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Classification of Kidney Ultrasound Images Using SVM Classifier

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***Abstract*: Medical Imaging applications in hospitals and laboratories have shown benefits in visualizing patient's body for diagnosis and treatment of disease. Ultrasound is considered as safest medical imaging technique and is therefore used extensively in medical and healthcare using computer aided system. In this project, four stage detection of kidney disease is implemented. Feature extraction process is proposed using GLCM features. Finally obtained features are reduced to optimal subset using principal component analysis (PCA). The results show that GLCM in combination with PCA for feature reduction gives high classification accuracy when classifying images using Support Vector Machine (SVM). This project Evaluated by mat lab tool.**

***Index Terms:* Feature Extraction, GLCM, Image Acquisition, PCM, SVM.**

I. INTRODUCTION

Kidney stones are on rise throughout the globe and majority of individuals with concretion disease don't notice the disease because it damages the organs slowly before showing symptoms. Kidney could be a bean shaped organ and present on either side of the spine. the most function of kidney is to manage the balance of electrolytes within the blood. Formation of stones in kidneys is thanks to blockage of urine congenital anomalies, cysts. differing types of kidney stones namely struvite stones, stag horn stones and renal calculi stones were analysed. concretion may be a solid concretion or crystal formed in kidneys from dietary minerals in urine. so as to urge obviate this painful disorder the urinary calculus is diagnosed through CT images so removed through surgical processes like ending of stone into smaller pieces, which then passthrough tract. If the dimensions of the stone grow to a minimum of 3 millimetres, then they'll block the ureter. This causes lots of pain mostly within the back lower and it should radiate to groin. Classification of urinary stone is completed based upon their location within the kidney (nephrolithiasis), ureter (ureterolithiasis), or bladder (cystolithiasis), or by their chemical composition. The stone could even be present inside minor and major calyces of the kidney or within the ureter. In medical imaging modalities, computed axial tomography is used because it's low noise, when put next to other modalities and thus provide results with maximum accuracy. The kidney malfunctioning could also be life intimidating.

II. ALGORITHM

Algorithm
Step1: Initialize the dataset and load the dataset
Step2. Preprocessing of the images
Step3. Extraction of features using GLCM
Step4. Feature Selection using PCA
Step5. Applying SVM classification
Step6. Prediction of Kidney Disease
Step7. Evaluating the accuracy, sensitivity and specificity parameters
Step8. Stopping the process

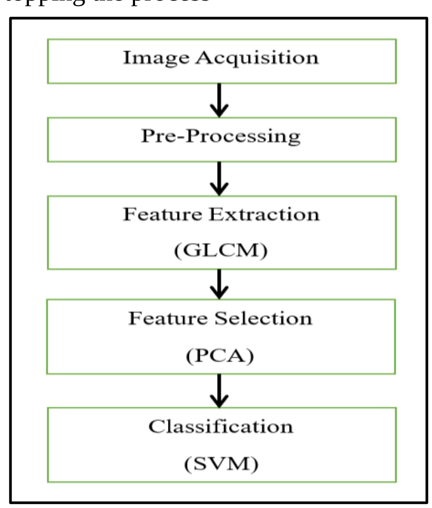


Fig1.Flow chart

III.PROPOSED METHODOLOGY

Support Vector Machine (SVM)

Support Vector Machine (SVM) is an algorithm that was developed for pattern classification but has recently been adapted for other uses, such as finding regression and distribution estimation. The data points are identified as being positive or negative, and the problem is to find a hyper-plane that separates the data points by a maximal margin. Support vector machine constructs a hyper plane or set of hyper planes in a high or infinite-dimensional space, which can be used for classification.

