**CAD system for Benign Focal Liver Lesions using GLCM Descriptors and SVM Classifier**

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**Abstract**

Early and accurate differential diagnosis between primary benign liver lesions (PBLLs) i.e. Hemangioma (HEM) and Focal Nodular Hyperplasia (FNH) is clinically significant as prognosis is different with the aggression of these lesions of the liver. This study proposes a CAD system design to classify PBLLs using 44 ultrasound images consisting of 20 HEM and 24 FNH images. The image dataset is augmented using geometric transformation i.e. rotation by 25º and 50º to yield 81 images consisting of 36 HEM and 45 FNH images. The images have been augmented to increase the dataset size for training and also for designing a robust classifier exhibiting rotation invariance. The non overlapping ROIs of size 32 × 32 pixels are extracted from inside of each lesion i.e. IROIs and one outside lesion ROI i.e. OROI for each lesion. The three types of texture feature vectors were extracted which are (1) Absolute Texture Feature Vector i.e. ATFV- Absolute features extracted from IROIs, (2) Ratio Texture Feature Vector i.e. RTFV- Ratio of Features extracted from IROIs and corresponding OROI, (3) Combined Texture feature Vector i.e. CTFV- concatenation of ATFV and RTFV. Thirteen second order statistics based GLCM-mean features computed at *d* =3 have been extracted to yield ATFV and RTFV of length (*l*= 13) and CTFV of length (*l*= 26). The support vector machine classifier has been used for classification tasks. The best C and best γ hyper-parameters of SVM classifier have been obtained using grid-search procedure. The ATFV, RTFV and CTFV yielded the classification accuracy (CA) values of 80.0 %, 80.0 % and 85 % respectively. The CTFV yielded the highest CA of 85.0 % indicating the role of textural characteristics of background liver for differential diagnosis of PBLLs.

**Keywords:** Liver lesions, Hemangioma, Focal Nodular Hyperplasia, Ultrasound Images, GLCM Features, Support Vector Machine Classifier.

**1. INTRODUCTION**

The liver is the most important tissue in the human body, performing over 500 vital functions. It stores vitamins and carbohydrates, produces bile (a digestive fluid), and cleanses poisons from the blood. Remarkably, the liver also has the ability to repair itself, underscoring its critical role as a vital organ. As the largest gland, the liver weighs between 1.1 and 1.6 kilograms and features a triangular shape with a pinkish-brown color in its normal state. It is soft in nature and consists of four lobes. Anatomically, the liver is located in the right upper quadrant of the abdominal cavity, just below the diaphragm, to the right of the stomach, and overlying the gallbladder. Its vascular structure includes hepatic arteries and portal veins. Liver diseases are categorized into two main types: diffused liver diseases and focal liver diseases. The diffused liver disease affect the entire liver, such as chronic active hepatitis, fatty liver, and cirrhosis; and focal liver diseases or Focal liver lesions, basically refers to the relative surrounding tissue which is damaged.

As ultrasound (US) or sonography is the first investigation for diagnosis of FLLs mainly due to its non-invasive nature while using high frequency sound waves to diagnose organ disease and guide the medical procedures. Focal Liver Lesions, can be benign or malignant. The benign lesions are non-cancerous whereas malignant lesions are cancerous in nature. Some of the most common benign FLLs include Hemangioma (HEM), the most prevalent type and focal nodal hyperplasia (FNH), the second most common.

Generally, the ultrasound examination of FLLs leads to observation of 4 types of echogenicity patterns which are hyperechoic, hypoechoic, isoechoic and anechoic. Hyperechoic lesions exhibit increased echogenicity, appearing brighter than the surrounding liver tissue.Isoechoic lesions demonstrate iso-echogenicity, which means they have the same echogenicity as the surrounding liver parenchyma.Hypoechoic lesions show decreased echogenicity, appearing darker than the surrounding liver tissue. Anechoic lesions are completely anechoic, which means they produce no echoes and appear black on ultrasound imaging.

Moreover, focal liver lesions can appear as a well circumscribed lesion in ultrasound appearance in general cases. However, these lesions may also lack these defining characteristics and may appear variable or poorly defined in some cases, requiring further evaluation with other imaging or biopsy for confirmation.

HEM, appears as bright, solid masses (hyperechoic) with clear, sharp borders (sharply defined). The brightness is due to red blood cells in the tumor's vessels reflecting sound waves. In general, liver hemangioma is smaller than 5 cm and has a round or oval shape.

FNH lesions in general features a central scar with a well-defined hyperechoic area and peripheral displacement of vessels, though the central scar is not always present. A large central artery is usually present with spoke wheel like centrifugal flow and portal veins are absent.

