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AN AUTOMATED SYSTEM TO IDENTIFY WILSON DISEASE BY KNN BASED ON SIFT FEATURES

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Abstract— Wilson disease is a pathology because of a gene mutation causing malfunction in the copper excretion from the organism. Therefore, copper accumulation in the human body gives rise to oxidative processes. Hence, Wilson disease causes several disorders including affecting tissues and organs. Neurological disorders leads to copper accumulation in the human body. Approximately 95% of individuals with neurological/psychiatric disorders shows a visible symptom in their eye known as Kayser-Fleischer ring. The characteristic sign of KF ring will be golden-brown or greyish in color, it occurs due to the copper deposition in the cornea. In the medical screening, it is consider as a diagnostic sign of Wilson disease. Our system proposed an innovative technique based on ocular biometric measurements to diagnose the disease . An image processing algorithm will detects the Kayser-Fleischer ring in the cornea through segmentation process. Biometric measurements provides further information on the severity level of Wilson disease. Also, an image processing algorithm is proposed to provide an invasive technique which is used to improve the accuracy of the severity measurements. As input image is performed using SIFT feature extraction. Finally the images will be classified as normal or affected using KNN classifier and Decision tree.

INDEX TERMS— Wilson disease, Kayser-Fleischer Ring, J based SEG, Biometric measurements, SIFT, KNN classifier and Decision tree classifier.

1. INTRODUCTION

Neurological disorder is a complex issue concerning with neurophysiology. The cause of such disorder is unknown. Normally, proper intake of copper is essential for the regular growth of our human body i.e. appropriate dose is essential. Transporter protein is one kind of protein which has the responsibility to carry the copper inside the cells. Patients with Wilson's disease are affected with chronic liver disease, hepatic failure, acute renal failure, neuropsychiatric disease such as disorder of movement, tremors, in the coordination and behavioral changes. Child inherits the defected gene from both carrying parents and also child affected from Wilson disease. There is a case for every 40000 births. The first clear sign of Wilson disease will be usually appears between the ages of 5 to 20 years. Wilson disease shows severe symptoms in both human brain and eye. *Wilson's disease is also called as "hepatolenticular degeneration", in which copper accumulates in the tissues; and the outcome will be neurological symptoms. Wilson disease is a rare genetic disorder that prevents the body from getting rid of copper deposition. A little amount of copper is essential to stay healthy, but too much of copper leads to poisonous.*

When the copper storage capacity of the liver is surpassed, then the copper will be passed into the blood.stream and it travels through other organs-including brain, kidney and eyes.A copper accumulation in eye leads to Kayser- Fleischer ring i.e (KF ring), it is the outcome of copper deposition in Descemet's membrane. The Normal eye is shown in Fig 1.1 and Eye affected with Wilson Disease is shown in Fig 1.2.

Fig 1.1 Normal eye

Fig 1.2 Eye affected with Wilson Disease

They will be appear in each eye as a greenish-brown ring around the edge of the cornea and also in the rim of the cornea. Then the iris part will be consider as the colored region present in the eye part i.e neighboring to the pupil. The cornea is the transparent outer membrane that contains the eye part completely. Without suitable equipment and treatments, symptoms tend to become progressively more critical and chronic, then the Wilson disease may be fatal. In Medical trails, presence of Kayser-Fleischer ring will be consider as a critical for detecting Wilson disease. The thickness or density of the ring depends upon on the severity level of the disease.

It is an asymptotic and it can be recognized by an normal eye. Actually Kayser-Fleischer ring is found in 95% of individuals in the all over world , so detection of Kayser-Fleischer ring is must in an early stage itself, so that it can be used for the diagnosis purpose as soon as possible.Wilson disease may be detected with the help of physical examination process and laboratory test results. During the physical examination process, a doctor might looks for the visible sign of Wilson disease. A special light called a slit lamp can be used to generate Kayser-Fleischer ring in the eye. Kayser-Fleischer are almost present in all people who are affected by Wilson disease and it shows the symptoms called neurological damage, but they are present in only 50 percent of those affected with the symptom called liver damage alone. Genetic testing may help to detect with Wilson disease in some kind of people, particularly those with a family history of the Wilson disease peoples. Wilson disease may be misdiagnosed only if it is rare and their symptoms are similar to those of other conditions.

