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Hybrid Scale Invariant Texture Model For Accurate Mammography Clinical Measurements

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Abstract - *The Local Binary Pattern (Lbp) And Its Variants Have Been Widely Investigated In Many Image Processing And Computer Vision Applications Due To Their Robust Ability To Capture Local Image Structures And Their Computational Simplicity. The Existing Lbps Extract Local Structure Information By Establishing A Relationship Between The Central Pixel And Its Adjacent Pixels. However, Most Lbps Miss The Relationship Among All Of The Pixels In The Local Region. Therefore, This Paper Proposes A Novel Model To Establish This Relationship By Introducing A Support Lbp. The Proposed Model Improves The Performance Of The Existing Lbp Methods And Results In Lower Sensitivity To Illumination Changes And Radiometric Variations. Moreover, The Proposed Model Has Been Successfully Investigated In Breast Cancer Classification Applications: With The Standard Lbp Under Radiometric Variation Conditions. Moreover, The Proposed Model Produced Satisfactory Results As Compared With The Standard Lbp Under The Mias Dataset. For Texture Classification Applications, The Proposed Model Improves The Classification Results From 81% To 90% As Compared With The Completed Lbp.*

Keywords *- Completed Local Binary Pattern (Clbp), Local Binary Pattern (Lbp), Local Derivative Pattern (Ldp), Support Local Pattern.*

I. Introduction

Recent Developments In Information Technology Modernize Many Disciplines Of Health Care Especially Biomedicine. Sophisticated Methods Have Been Proposed To Automatically Extract, Useful Information From Radiology Images Leading To The Discovery Of New Knowledge. The Accuracy Of Any Diagnosis Method Using Medical Imaging Technologies Depends On The Quality Of Medical Images And Expertise Of Radiologist [1]. Computer Aided Diagnosis (Cad) Aims The Identification And Localization Of Abnormalities At An Early Stage, Which Prevents The Further Spread Of Abnormality With The Help Of Proper Clinical Management. The Work In This Dissertation Consists Of Two Phases, Phase 1- The Classification Of Mammogram And Placental Images, Phase 2- Their Retrieval.

These Two Phases Are Preceded By Preprocessing And Feature Extraction Methods. This Study Is A Novel Approach In Placental Grading And The Contributions In Digital Mammogram Analysis, Having Scope For Further Research. This Chapter Gives An Introduction Of The Problem Domain, Challenges, Motivation, Significance And Major Contributions Of The Work. Breast Cancer Is The Second Major Cause Of Cancer Death In Women [2]. It Affects The Health And Lives Of Millions And Millions Of Women World Over. In Recent Years We Notice A Rapid Growth In The Number Of Breast Cancer Patients In All Countries Irrespective Of Development.

Every Digital Image Is Composed Of Repeated Pattern Elements Called Texture. The Texture Patterns Are Used To Discriminate Between Different Segmented Regions Of An Image (Or Different Images) And Classify Them. There Are Different Methods For Representing And Analyzing Texture. Among Them The Following Three Are Most Widely Used. Lbp Is A Nonparametric Method That Extracts The Structure Of The Local Region Based On The Differences In Intensity Between The Central Pixel And Its Adjacent Pixels. Generally, We Can Classify The Lbp And Its Variants Into Five Main Categories: Multiscale Analysis, Handling Rotation, Handling Color, Complementary Descriptors, And Feature Selection And Learning, As In [3].

Texture Classification Has Been One Of The Most Popular And Successful Applications That Has Used Lbp During The Past Few Years. Texture Classification Is An Application That Is Used To Assign An Unknown Texture To The Set Of Predefined Textures. The Assignment Process Can Be Based On The Training Of Images.

II. Mammography

Mammography Allows Intervention At An Early Stage Of Cancer Progression. Early Detection Of Lesions Using Mammogram Reduces Disease Specific Mortality. Mammogram Findings Vary Depending On The Physical, Mechanical And Biological Characteristics Of Tissue Under Examination.

III. Statistical Moments

We May Use Different Statistical Moments To Describe The Texture Of A Digital Image. Like
(I) Mean Gray Level Intensity Of A Region,
(Ii) Variance Of Intensities Of A Region,
(Iii)Skewness, Which Described How Much Symmetric The Intensity Distribution Is About The Mean,
(Iv) Kurtosis, Which Describes How Flat The Intensity Distribution Is. Another Statistical Way To Describe Texture Is Construction Of Gray Level Co-Occurrence Matrix.

It Is Done By Statistically Sampling The Way Certain Gray-Levels Occur In Relation To Other Grey-Levels. For A Position Operator P, We Can Define A Matrix Pij That Counts The Number Of Times A Pixel With Grey-Level I Occurs At Position P From A Pixel With Grey-Level J. If We Normalize The Matrix P By The Total Number Of Pixels So That Each Element Is Between 0 And 1, We Get A Gray-Level Co-Occurrence Matrix C.

Researchers Define The Co-Occurrence Matrix In Two Ways: (I) By Defining The Relationship Operator P By An Angle Θ And Distance D, (Ii) By Ignoring The Direction Of The Position Operator And Considering Only The (Bidirectional) Relative Relationship.