**1.1 A brief of Studies carried out on FNH and HEM classifications**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Authors (year)** | **Description** | | | | | |
| **Classes** | **Images per class** | **Total Images** | **No. Of ROIs** | **ROI Size** | **Classifier Used** |
| Virmani1 , et al.  (2013) | NOR  CYST  HEM  HCC  MET | NOR - 21  CYST - 12  HEM - 15  HCC - 28  MET - 32 | 108 | 491 (SROIs - 111, IROIs - 380) | 32x32 | KNN  PNN  BPNN |
| Virmani2, et al.  (2013) | CYST  HEM  MET HCC  NOR | CYST-12  HEM - 15  MET - 32  HCC - 28  NOR - 21 | 108 | 491  (IROIs: 380,  SROIs: 111) | - | PCA-SVM |
| Manth3, et al.  (2016) | HEM  HCC | HEM - 16  HCC - 28 | 44 | 204  (IROIs: 160, SROIs: 44) | 32x32 | SVM  SSVM |
| Virmani4, et al.  (2013) | CYST  HEM  MET  HCC  NOR | CYST - 12  HEM - 15  MET - 32  HCC - 28  NOR - 21 | 108 | 491  (IROIs: 380,  SROIs: 111) | 32×32 | PCA-NN  ( Ensemble of  neural  networks) |
| Virmani5, et al.  (2013) | NOR  CIRR | NOR – 15  CIRR – 16 | 31 | 120  (NOR -60,  CIRR - 60) | 32x32 | SVM |
| Bansal6, et al.  (2019) | HCC – Small and Large  MET – Typical and Atypical | HCC: 27  13 small  & 14 large  MET : 24  12 Typical &  15 Atypical | 51 | 174  (SLROIs: 54 , WLROIs: 120) | 32×32 | SVM |
| Virmani7, et al.  (2014) | NOR  CIRR  HCC | Normal–15  cirrhotic-16  HCC – 25 | 56 | 180  (60 normal,  60 cirrhotic,  60 HCC) | 32×32 | SVM |
| Xu SS-D8, et al.  (2019) | HCC  Liver abscess | HCC - 44  Liver abscess - 35 | 79 | 800  (400 HCC,  400 liver abscess) | 32x32 | SVM |
| Balasubramanian9, et al.  (2007) | NOR  CYST  BENIGN  MALIGNANT | - | - | 200  (40 from each category) | 10x10 | BPN  K means classifier |
| Bharti10, et al.  (2018) | NOR  CHRONIC  CIRRHOSIS  HCC | NOR - 48  CHRONIC - 50  CIRRHOSIS-50  HCC – 41 | 189 | 754  (192 Normal, 200 Chronic, 200 Cirrhosis, 162 HCC) | 32x32 | SVM  K-NN  RF K-NN |
| Hwang11, et al.  (2015) | CYST  HEM  MALIGNANCIES | CYST - 29  HEM -37  MALIGNANCIES -33 | 99 | - | 52x52 | FFNN |
| Aborisade12, et al.  (2014) | NOR  PLCC  HCC | NOR- 18  PLCC - 42  HCC - 30 | 90 | - | - | K-NN  Bayes classifier  SVM |
| Poonguzhali13, et al.  (2007) | NOR  CYST  Benign  Malignant | - | - | 180  (45 from each type) | 10x10 | Neural Network |
| Suganya14, et al.  (2012) | CYST  Hepatoma  Cavernous hemangioma  Normal | 40 CYST , 37 Hepatoma , 13 Cavernous hemangioma, 30 Normal) | 120 | 80  For each kind of pattern | 23x23 | Kohonen SOM classifier |
| Suganya15, et al.  (2013) | Normal  fatty  CYST  Cirrhosis | Normal – 40 fatty – 40 CYST – 40 Cirrhosis – 40 | 160 | - | PBR  (100x100) | SVM |
| Sujana16, et al.  (1996) | Normal  Hemangioma Malignancy | Normal-40  Hemangioma-15 Malignancy-30 | 85 | - | 100-pixel block | Neural network  LDA , BPNN |
| Hassan17, et al.  (2015) | CYST  HEM  HCC | - | 110 | - | - | Multi - SVM |
| Manth18, et al.  (2019) | HEM  HCC  MET | HEM-16  HCC-28  MET-32 | 76 | IROIs: 255, SROIs: 76 | 32 x 32 | SSVM |
| Sakr19, et al.  (2014) | CYST  HEM  HCC  Normal | - | 94 | - | - | Multi-SVM using k-fold Cross Validation |
| Mittal20, et al.  (2011) | Normal  CYST  HCC  HEM  MET | Normal-16  CYST- 17  HCC- 15  HEM- 18  MET-45 | 111 | 800 SROIs | 25×25 | NN |
| Yoshida21, et al.  (2003) | HEM  HCC  MET | HEM-17  HCC- 11  MET- 16 | 44 | 193 ROIs  (50 HEM, 87 HCC, 56 MET) | 64x64 | ANN |
| Poonguzhali22, et al.  (2007) | NOR  CYST  BENIGN MASSES  MALIGNANT MASSES | - | - | - | 10x10 | K means Clustering |
| Minhas23, et al.  (2012) | Fatty  Normal  Heterogeneous | FLD-30  Normal-39  Heterogeneous-19 | 88 | 88 | 64x64 | SVM |
| Jeon24, et al.  (2013) | CYST  HEM  Malignancies | CYST-50  HEM-50  Malignancies-50 | 150 | 150  One lesion from each image | - | SVM |
| Manth25, et al.  (2016) | HEM  HCC | HEM-16  HCC-28 | 44 | 204 (160 IROIs and 44 SROIs) | 32x32 | SSVM |
| Virmani26, et al.  (2011) | NOR  CIRR | NOR-22  CIRR-12 | 34 | 121 SROIs  (82 NOR, 39 CIRR) | 40x40 | NN  SVM |
| Virmani27, et al.  (2013) | NOR  CYST  HEM  HCC  MET | NOR-21  CYST-12  HEM-15  HCC-28  MET- 32 | 108 | 491  (SROIs: 111, IROIs: 380) | 32x32 | PCA-SVM |
| Mittal28, et al.  (2011) | CYST  HCC  Hemangioma  Metastases  Normal | CYST-17  HCC- 15  Hemangioma-18  Metastases-45 Normal-16 | 111 | 800 SROIs | 25x25 | 5-class NN  Binary NN |
| Schmauch B29, et al.  (2019) | Homogeneous liver  Angioma  Metastasis  HCC  CYST  FNH | Homogeneous liver - 258  Angioma - 17  Metastasis - 48  HCC - 6  CYST - 30  FNH - 8 | 367 | - | - | Deep Learning  (ResNet) |
| Schmiedt30  , et al.  (2022) | HCC  HEM  FNH | HCC - 186 HEM - 112  FNH - 60 | 358 | - | - | CNN  RNN |
| 1. Kondo31, et al.   (2017) | HEM  FNH  HCC  MET | HEM - 22  FNH – 5  HCC - 35  MET - 32 | 94 | - | - | SVM |
| Q. Huang32 *et al*.,  (2020) | FNH  HCC | Set 1  FNH - 155  HCC - 49  Set 2  FNH - 102  HCC - 36 | 342 | - | 100x100 | SVM |
| Zhou33 et al.  (2022) | FNH  HCC | FNH - 101  HCC - 85 | 186 | - | 100x100  32x32 | KNN  SVM  MLP |
| Sîrbu34 et al.  (2020) | FNH  HCC  HEM  HYPERM  HYPOM | FNH - 17  HCC - 33  HEM - 23  HYPERM - 11  HYPOM - 11 | 95 | - | - | CNN |
| Gatos35 et al.  (2015) | FNH  HEM  HCC  MET | FNH - 13  HEM - 17  HCC - 16  MET – 6 | 52 | - | - | SVM |
| Yadav36 et al.  (2022) | Benign  Malignant | BENIGN – 30  MALIGNANT – 30 | 60 | - | - | PNN  KNN  SVM |
| Virmani37 et al.  (2022) | Primary and Secondary Malignant | - | - | - | - | PNN |
| 1. B. Subramanya38 et al.(2019) | Fatty  CIRR | Fatty – 13  CIRR – 16 | 29 | 60  LROIs for both | 32x32 | KNN – DEFS |