In medical prosecutions, the presence of Keyser-Fleischer ring is considered as a severe level for diagnosing those patients. But having some false negative diagnoses are also possible. Hence the suggested technique is non-innovative and it is based on eye image processing by means of a segmentation algorithm. Biometric measurements provide further information about the severity level of Wilson disease. Automated detection technique is developed to diagnose Wilson disease with image processing algorithm method. To measure the severity level of Wilson disease, biometric measurements will be used. It aim is to reduce the possible human interpretation error. Section II deals with the related works. Section III provides detail description about methods and approaches. Section IV shows experimental result of biometric measurements and feature extraction. Section V provides final conclusion on the findings and perspectives for future work.

II. RELATED WORKS

In [1] The main goal is that without any help of medical tools it is used to improve the accuracy level of present methods and also it will reduce the potential errors. Feature extraction is done with thehelp of gray level co-occurrence matrix (GLCM). Classification is done with the help of support vector machine for more accuracy. In [2] The goal is that without any medical trails and also with the help of ocular biometric measurements it can be able to reduce human making of errors as possible. Image processing algorithms such as JSEG segmentation is used to detect Kayser-Fleischer ring. In [3] The aim is to provide a non-invasive diagnostic technique to improve the accuracy of current methods and also it is used to reduce possible interpretation error. In [4] An unsupervised color-texture regions of segmentation algorithm is ideal for this purpose, since it test the homogeneity of the given color-texture pattern, which is computationally more possible than the model performance measures of estimation technique.

It also deals with the following assumptions for more acquired images. In [5]A review of various segmentation approaches are used in iris recognition technique. The survey is represented in tabular form for quick reference. In [6]The proposed system depends upon on two different aspects of databases then the obtained results shows that the proposed system is robust, fastest among all and effectively detect the presence of lesions in the liver, and also it count the distinctly identifiable lesions finally it compute the area of liver affected by tumor lesion with good quality results and it extract lesions from various abdominal CT in less than 0.15 s/slice. In [7] Filtering is applied to remove noise and it is used to enhance the strength of edges founded by a noise-protected edge detector.

A seed growing-merging method used for both improved contrast map and also for original J-map will be constructed by J-segmentation to segment the given image. Experiments results on natural color-texture images and color medical images provides the improved results. In [8] A high index of suspicion is required for the early detection of Wilson's disease in the children and young peoples with neurological disease. Initiation of treatment at an early stage can prevent the complications. In [9] Initiation of treatment at an early stage can prevent the complications. In [10] A novel algorithm can able to obtain the noisy of a generic image sensor without the help of controlled environment is needed. Starting from the collection of various heterogeneous CFA images, by using a voting based estimator, the performance measures of the noisy model will be estimated. In [11] The experimental results provide significant improvement in the segmentation accuracy. In [12] This setup simulates the imaging of a simple nested organic structure for using T-ray CT imaging to achieve T-ray pulsed signal classification of heterogeneous layers.

III. METHODS AND APPROACHES

Image segmentation for the KF ring had been identified, segmented and analyzed through a JSEG process. The essential idea of JSEG is used to separate the segmentation process into two individual processed stages, color quantization and spatial segmentation. Quantization is performed in color space without assuming any spatial distributions. During color quantization process the image quality is not be the quality image. Standard 256 color palette is assuming in order to enlarge the set of representation colors to single out various neighboring regions of pixels. Therefore based on 256 palette, color set is obtained.

3.1 SEVERITY MEASUREMENTS:

To calculate the severity level of Wilson disease from the following steps: Fig 3.1 shows block diagram of the proposed system.

