actual** Non Olive Tree | 114 | 7 |

Table 3.14. Confusion Matrix of KNN with Color Histogram Feature and HOG Feature

| **KNN** | **Predicted** Olive Tree | **Predicted** Non Olive Tree |
|---|---|---|
| **Actual** Olive Tree | 212 | 4 |
| **Actual** Non Olive Tree | 78 | 8 |

Table 3.15. Confusion Matrix of LDA with Color Histogram Feature and HOG Feature

| **LDA** | **Predicted** Olive Tree | **Predicted** Non Olive Tree |
|---|---|---|
| **Actual** Olive Tree | 239 | 3 |
| **Actual** Non Olive Tree | 51 | 9 |

Table 3.16. Confusion Matrix of SVM with Color Histogram Feature and HOG Feature

| **SVM** | **Predicted** Olive Tree | **Predicted** Non Olive Tree |
|---|---|---|
| **Actual** Olive Tree | 231 | 3 |
| **Actual** Non Olive Tree | 59 | 9 |

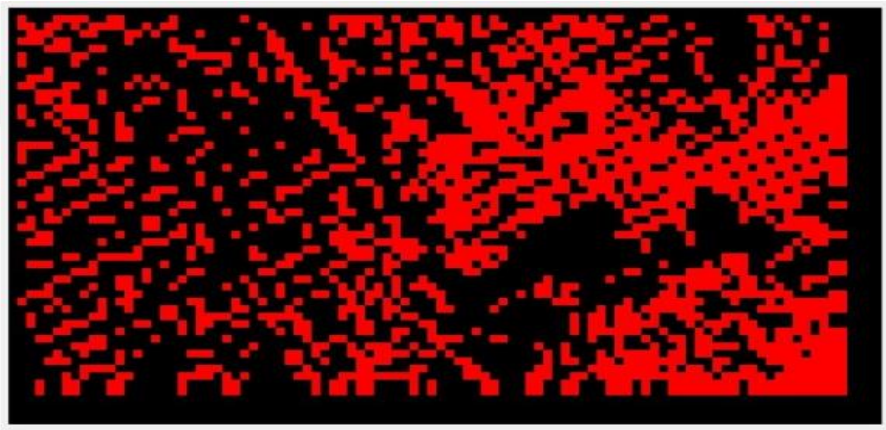

Figure 3.20. The result of KNN algorithm when using the combination of color histogram and HOG features

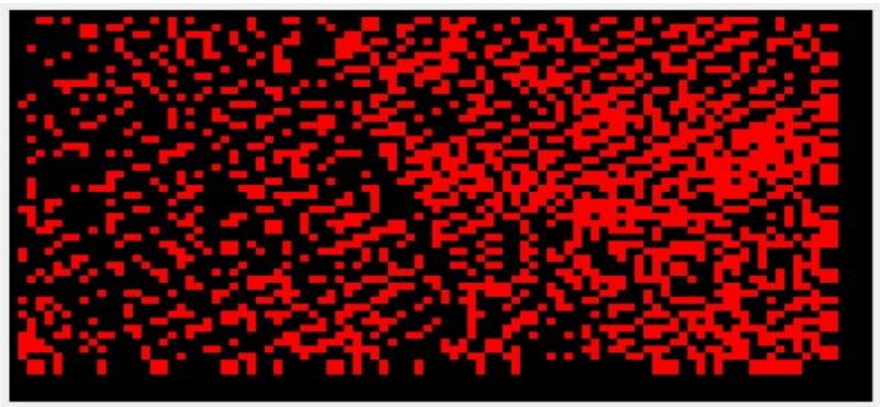

Figure 3.21. The result of LDA algorithm when using the combination of color histogram and HOG features

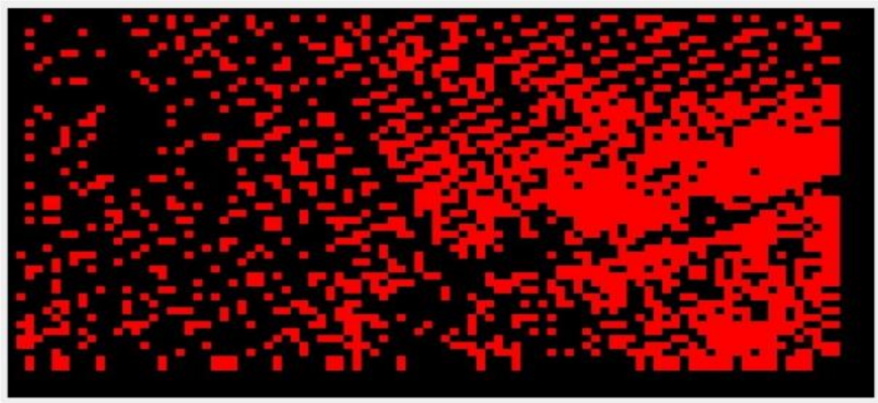

Figure 3.22. The result of SVM algorithm when using the combination of color histogram and HOG features