**1.2 Sonographic Appearances of HEM**

The most common type of benign liver tumor, Hemangioma is also known by the name Hematoma. It can be present in any part of the body but it is commonly present in the liver itself. It is mainly due to presence of excessive normal tissue in an abnormal area/region of the body. It is generally detected incidentally. Most of them cause no symptoms and requires no treatment.

Generally, in most cases HEMs are well circumscribed and uniformly hyper echoic lesions. In 70% of cases the sonographic appearance is typical**.** The sample images of HEM are shown in Fig 1.

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| Sonographic appearance HEM.png |
| **Fig 1:** Sample images of HEM from ultrasoundcases.info [2] (a),large HCC ultrasoundcases.info ultrasoundcases.info ()()()(a) contains 2 lesions (b) and (c) contains Solitary Lesions. |

**1.3 Sonographic Appearances of FNH**

FNH is the second most common benign liver tumor. Ordinarily it has a scar at the center which identifies it as a Benign FNH lesion. It has no potential to become cancerous. Its size is less than 5 cm and it is present in about less than a percent (<1%) of population. It does not have significant symptoms to detect, rather it is detected incidentally. It is generally diagnosed through scans. Generally they do not require any treatment. The sample images of FNH are shown in Fig 2.

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| **Sonographic appearance FNH.png** |
| **Fig 2:** Sample images of FNH from ultrasoundcases.info. [2] (a), (b) and (c) contains Solitary Lesions. |

Hence, an effective CAD system for characterizing FLLs using ultrasound is highly sought after.

**1.4 Limitations of US images**

For differential diagnosis between solid FLLs like FNH and HEM radiologists don’t rely on US examinations alone because of varying overlapping sonographic appearances between them. Therefore, in order to assure the diagnosis, radiologists resort to the administration of contrast agents, additional imaging procedures like CT, MRI etc. that are costlier and time consuming, or some invasive procedures such as a biopsy. Moreover, US is particularly effective in distinguishing between CYSTic and solid FLL while CT and MRI excel in providing sensitivity for differential diagnosis among solid FLLs. Hence, US may not be as sensitive or specific in distinguishing between solid FLLs like FNH and HEM. [6]

**1.5 Comparative Benefits of Liver Ultrasound Imaging**

Ultrasound is considered as first examination for the characterization of focal liver lesions because it is (a) Non-ionizing, non-invasive and inexpensive in nature. It has (b) Real time imaging capabilities. [6]

In comparison contrast-enhanced US (CEUS), contrast-enhanced computed tomography and magnetic resonance imaging (MRI) offer higher sensitivity for characterization of focal liver lesions but at the same time these modalities are expensive and they impose greater operational inconvenience, even they are not widely available. [6]

**1.6 Motivation**

The literature review reveals a significant gap in studies focusing on classifying benign liver lesions, specifically FNH and HEM. This study aims to address this gap by developing and evaluating a CAD system for accurately differentiating between FNH and HEM using ultrasound images, thereby enhancing clinical decision-making by radiologists.