3.1.1 Color Quantization:

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- Color Quantization process have the capacity to reduce possible number of colors present in the image. The colors in the image are quantized to various representing classes, then the quantized classes will be used to separate the regions in the image.
- The image color pixels are replaced by their corresponding color class labels, hence it is obtaining a class-map of the image.

3.1.2 Spatial segmentation:

Considering a 2-D plane xy. Let (xy) provides the label of the pixel with position called(xy). It is the value of class-map at the position of image. The image is divided into Nc classes. Let CM be the new class-map image. CMi represents the set of all pixels contained in the i-th class, where i=1. Assume m to be the spatial mean for all data points z=(x,y) in CM.

$$m = 1/Ndp \sum_{z \in CM} Z \qquad (1)$$

$$mi = 1/Ndp,i \sum_{\in CMi} Z \qquad (2)$$

where Ndp is the no of data points or pixels. Let mi be the spatial mean of the Ndp, i indicates data points of the class CMi: Assume that VT be the total variance of all data points in CM

$$VT = \sum_{z \in CM} \|Z-m\|^2 \qquad (3)$$

CM is the total variance of the pixels belonging to the same class CMi:

$$VT,CM = \sum_{i=1}^{Nc} \sum_{z \in CM} \|Z-m\|^2 \qquad (4)$$

The degree of distribution of the color classes J can be obtained by the following expression:

$$J = \frac{VT-VT1,\ CM}{VT,\ \overline{CM}} \qquad (5)$$

The range of distribution will give useful information about the range of classes in class-map. It is used to analyze the segmentation process. In another way, if several homogeneous color regions are present and the classes are clustered for the specific regions of the image, then the range of distribution J will be higher, to finish the spatial segmentation process.

The average Jm distribution value will give the information about performance of segmentation process. If the class-map is partition into k regions, the average Jm value is obtained as sum on the whole, all the regions of the local Jk values are estimated in the k^{-th} region:

$$J = 1/Ndp \sum Nk.Jk \qquad (6)$$

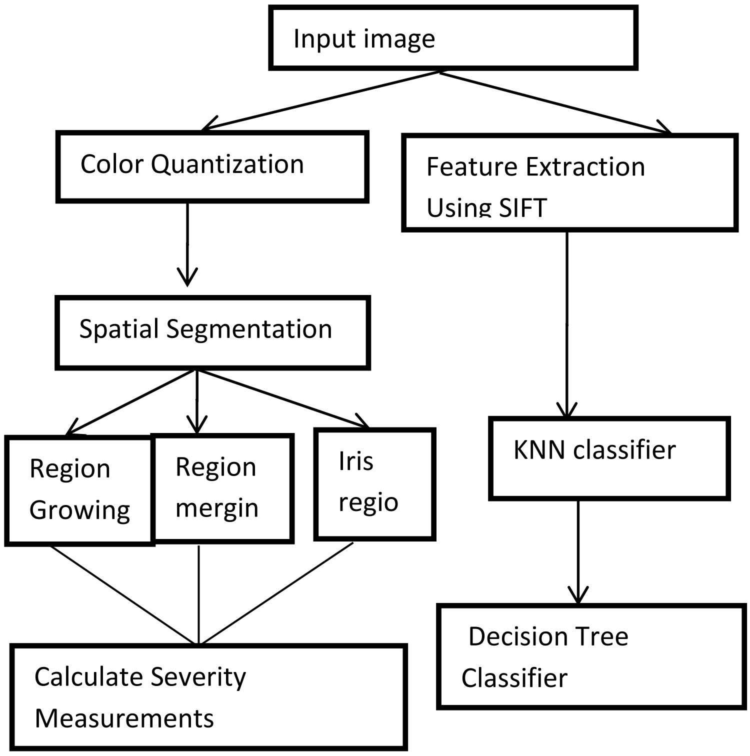


Fig 3.1 shows block diagram of the proposed system.

Severity measurements Wilson disease classification

where N_k is the number of pixels present in the K^{-th} region. Lower Jm values shows good segmentation results. A J-image is created as a gray-scale image, whose pixel values are the Jk values measured over the local windows centered on each pixel.