### 3.4. Discussions

In this thesis according to the results we can obtained that the first and the second methods shows high performance and the first method contains image processing techniques including (Uneven Illumination Correction, Gaussian filter, Standard Deviation filter, Circular Hough Transform), and the second method which contains image processing techniques with unsupervised machine learning algorithms including Histogram Equalization, 3 filters for noise removing like Mean, Median, and Wiener implemented, after that segmentation stage which includes 3 unsupervised machine learning clustering techniques like K-means, Fuzzy c-means, and Expectation Maximization algorithms, after this stage, Morphological operations performed to make some operations like erosion, dilation, open, close, hole filling, and removing unwanted range of areas to make the image clearer and ready for the last step which is Circular Hough Transform to detect the circular objects and at the end we counted automatically these objects as an olive trees. In the first method, we can see that there is over detection especially in the hug green zone in the center bottom of the image which is basically not an olive tree and the detection result was more than the actual olive trees in the image by 3 to 9 detection as a trees but it is not actual tree and this is the problem of detecting the big green zone as an olive tree and the second method overcome this over detection and prevents too many counting of this big zone. In the second method, we can observe that this method can overcome the problem of over detection and this problem solved by morphological operation, we made some operation to make the image clearer and we remove unwanted shapes or objects such as the huge green zone by implementing removing too big areas. Many results we obtained from this method, most of them were desirable and we can expect this many good results come from firstly be improve the light of the image and implement a different filters to remove the noises, and secondly by applying many clustering techniques which make the next steps easier for detection. FCM clustering technique was suitable with all filters; meanwhile K-means made better outcome with Mean and Wiener filters, EM gives better result with Wiener filter. There is a reason for choosing more than one filer in the second method is that we cannot expect the noise source of types, so we implemented linear and nonlinear filters for this purpose.

In practice, we found that the third method of this thesis which used image processing with supervised machine learning algorithms like (Support vector machine, K Nearest Neighbors, and Linear Discriminant Analysis) shows undesirable result, in spite of using Histogram Orientation Gradient and Color Histogram as a features to go for the training step and then the classification step which comprise the three supervised machine learning algorithms. We can expect that this undesirable result happened because of essentially the training data is not enough, in this method we make 2 classes for classification purpose the first class includes olive tree images meanwhile the second class contains non olive tree images like ground and house, the number of the training data is 580 for each class and that is not enough because we need more data of olive tree to train, using the combination of HOG features with Color Histogram features improve the detections but still not give us the desirable outcome.

### 3.5. Comparing with other studies

In the study of (Khan, 2018), they used unsharp mask directly without improving the illumination of the image, while my study implemented tow techniques for correction the light of the image which are Uneven Illumination and Histogram Equalization and that means my study has advantage cause of illumination correction before using filters and other preprocessing techniques and that implies my study can deal with different illuminations happened by weather changes such as cloudy or sunny because the first step is illumination redistribution or correction whatever if the input image has too bright or shinny or dark zones. Also (Khan, 2018) for segmentation purpose they used multilevel thresholding, whereas my study used 3 clustering unsupervised machine learning algorithms for segmentation. (Kestur, 2018) utilized one supervised technique and compare it with K-means algorithm, while in my study we compared my study with 3 unsupervised machine learning algorithm K-mean, FCM, and EM. Also in my study we used just image processing techniques it has simple steps and without machine learning algorithms. (Kestur, 2018) used images contain small number of trees with high resolution or at least not as our image which we used in this study which includes about 618 olive trees and affected by weather and illumination, that is also a challenge to overcome the unbalanced distribution of the light and there are many other objects like car, house, and big green zone in addition the huge number of the olive trees in our image.

# 4. CONCLUSION

Olive trees and olive oil have significant impact in the economy, health, and other important fields. This study proposed image processing technique with machine learning algorithms specially Unsupervised (Clustering) and Supervised (Classification) to detect and count the olive trees. Fundamentally, the challenge was treating with unbalanced light distribution for the image. Several methods preformed to get better results, the first method utilized Uneven Illumination Correction, Gaussian filter, Standard Deviation filter and Circular Hough Transform to detect olive trees. The second method used Histogram Equalization, Mean, Median, and Wiener filters with 3 Unsupervised algorithms (Clustering technique) are K-means, Fuzzy –mean, and Expectation Maximization algorithms and Morphological Operations then Circular Hough Transform. The third method implemented Supervised algorithms (Classification) are K-Nearest Neighbor, Linear Discriminant Analysis, and Support Vector Machine to detect and count Olive trees. Obviously, the first and the second methods demonstrate good results, the reason of that is the small number of the training data; we want thousands of images to train to get a desirable result.

To conclude, the first and the second method illustrates high performance, the first method used simple image processing techniques to get the desirable result, the second method used image processing techniques in addition to unsupervised machine learning algorithm called clustering technique obtained also eligible outcomes. Because of lack in training data, the supervised machine learning algorithms shows undesirable result.

As a future work, a huge training data for olive trees should be available to obtain and use it, more supervised machine learning algorithms can implement, and deep learning techniques such as CNN, Fast R-CNN or Faster R-CNN can perform for saving efforts and getting higher performance, also multispectral image like ultraviolet, infrared, x-ray or other bands to obtain more information.

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