The selection of FNH-HEM binary classification using ultrasound images addresses key clinical needs due to the commonality and overlapping sonographic features of these benign liver lesions. B-mode ultrasound's limitations, such as reduced sensitivity for small or isoechoic lesions and challenges in distinguishing between FNH and HEM limits the necessity for an enhanced diagnostic approach.[7] While advanced imaging techniques like CT and MRI offer greater sensitivity, they are pretty expensive and less accessible.[6]

A reliable CAD system based on ultrasound could offer a non-invasive and cost-effective alternative for differential diagnosis. It can enhance diagnostic accuracy, reduce the need for more invasive and costly procedures and ultimately improve patient outcomes. Additionally, it aims to reduce misclassification during the diagnostic process while simultaneously acting as a second opinion to radiologists so that they can accurately characterize liver disorders and verify their diagnoses.[6]

**2. MATERIALS & METHODS**

**2.1 Materials**

*2.1.1 Data Description*

A total of 44 images were collected from a publicly available source. Each image is of 300×255 pixels in size and displayed in grayscale with 256 tones. The display system used for viewing these images could show the full acquisition matrix, allowing a 1:1 match of image pixels to display pixels.

The description of the collected publicly available dataset is shown in Fig.3, which consists of 44 ultrasound images. It illustrates (1) the distribution of these images between FNH and HEM and (2) the distribution of the total ROIs extracted from the dataset, further categorized into SROIs and IROIs is shown in Fig.6.

**Source:** https://www.ultrasoundcases.info/cases/abdomen-and-retroperitoneum/liver/[40]

*2.1.2 Data Collection Protocols*

The following protocols were followed for data collection: (1) the sonographic appearance and characteristics of two benign classes i.e. FNH and HEM were studied from different Medical Imaging journals, articles and researches published so far, (2) the image containing only single type of lesion of a class were considered only. The dataset distribution considered is shown in Fig 3.

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| **Fig 3:**Dataset distribution |

**2.2 Data Augmentation**

Data augmentation is required to increase the diversity of the training dataset, which helps in improving the robustness and generalization of the machine learning model. By applying geometric transformations like rotations, the model can better handle variations caused due to sudden movement by the patient and reduce over-fitting of the model over the dataset, leading to more accurate and reliable performance on unseen data.

The Sample images obtained in Training Data were augmented using Geometric transformation (Rotation). Each individual image is rotated at certain angles. In both of the cases HEM images and FNH images were rotated at the angles 25º and 50º.

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| Augmentation.png |
| **Fig 4:** Sample images of HEM & FNH after Augmentation. (a) HEM image, (b) HEM image rotated at 25º and (c) HEM image rotated at 50º, (d) FNH Image, (e) FNH image rotated at 25º and (f) FNH image rotated at 50º. |

* 1. **Selection of ROIs**

*2.3.1 Protocol for ROIs – IROIs & SROIs selection.*

The following protocols were followed for cropping ROIs from the image database:

(1) ROIs were cropped using Python software. The algorithm loaded the image, defined a 32x32 pixel square ROI (1,024 pixels in total), moved the ROI pointer to desired locations, and cropped the ROIs simultaneously after fixing positions of all ROIs for a particular image.

(2) Two types of ROIs were used, inside ROIs (IROIs) and surrounding ROIs (SROIs). For each lesion class, maximum non-overlapping IROIs were cropped from regions within the lesion boundary excluding the boundary itself and avoiding necrotic areas. While SROIs were extracted from the surrounding area of the lesion also avoiding the necrotic tissues.

(3) For each IROI in a lesion, a corresponding SROI was cropped from the surrounding liver tissue, avoiding in-homogeneous structures like liver ducts, portal veins and blood vessels.

The sample images for HEM and FNH cases from the acquired image database with marked IROIs and SROIs are shown in Fig.5

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| **ROI extraction.png** |
| **Fig 5:** Sample images with Marked ROIs. (a),(b) and (c) contains marked IROIs and SROI of HEM and (d),(e) and (f) contains marked IROIs and SROI of FNH. |

The Data set description and Training-Testing Data Spilt is shown in Fig 6.

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| **Fig 6:** Dataset Description and Train-Test Data Split. |

To avoid any biased results, the ROIs from one image set are used for training and the ROIs from the other image set are used for testing.