3.1.3 Region growing:

A region-growing method is used to complete the segmentation process. The spatial segmentation starts to segment the regions with an initial stage of large scale until the fixed minimum scale is found.

The region-growing algorithm is applied recursively and the process is repeated until the newly segmented regions may find at the next lower scale.

- It is used to segment the image based on the multi-scale J-images and finally they are merged to obtain the segmented image.

- The region-growing algorithm is applied recursively and then the process will be repeated until the newly segmented regions may find at the next lower scale.
- The new regions of the segmented image area are obtained by means of region growing algorithm.

3.1.4 Region merging:

Region merging can be able to merge depends upon on the color similarity. Assuming that the RGB color system, let l1= (R1, G1, B1) be the label of the first region and l2= (R2, G2, B2) be the label of the second region.
The Euclidean color distance can be evaluated by the following expression:

$$\Delta D=\sqrt{(R1-R2)^2+(G1-G2)^2+(B1-B2)^2} \quad (7)$$

Adjacent regions are merged only if this distance is lower than a fixed threshold level ΔDref. This threshold level is equal to the standardized deviation of the labels of the K^{th} neighboring region. In detail when the region merging is finished, the segmentation process will be completed.

3.1.5 Iris region:

In order to identify the % of severity in the cornea, iris part should be segmented. Therefore this iris segmentation helps for more accurate calculation of the copper stored in the cornea.

3.1.6 Severity measurements:

In order to estimate the severity level of disease, a ocular parameter has been specified. The algorithm measures the extent of the Kayser-Fleischer ring by counting the number of pixels present in the affected eye image. Let N_k-f r, be the number of pixels belongs to the Kayser-Fleischer ring. In order to evaluate the % of the oxidized eye area, the region of the iris part is noted it. Let N_e be the number of pixels of iris region. In this way, it is possible to evaluate the extent of the Kayser-Fleischer ring by the equation:

$$\%p= N_k\text{-f } r/Ne \qquad (8)$$

Table 1 shows ratio of KF ring in iris(%) of the affected images. This measurement indicates that information on the % of the extent in the corneal region affected from the copper accumulation. The copper has an oxidized effect on the tissue region and it causes golden brown sign in the iris region. Thus by measuring the extension of oxidized process in the iris region, severity level can be detected and immediate treatment can be done, only if the presence of K-F ring is considered as the severe stage of Wilson disease.

Table 1: Ratio of KF ring in iris(%) of the affected images

Input image	Ratio of KF ring in iris (%)
1(a)	10
1(b)	59
1(c)	75
1(d)	98

1(a)

1(b)

1(c)

1(d)

3.2 WILSON DISEASE CLASSIFICATION

In this method, Wilson disease is identified and classified using SIFT, classification is done using KNN & Decision tree classifier in the following steps:

3.2.1 FEATURE EXTRACTON USING SIFT(SCALE-INVARIANT FEATURE TRANSFORM)

SIFT is an efficient algorithm used to identify and describe the local features in the given images. Relative positions between them in the original images should not change from one image to another image. SIFT identify and uses a larger number of features from the images, which reduces the possible outcome of the errors caused by these local variations in the average error of all feature matching errors. For any given object in an image, interesting points on the given object will be enlarged to provide a “feature description” of the given object.

This description extracted from a training datasets, then it can be used to detect the object when it needs to locate the object in a test image containing many other objects. To perform reliable recognition, it is noted that the features are extracted from the training image will be detectable even under the changes in image scale, noise and illumination. SIFT is an efficient algorithm for extracting constant features from the given images. The enlarged key points are robustic to the changes in scale, orientation, shear, position and illumination.

It contains four major steps

- Detection of scale-space Extrema.
- Key point localization.
- Orientation assignment.
- Key point descriptor.