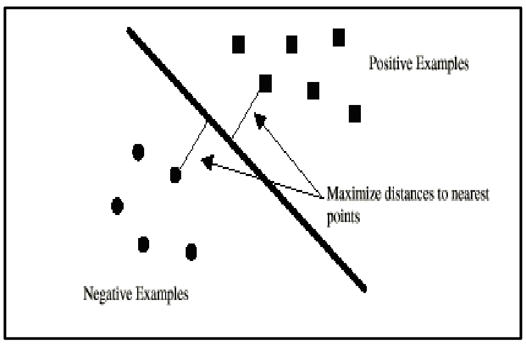


Fig 2. Support Vector Machine (SVM)

More formally, asupport vector machine constructs a hyper plane or set of hyper planes in a high or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyper plane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier. Whereas the original problem may be stated in a finite dimensional space, it often happens that the sets to discriminate are not linearly separable in that space. For this reason, it was proposed that the original finite-dimensional space be mapped into a much higher-dimensional space, presumably making the separation easier in that space. To keep the computational load reasonable, the mappings used by SVM schemes aredesigned to ensure that dot products may be computed easily in terms of the variables in the original space, by defining them in terms of a kernel function K(x,y) selected to suit the problem. The hyper planes in the higher-dimensional space are defined as the set of points whose dot product with a vector in that space is constant. The vectors defining the hyper planes can be chosen to be linear combinations with parameters α^i of images of feature vectorsx_i that occur in the data base. With this choice of a hyper plane, the points x in the feature space that are mapped into the hyper plane are defined by the relation.

$$\sum_i \alpha_i k(x_i, x) = \text{constant}$$

Note that if becomes small as grows further away from, each term in the sum measures the degree of closeness of the test point to the corresponding data base point. In this way, the sum of kernels above can be used to measure the relative nearness of each test point to the data points originating in one or the other of the sets to be discriminated. Note the fact that the set of points mapped into any hay a result, allowing much more complex discrimination between sets which are not convex at all in the original space.

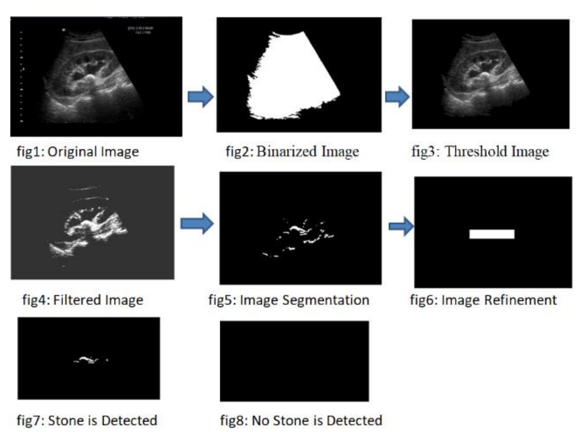
PARAMETRIC EVALUATION

- Sensitivity: $S_e = \frac{TP}{TP+FN}$ = (47/(47+3))*100 = 94%
- Specificity: $S_p = \frac{TN}{TN+FP}$ = (18/(18+2))*100 = 90%
- Accuracy: $A_c = \frac{TP+TN}{TP+TN+FP+FN}$ = ((47+18)/70)*100 = 92.85%
- Precision: $P_e = \frac{TP}{TP+FP}$ = (65/(65+1))*100 = 98.48%

TP- True Positive, FP- False Positive
TN- True Negative, FN-False Negative

V. RESULTS AND DISCUSSION

In this paper, Preprocessing of the images from figure 1 to figure 7. Extraction of features using GLCM and Feature Selection using PCA finally by applying SVM classification prediction of kidney disease and evaluating the accuracy, sensitivity and specificity parameters



IV.CONCLUSION

In this paper, an image analysis approach for extracting and selecting useful features is successfully performed. This approach consists of four parts: preprocessing, feature extraction, selection and classification. Preprocessing was used to find pixels of interest, to remove noise and background to achieve higher quality images. Thereafter, GLCM was applied to find out features and 44 features were found out. On analyzing features, it was found that cluster shade, cluster prominence, Sum of squares dominates over other features. Finally, feature selection was achieved using PCA algorithm and out of 44 features, 12 most useful features are selected. The proposed approach for feature selection is promising for classification. These selected features are used for classifying kidney ultrasound images using SVM in different categories: normal, kidney stone, cystic, kidney tumor etc.

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