*2.3.2 Selection of ROI size*

The size of the ROI is a consideration while creating a CAD system. A ROI size of 23×23 was used by Suganya et al.[14],10×10 pixels was used by Sujana et al. [16],Poonguzhali et al. [13] while 25×25 pixels used by Mittal et al. [20] to computed texture characteristics. Virmani et al. [1,2,4,5,7] employed a 32×32 pixel ROI size. It is important to note that,

23×23,10×10, or even 25×25 pixels gives smaller number of pixels, while to estimate acceptable statistics minimum 800 pixels are required while deciding the size of the ROI. It is possible that Yoshida et al. [21] utilized high-resolution scanned photos rather than actual US images, which is why 64 by 64 pixels was chosen as the ROI size in their study.

Moreover, keeping in note of the lesions present in current database used for this study, choosing a large ROI size would be challenging given the size of lesions is quite small. To abide by the ROI selection protocol specified in section 2.3.1, in order to extract maximal number of non-overlapping ROIs, avoiding inclusion of lesion-boundary pixels, the ROI size of 32×32 pixels was deemed adequate for this investigation.

**2.4 Methodology**

* + 1. *Proposed CAD system*

For implementation of proposed SVM classifier based CAD system, the image database containing 44 images was collected from publicly available source [2].The SVM classifier based CAD system consists of feature extraction module.

The feature extraction module consists of 13 GLCM-Mean features calculated from extracted ROIs (IROIs and SROIs) extracted from 44 US images of the size 32x32 containing 1,024 pixels in total. The texture features calculated in feature extraction module are divided into 3 sub-categories: for IROI, for Ratio (IROI/SROI) which are texture features calculated based on SROI, and lastly concatenated features (IROI+Ratio) features.

The proposed CAD system incorporates classification module in single step, when the SVM classifier is presented with the input feature vector it gives result as two class classification of HEM and FNH. Further, post-classification of classes, the overall prediction accuracy and ICA (individual class accuracy) of each class was also calculated using the Confusion Matrix.

The block diagram of proposed SVM based CAD system for classification of FLLs from US images is shown in Fig. 7.

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| CAD System.png |
| **Fig.7:** Experimental workflow of CAD system design |

2.3.2 *Methodology*

The sequential process for assessing the accuracy of the proposed SVM CAD system involves several steps. Initially, the dataset, consisting of 44 ultrasound images, was categorized into two types of liver lesions: 20 images of HEM and 24 images of FNH. These images were then split into training and testing sets, with 27 images used for training (12 HEM and 15 FNH) and 17 images for testing (8 HEM and 9 FNH). Following this, a total of 372 Regions of Interest (ROIs) were extracted from the 44 images. These ROIs were divided into 295 training ROIs and 77 testing ROIs. Specifically, the training set included 109 inside ROIs (IROIs) and 36 surrounding ROIs (SROIs) for HEM (total 145 ROIs) and 105 IROIs and 45 SROIs for FNH (total 150 ROIs). The testing set comprised 30 IROIs and 8 SROIs for HEM (total 38 ROIs) and 30 IROIs and 9 SROIs for FNH (total 39 ROIs).

For the Feature extraction,13 texture features were extracted from these ROIs using the Gray-Level Co-occurrence Matrix (GLCM) method. The GLCM values were calculated using the GLCM-Mean methodology over inter-pixel distance d ranging from 1 to 4 value, resulting in two initial feature vectors: the IROI Feature Vector (IROIFV) for IROIs and the SROI Feature Vector (SROIFV) for SROIs. After calculating these features, a Ratio Feature Vector (RFV) was created by dividing each feature value in the IROIFV by the corresponding value in the SROIFV. Additionally, a Concatenated Feature Vector (CFV) was formed by combining the IROIFV and RFV.

These three feature vectors IROIFV, RFV, and CFV were then used as inputs for the Support Vector Machine (SVM) classifier. The SVM classifier was employed to classify the images into HEM and FNH categories and to evaluate the accuracy of the classification.

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| **Fig 8:** Methodology adopted |

**3. FEATURE EXTRACTION**

Overall, texture feature extraction into three broad methods: statistical methods, spectral methods, and spatial filtering based methods, with further subdivisions tailored to each specific technique used within these categories.

1. **Statistical Methods:** These methods involve using statistical properties to describe texture features. The subcategories under statistical methods are:

(a) First Order Statistics (FOS): These are based on the statistics calculated directly from the

Pixel intensity values of an image. **E.g.** Mean pixel intensity of Image.

(b) Second Order Statistics (SOS): These involve pair wise statistics and focus on how certain combinations of pixel intensity values occur. **E.g.** Gray Level Co-occurrence Matrix (GLCM).

(c) Higher Order Statistics (HOS): These involve statistics beyond second-order,often describing more complex textures through the lengths of consecutive runs of pixels having the same intensity value. **E.g.** Gray Level Run Length Matrix (GLRLM).

2. **Spectral Methods:** These methods use transformations and analysis in the frequency domain to extract texture features. The subcategories under spectral methods are:

(a) Fourier Power Spectrum (FPS): This technique uses the Fourier transform to analyze the frequency components of the image.

(b) Gabor Features: These involve using Gabor filters, which are band-pass filters that capture both spatial and frequency information, making them useful for texture analysis.