3.2.1.1 Detection of Scale-space Extrema

Detection of Scale-space Extrema construct Gaussian scale space function from the input image. This is extracted by convolution of the original image with Gaussian functions of differing widths. The scale space will be characterised as a function $L(x, y, \sigma)$ that is produced from the convolution of a variable scale Gaussian, $G(x, y, \sigma)$ with an input image, $I(x, y)$:

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

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

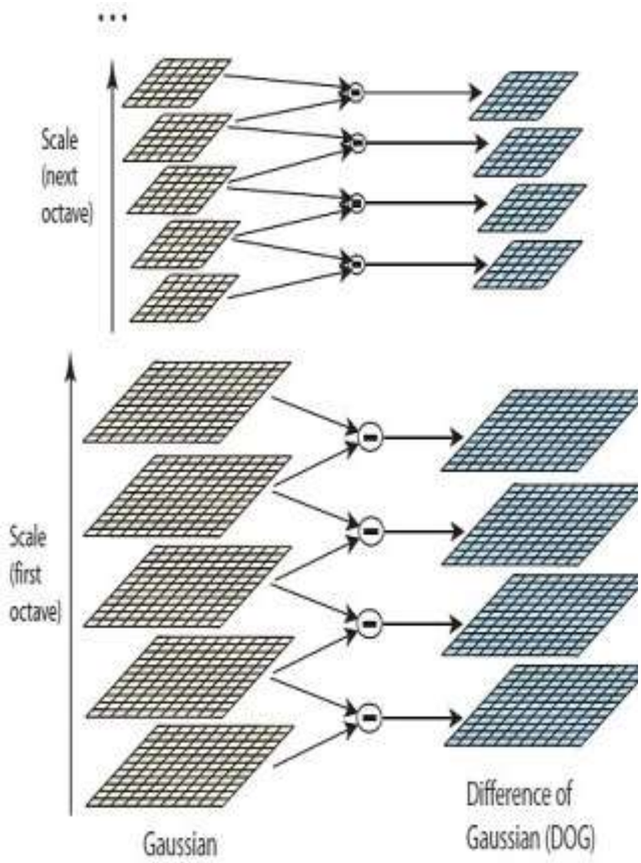
To efficiently identify stable key-points, difference of Gaussians will be calculated by simple image subtraction of two nearby scales denoted by a constant multiplicative factor k.

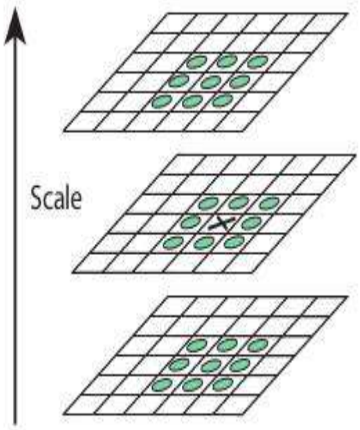
$$D(x, y, \sigma) = [G(x, y, k, \sigma) - G(x, y, \sigma)] * I(x, y)$$

$$= L(x, y, k, \sigma) - L(x, y, \sigma)$$

To find the local maxima and minima of $D(x, y, \sigma)$ of each pixel will be compared with its 8 neighbours at the same scale, and its 9 neighbours up and down one scale. If this value contains minimum or maximum of all these points, then this point is denoted as an Extrema. If the pixel value contains the maximum or minimum among all compared pixels, it is called as a candidate key point.

The identification and description of local image features can be used to help in object recognition purposes. The SIFT features are local and it is based on the appearance of the object at particular points and are different to image scale and rotation. They will also reliable changes in illumination, noise, and minor changes in the viewpoint. They are highly distinctive, relatively easy to enlarge and allow for correct object identification with low probability of mismatch.





3.2.1.2 Key point localization

Extraction of extreme points produces many different key points.