P Left=P Right, P Horizontal= P Left+ P Right.
Iii.Local Binary Pattern

Local Binary Patterns (Lbp) Feature Is Used For Feature Extraction Of Digital Images In Computer Vision. Lbp Was First Described In 1994 By Timo Ojala [4, 5]. The General Idea Behind Lbp Feature Vector Calculation Is Done Using The Following Steps:-

- Divide The Examined Window Into No Of Cells.
- For Every Pixel Of A Cell, Following The Pixels Along A Circle, I.E. Clockwise Or Counter-Clockwise, With Radius R, Compare The Pixel To Each Of Its P Neighbors If The Center Pixel's Value Is Greater Than The Neighbor, Write "1". Otherwise, Write "0".
- This Gives A P-Digit Binary Number.
- Compute The Histogram, Over The Cell, Of The Frequency Of Each Such P-Digit Binary Number.
- Normalize The Histogram (Optional).
- Concatenate The (Normalized) Histograms Of All Cells. This Gives The Feature Vector For The Whole Image.
-

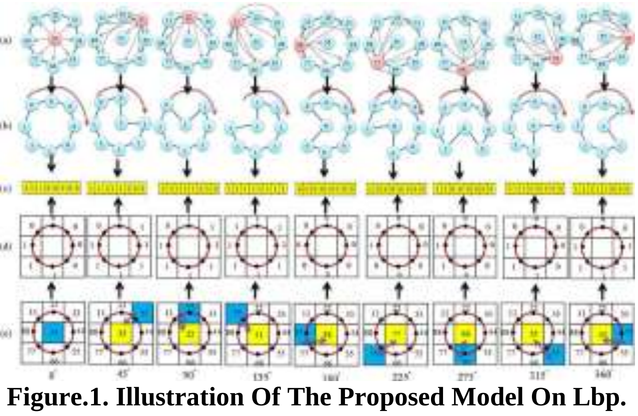

Figure.1. Illustration Of The Proposed Model On Lbp.

The Feature Vector Now Can Be Processed Using Some Machine-Learning Algorithm, To Produce A Classifier.

IV. .Distortion Analysis

The Images Can Be Distorted In Embedding Process Because Of Changing Pixel Bits.
Distortion Is Measured By Means Of Two Parameters Namely, Mean Square Error (Mse) And Peak Signal To Noise Ratio (Psnr).
Mse Can Be Calculated By

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(X_{ij} - Y_{ij})^2$$

The Psnr Is Calculated Using

$$PSNR = 10\log_{10}\left\{\frac{I^2{}_{\max}}{MSE}\right\}dB$$

Imax Is The Maximum Intensity Value Of Each Pixel Which Is Equal To 255 For 8 Bit Gray Scale Images. Higher Value Of Psnr Leads To Better Image Quality. Results Of Steganography For Lena And Baboon Digital Images Is Represented In Figures 8 And 9 Respectively And Full Embedding Capacity Is Considered For M=1 To 4.

The Size Of These Images Is 256*256 Pixels. As Shown Here, Message Embedding Is Done With No Dramatic Changes In Image Quality.

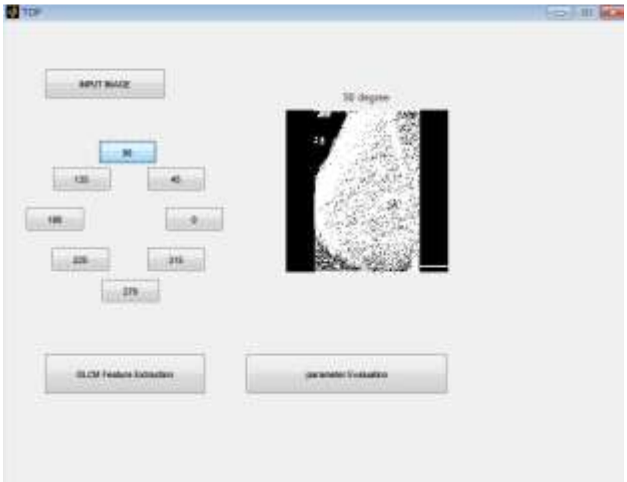

Figure 2 Orientation Lbp Pattern

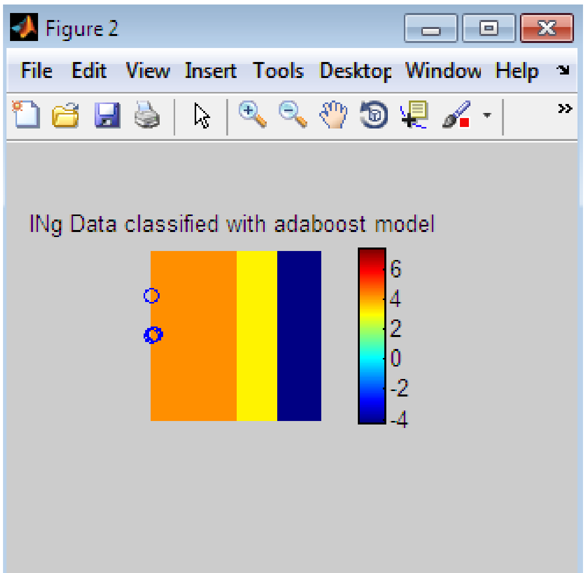

Figure 3 Classification Output

V. Conclusion

Here In This Paper We Proposed Set Of Texture Extraction Methods To Get More Discriminative Information In Various Directions To Improve The Segmentation Accuracy. The Local Binary Pattern (Lbp) And Its Variants Is Investigated For Automatic Segmentation Due To Their Computational Simplicity. Mri Brain Image Is Detected For Normal And Abnormal Condition By Using Texture Classification Measures.

This System Shows 90% Efficiency By Testing 20 Images By An Adaboost Classifiers For Detecting Abnormality.

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