3. **Spatial Filtering Based Methods:** These methods involve the application of spatial filters to extract texture features. The subcategories under spatial filtering based methods are:

(a) LAWS' Texture Energy Measure (TEM): This technique involves using a set of

Convolution masks defined by Laws to measure texture energy through local spatial filtering.

For the current study for binary, we used GLCM technique of Second Order Statistics (SOS) category for extracting features.

Texture features extraction methods can be classified as shown in Fig 8.

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| **Fig 9:** Broad classification of texture features. |

**3.1 GLCM: Gray-level Co-occurrence matrix**

The most widely used Second order statistical method for texture analysis. An image is made up of pixels with a specific gray level (intensity). GLCM is a tabulation of how often different combinations of gray levels occur in an image or section of an image. It is also referred as co-occurrence distribution. It can be calculated at any angle and any offset. For example, we can consider. In total 8 angles which are [0, 45, 90, 135, 180, 225, 270, and 315]

as shown in Fig.9 for understanding the GLCM calculation. While calculating GLCM find number of Co-occurrence of pixel i to neighboring pixel j, at certain Angles and Distance as shown in fig 10. Diagonal of this Co-occurrence matrix represents the homogeneous region in image, while the Non-diagonal values represent Heterogeneous region in image.

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| GLCM.png | CM of image.png |
| **Fig 10:** Angles at which GLCM can be calculated | **Fig 11:** Sample GLCM tabulation for 4 bit image. |

In the present study the SOS (Second Order Statistics) GLCM features are considered for analysis as shown in Table 1. The methodology adopted and its workflow is shown in Fig. 9.

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| **Table 1 : F1 to F13 GLCM Features** | |
| **Feature ID** | **Feature Name** |
| **1** | **F1 :** Angular Second Moment (ASM) |
| **2** | **F2 :** Contrast |
| **3** | **F3 :** Correlation |
| **4** | **F4 :** Sum of Squares-Variance |
| **5** | **F5 :** Inverse Difference Moment (IDM) |
| **6** | **F6 :** Sum Average |
| **7** | **F7 :** Sum Variance |
| **8** | **F8 :** Sum Entropy |
| **9** | **F9 :** Entropy |
| **10** | **F10 :** Difference Variance |
| **11** | **F11 :** Difference Entropy |
| **12** | **F12 :** Information Measures of Correlation-1 (IMC-1) |
| **13** | **F13 :** Information Measures of Correlation-2 (IMC-2) |

The process of extracting Texture features from an image using GLCM method involves various steps as shown in fig 11. This includes the conversion of original image into a Co-occurrence matrix based on relationship between two pixels specified with a distance and angle. This Co-occurrence matrix is then converted into a Symmetric matrix to tabulate the relationship between two pixels in both directions (one from 1st pixel to 2nd pixel and another one from 2nd pixel to 1st pixel). This Symmetric matrix is then converted into a Normalized matrix providing the probability of presence of each pixel value. 2nd Order Statistics are applied on this Normalized matrix in order to get the Set of Features, which are further used for the classification task.

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| GLCM process.png |
| **Fig 12:** GLCM Process to extract texture features. |

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| **Formulas to compute GLCM (mean) descriptors:** |
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**4. CLASSIFIER**

**4.1 SVM – Support Vector Machine**

It is one of the most popular machine learning algorithms. It falls under the category of supervised learning. SVM can be used for both “classification” as well as “regression” problem. However it is primarily used for the classification task in Machine learning.

It is based on the Logistic regression but with some added functionalities to improve performance. The logistic regression algorithm gives a best fit line that separates the data points; similarly SVM provides a best fit line that separates the data points. This best fit line in SVM is called “hyper plane”. But additionally along with the hyper plane SVM also gives Marginal planes that separate the data points.

The main aim of this algorithm is to provide the hyper plane and the marginal planes with the maximum margin. There are two types of marginal planes, namely “hard marginal plane” and “soft marginal plane”. The marginal plane that completely differentiates the data points is called hard marginal plane, while the marginal plane that doesn’t completely differentiates the data points and few are left to be separated is called soft marginal plane.

SVM chooses the extreme points that help in creating the hyper plane. These extreme cases are called “support vectors”. There can be many lines that can separate the support vectors but the line with maximum marginal distance from the support vectors is the hyper plane as shown in Fig 11.

|  |
| --- |
| X1 |
| **Fig 11:** Support Vector Machine Classifier. |

In real world scenario we may not always have linearly separable data. In order to separate the non linear support vectors, we use the kernel trick to achieve accuracy separating the support vectors. In this the lower dimensional feature space is converted into higher dimensional feature space in order to easily separate the support vectors. There are various kernels used like RBF (radial bias function), Polynomial and Sigmoid etc. The sample image of data points before applying RBF kernel is shown in Fig 12 and after applying RBF kernel is shown in Fig 13.

|  |
| --- |
|  |
| **Fig 12:** Sample data points before applying “RBF” kernel |

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|  |
| **Fig 13:** Sample data points after applying “RBF” kernel |