Interpolation of nearby data for accurate position

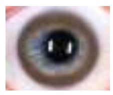
For each candidate key point, interpolation of nearby data is used to exactly determine its correct position. The initial approach was just locate each key point at the location stage and then scale of the candidate key point. The new approach will calculates the interpolated location of the extremum, which improves matching and stability. The interpolation is performed using the quadratic Taylor expansion of the Difference-of-Gaussian scale-space function, D(x,y,σ) with the candidate key point as the origin. This Taylor expansion is given by:

$$D(\mathbf{x}) = D + \frac{\partial D^T}{\partial \mathbf{x}}\mathbf{x} + \frac{1}{2}\mathbf{x}^T \frac{\partial^2 D}{\partial \mathbf{x}^2}\mathbf{x}$$

where D and its derivatives are evaluated at the candidate key point and X=(x,y,σ) is the offset from this point. The location of the extremum, $\hat{\mathbf{x}}$, is determined by taking the derivative of this function with respect to X and setting it to zero. If the offset $\hat{\mathbf{x}}$ is larger than 0.5 in any dimension, then that's an indication that the extremum lies closer to another candidate key point.

The following two kinds of points are eliminated namely

- ❑ Low-contrast key points
- ❑ Poorly localized edge key points



3.2.1.3 Orientation Assignment

The orientation assignment are used to identify the key points are invariant to rotation. The gradient magnitude m(x, y) and orientation Θ(x,y) is computed using

$m(x,y)=\sqrt{}(L(x+1,y)-L(x-1,y))^2+\sqrt{}(L(x,y+1)-L(x,y-1))^2$

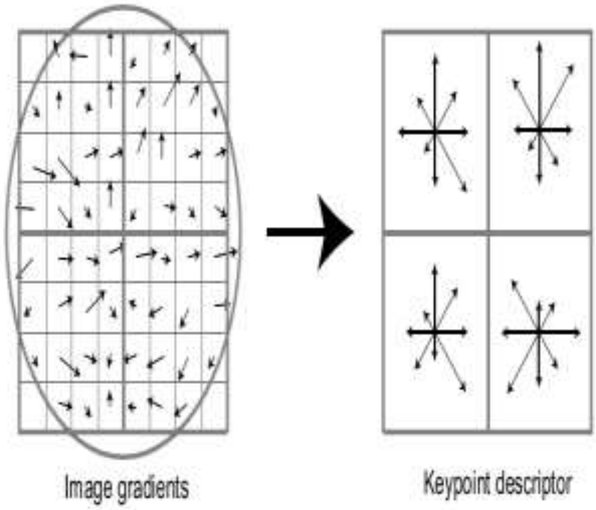
$\Theta(x,y)=\tan^{-1}\ (L(x,y+1)-L(x,y-1))\ /\ (L(x+1,y)-L(x-1,y))$

The magnitude and direction calculations for the gradient are performed for every pixel in a neighboring region around the key point in the Gaussian-blurred image L. An orientation histogram with 36 bins is formed, with each bin covering 10 degrees. Each sample in the neighboring window will be added to a histogram bin is weighted by its gradient magnitude and by a Gaussian-weighted circular window with a σ that is 1.5 times that of the scale of the key point. The peaks in this histogram correspond to dominant orientations. Once the histogram is filled, the orientations corresponding to the highest peak and local peaks that are within 80% of the highest peaks are assigned to the key point. In the case of multiple orientations being assigned, an additional key point is created having the same location and scale as the original key point for each additional orientation. Multiple orientations assigned to key points from an orientation histogram.

3.2.1.4 Key point descriptors

First a set of orientation histograms is created on 4x4 pixel neighborhoods with 8 bins each. These histograms are computed from magnitude and orientation values of samples in a 16 x 16 region around the key point such that each histogram contains samples from a 4 x 4 sub regions of the original neighborhood region. The magnitudes are further weighted by a Gaussian function with σ equal to one half the width of the descriptor window. The descriptor then becomes a vector of all the values of these histograms. Since there are 4 x 4 = 16 histograms each with 8 bins the vector has 128 elements. This vector is then normalized to unit length in order to enhance invariance to affine changes in illumination. To reduce the effects of non-linear illumination a threshold of 0.2 is applied and the vector is again normalized.

Longer descriptors continue to do better but not by much and there is an additional danger of increased sensitivity to distortion and occlusion. It is also shown that feature matching accuracy is above 50% for viewpoint changes of up to 50 degrees. Therefore SIFT descriptors are invariant to minor affine changes. To test the distinctiveness of the SIFT descriptors, matching accuracy is also measured against varying number of key points in the testing database, and it is shown that matching accuracy decreases only very slightly for very large database sizes, thus indicating that SIFT features are highly distinctive.



3.2.2 K-NEAREST NEIGHBOURS (K-NN) CLASSIFIER

The output depends on whether k-NN is used for classification or regression:

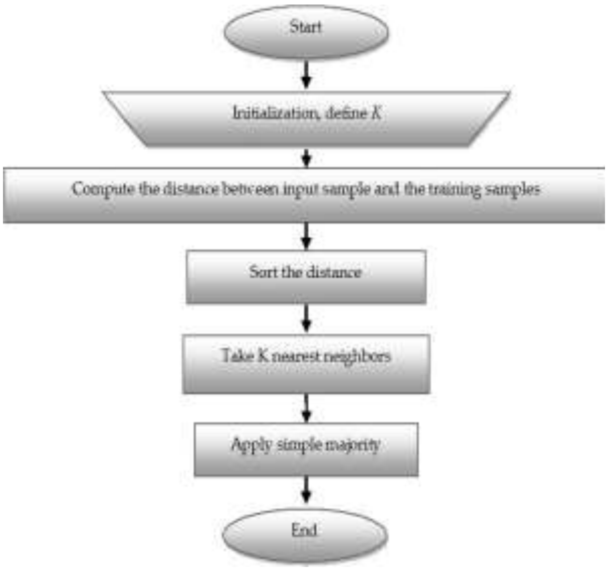
In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors. If k = 1, then the object is simply assigned to the class of that single nearest neighbor.

In k-NN regression, the output is the property value for the object. This value is the average of the values of its k nearest neighbors.

Both for classification and regression, it can be useful to assign weight to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of 1/*d*, where *d* is the distance to the neighbor.

The neighbors are taken from a set of objects for which the class (for *k*-NN classification) or the object property value (for *k*-NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required.

A shortcoming of the *k*-NN algorithm is that it is sensitive to the local structure of the data. The algorithm has nothing to do with and is not to be confused with *k*-means, another popular machine learning technique.

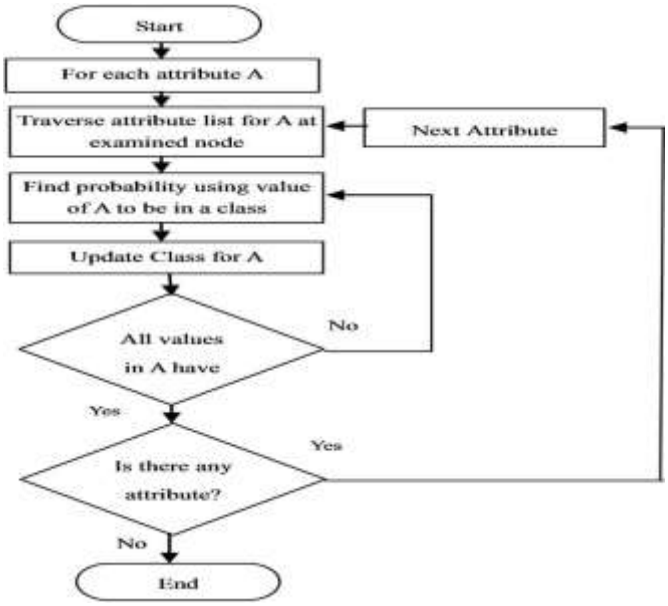


Parameter Selection- The best choice of *k* depends upon the data; generally, larger values of *k* reduce the effect of noise on the classification, but make boundaries between classes less distinct. The special case where the class is predicted to be the class of the closest training sample is called the nearest neighbor algorithm.

The accuracy of the *k*-NN algorithm can be severely degraded by the presence of noisy or irrelevant features, or if the feature scales are not consistent with their importance. Much research effort has been put into selecting or scaling features to improve classification. In binary classification problems, it is helpful to choose *k* to be an odd number as this avoids tied votes. One popular way of choosing the empirically optimal *k* in this setting is via bootstrap method.