**4.2 Hyper parameters for tuning the SVM classifier- C and Gamma (γ):**

C - It is a hypermeter in SVM to control error. It tells about how many points can be avoided in misclassification of data points. It is used to overcome the condition of over fitting. Gamma (γ) – Gamma (γ) is used when we use the Gaussian RBF kernel. If you use linear or polynomial kernel then you do not need gamma only you need C hypermeter.

|  |  |
| --- | --- |
| **High c.png** | **Low c.png** |
| **Fig 14.1:** The effect of hyper parameter tuning when C is high. | **Fig 14.2:** The effect of hyper parameter tuning when C is low. |

|  |  |
| --- | --- |
| **High gamma.png** | **Low gamma.png** |
| **Fig 15.1:** The effect of hyper parameter tuning when Gamma (γ) is high. | **Fig 15.2:** The effect of hyper parameter tuning when Gamma (γ) is low. |

Gamma (γ) is a hyper parameter which we have to set before training model. Gamma (γ) decides that how much curvature we want in a decision boundary. Gamma (γ) high means more curvature. The effect of (γ) hyper parameter tuning is shown in Fig 15. The optimal values for C and γ for design of SVM model are obtained by extensive search, carried out in the parameter space for the values of C є {2-4, 2-3… 215}, γ є {2-12, 2-11… 24} using 5 fold cross validation on training data. The LibSVM library was installed for implementing SVM classifier [5].

**5. EXPERIMENTS AND RESULTS**

**5.1 Experiments**

To achieve optimal accuracy, an experiment was conducted in the current study to evaluate the performance of GLCM-M features in the differential diagnosis between HEM and FNH cases using an SVM classifier. The outcomes of these experiments are detailed in the results section, specifically from Tables 2-4.

**5.2 Results**

The comprehensive tables in this sections provides a clear comparison of the classification performance of SVM using different feature vectors, highlighting the overall accuracy and individual class accuracies for each feature vector for each class.

Table 2 presents a detailed analysis of the performance metrics of a Support Vector Machine (SVM) classifier using different GLCM-Mean feature vectors for d=1. The table is structured to show the results for three types of feature vectors: IROI Feature Vector with 13 features, Ratio Feature Vector with 13 features, and Concatenated Feature Vector with 26 features. For each feature vector, the table provides a confusion matrix, overall accuracy, and individual class accuracies for two classes: HEM and FNH. The confusion matrix for IROIFV shows that 27 HEM instances were correctly classified as HEM, 3 HEM instances were misclassified as FNH, 7 FNH instances were misclassified as HEM, and 23 FNH instances were correctly classified as FNH. This results in an overall accuracy of 83.3% for IROIFV, with an individual class accuracy of 90.0% for HEM and 76.7% for FNH. For RFV, the confusion matrix indicates that 26 HEM instances were correctly classified as HEM, 4 HEM instances were misclassified as FNH, 12 FNH instances were misclassified as HEM, and 18 FNH instances were correctly classified as FNH. This yields an overall accuracy of 73.3%, with individual class accuracies of 86.7% for HEM and 60.0% for FNH. Lastly, the confusion matrix for CFV shows that 28 HEM instances were correctly classified as HEM, 2 HEM instances were misclassified as FNH, 7 FNH instances were misclassified as HEM, and 23 FNH instances were correctly classified as FNH. This results in the highest overall accuracy of 85.0%, with individual class accuracies of 93.3% for HEM and 76.7% for FNH.

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| --- | --- | --- | --- | --- | --- | --- |
| **Table 2: Classification Performance of SVM with GLCM – M D1** | | | | | | |
| **Feature Vector (*l*)** | **Confusion Matrix** | | | **Accuracy (%)** | **ICA (HEM) (%)** | **ICA (FNH) (%)** |
| **IROIFV (13)** |  | **HEM** | **FNH** | **83.3** | **90.0** | **76.7** |
| **HEM** | **27** | **3** |
| **FNH** | **7** | **23** |
| **RFV (13)** |  | **HEM** | **FNH** | **73.3** | **86.7** | **60.0** |
| **HEM** | **26** | **4** |
| **FNH** | **12** | **18** |
| **CFV (26)** |  | **HEM** | **FNH** | **85.0** | **93.3** | **76.7** |
| **HEM** | **28** | **2** |
| **FNH** | **7** | **23** |

Note: ICA - Individual Class Accuracy, IROIFV – IROI Feature vector, RFV – Ratio Feature vector, CFV – Concatenated Feature Vector and GLCM – M d1 – GLCM Mean features at distance 1.

Similarly, Table 3 presents a detailed analysis of the performance metrics of a Support Vector Machine (SVM) classifier using different GLCM-Mean feature vectors for d=2. The table is structured similarly like Table 2 and 3. For each feature vector, the table provides a confusion matrix, overall accuracy, and individual class accuracies for two classes: HEM and FNH. The confusion matrix for IROIFV shows that 25 HEM instances were correctly classified as HEM, 5 HEM instances were misclassified as FNH, 8 FNH instances were misclassified as HEM, and 22 FNH instances were correctly classified as FNH. This results in an overall accuracy of 78.3% for IROIFV, with an individual class accuracy of 83.3% for HEM and 73.3% for FNH. For RFV, the confusion matrix indicates that 27 HEM instances were correctly classified as HEM, 3 HEM instances were misclassified as FNH, 7 FNH instances were misclassified as HEM, and 23 FNH instances were correctly classified as FNH. This yields an overall accuracy of 83.3% for RFV, with individual class accuracies of 90.0 for HEM and 76.7% for FNH. At last, the confusion matrix for CFV shows that 28 HEM instances were correctly classified as HEM, 2 HEM instances were misclassified as FNH, 7 FNH instances were misclassified as HEM, and 23 FNH instances were correctly classified as FNH. This results in the highest overall accuracy of 85.0%, with individual class accuracies of 93.3% for HEM and 76.7% for FNH.