3.2.3 DECISION TREE CLASSIFIER

Decision tree learning uses a decision tree as a predictive model which maps observations about an item to conclusions about the item's target value. Tree models where the target variable can take a finite set of values are called classification trees. In these tree structures, leaves represent class labels and branches represent conjunctions of features that lead to those class labels. Decision trees where the target variable can take continuous values are called regression trees.



In decision analysis, a decision tree can be used to visually and explicitly represent decisions and decision making. In data mining, a decision tree describes data but not decisions; rather the resulting classification tree can be an input for decision making. This page deals with decision trees in data mining.

Decision tree learning is a method commonly used in data mining. The goal is to create a model that predicts the value of a target variable based on several input variables. An example is shown below. Each interior node corresponds to one of the input variables; there are edges to children for each of the possible values of that input variable. Each leaf represents a value of the target variable given the values of the input variables represented by the path from the root to the leaf.

A decision tree is a simple representation for classifying examples. For this section, assume that all of the features have finite discrete domains, and there is a single target feature called the classification. Each element of the domain of the classification is called a class. A decision tree or a classification tree is a tree in which each internal (non-leaf) node is labeled with an input feature. The arcs coming from a node labeled with a feature are labeled with each of the possible values of the feature. Each leaf of the tree is labeled with a class or a probability distribution over the classes.

Data comes in records of the form:

$$(\mathbf{x}, Y) = (x_1, x_2, x_3, ..., x_k, Y)$$

The dependent variable, Y, is the target variable that we are trying to understand, classify or generalize. The vector x is composed of the input variables, x_1, x_2, x_3 etc., that are used for that task.

KNN and Decision tree train the given set of images. Two classes are assigned, class 1 contain normal images and class 2 contain affected images. KNN train 76 datasets contains in both class 1 and class 2.Performance measures will be calculated using accuracy, specificity, sensitivity. Both classifier shows the performance measures with the given of images.

IV.EXPERIMENTAL RESULT OF BIOMETRIC MEASUREMENTS AND FEATURE EXTRACTION

Experimental result of biometric measurements shows the severity level of Wilson disease. Fig 4.1 shows KF ring. Fig 4.2 shows JSEG process of Color quantization. Fig 4.3 shows Spatial segmentation. Fig 4.4 shows Region growing. Fig 4.5 shows Iris region.

Fig 4.1 KF ring

Fig 4.2 Color quantization

Fig 4.3 Spatial segmentation

Fig 4.4 Region growing

Fig 4.5Iris region

The database contains a collection of normal and affected images. KNN and Decision tree trains 76 images contains in both class 1 and class 2. The training has been performed for both normal database and affected database. KNN and Decision tree tests the images for calculating performance measures.

Table 2: Performance measures using KNN and Decision tree classifier

Performance measures	% KNN	Decision tree
Accuracy	94	92
Sensitivity	100	97
Specificity	90	87

V. CONCLUSION AND FUTURE WORK

In our system, the JSEG algorithm, identify the presence of Kayser– Fleischer ring in the eye, KF ring is the characteristic sign of Wilson disease. In an existing method, Medical tools was used, it shows human possible errors. Automated detection algorithm was proposed using image processing algorithm i.e JSEG segmentation. Through ocular measurements more information on the area extent of the cornea affected from the Kayser–Fleischer ring is considered and thus improved the knowledge on the serious level of the pathology in Wilson disease. The measurements is able to allow the technician to get more information about the effects of the copper deposition in the cornea. With the set of input image, feature extraction is performed using SIFT, it contains four major categories, it extract the n-number of possible key points in the given image. Those n-number of key points are useful to classify using KNN and Decision tree. It measures performance calculation using accuracy, specificity, sensitivity. In the classification, the final result would be the presence or absence of the Kayser-Fleischer ring, the presence of KF ring indicates the Wilson disease.

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