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| --- | --- | --- | --- | --- | --- | --- |
| **Table 3: Classification Performance of SVM with GLCM – M D2** | | | | | | |
| **Feature Vector (*l*)** | **Confusion Matrix** | | | **Accuracy (%)** | **ICA (HEM) (%)** | **ICA (FNH) (%)** |
| **IROIFV(13)** |  | **HEM** | **FNH** | **78.3** | **83.3** | **73.3** |
| **HEM** | **25** | **5** |
| **FNH** | **8** | **22** |
| **RFV(13)** |  | **HEM** | **FNH** | **83.3** | **90.0** | **76.7** |
| **HEM** | **27** | **3** |
| **FNH** | **7** | **23** |
| **CFV(26)** |  | **HEM** | **FNH** | **85.0** | **93.3** | **76.7** |
| **HEM** | **28** | **2** |
| **FNH** | **7** | **23** |

Note: GLCM – M d2 – GLCM Mean features at distance 2.

At last, Table 4 presents a detailed analysis of the performance metrics of a Support Vector Machine (SVM) classifier using different GLCM-Mean feature vectors for d=3. The table is structured similarly like Table 2. For each feature vector, the table provides a confusion matrix, overall accuracy, and individual class accuracies for two classes: HEM and FNH. The confusion matrix for IROIFV shows that 26 HEM instances were correctly classified as HEM, 4 HEM instances were misclassified as FNH, 8 FNH instances were misclassified as HEM, and 22 FNH instances were correctly classified as FNH. This results in an overall accuracy of 80.0% for IROIFV, with an individual class accuracy of 86.7% for HEM and 73.3% for FNH. For RFV, the confusion matrix indicates that 24 HEM instances were correctly classified as HEM, 6 HEM instances were misclassified as FNH, 6 FNH instances were misclassified as HEM, and 24 FNH instances were correctly classified as FNH. This yields an overall accuracy of 80.0% for RFV, with individual class accuracies of 80.0 for HEM and 80.0% for FNH. Lastly, the confusion matrix for CFV shows that 27 HEM instances were correctly classified as HEM, 3 HEM instances were misclassified as FNH, 6 FNH instances were misclassified as HEM, and 24 FNH instances were correctly classified as FNH. This results in the highest overall accuracy of 85.0%, with individual class accuracies of 90.0% for HEM and 80.0% for FNH.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table 4: Classification Performance of SVM with GLCM – M D3** | | | | | | |
| **Feature Vector (*l*)** | **Confusion Matrix** | | | **Accuracy (%)** | **ICA (HEM) (%)** | **ICA (FNH) (%)** |
| **IROIFV(13)** |  | **HEM** | **FNH** | **80.0** | **86.7** | **73.3** |
| **HEM** | **26** | **4** |
| **FNH** | **8** | **22** |
| **RFV(13)** |  | **HEM** | **FNH** | **80.0** | **80.0** | **80.0** |
| **HEM** | **24** | **6** |
| **FNH** | **6** | **24** |
| **CFV(26)** |  | **HEM** | **FNH** | **85.0** | **90.0** | **80.0** |
| **HEM** | **27** | **3** |
| **FNH** | **6** | **24** |

Note: GLCM – M d3 – GLCM Mean features at distance 3.

*5.2.2 Best Hyperparamters – best* ***c*** *& best-****γ***

From the experiments conducted using the SVM classifier which uses the hyper parameter tuning, the best c and best-γ observed were tabulated from Table 5-7.

**Table 5: Best c and Best-γ from GLCM – M D1**

|  |  |  |
| --- | --- | --- |
| **Feature**  **Vector (*l*)** | **Best c** | **Best-γ** |
| IROIFV (13) | 16384 | 0.03 |
| RFV (13) | 64 | 1 |
| CFV (26) | 16384 | 0.03 |

**Table 6: Best c and Best-γ from GLCM – M D2**

|  |  |  |
| --- | --- | --- |
| **Feature**  **Vector (*l*)** | **Best c** | **Best-γ** |
| IROIFV (13) | 8192 | 0.12 |
| RFV (13) | 4 | 8 |
| CFV (26) | 8192 | 0.12 |

**Table 7: Best c and Best-γ from GLCM – M D3**

|  |  |  |
| --- | --- | --- |
| **Feature**  **Vector (*l*)** | **Best c** | **Best-γ** |
| IROIFV (13) | 4096 | 0.25 |
| RFV (13) | 16 | 2 |
| CFV (26) | 4096 | 0.25 |

**6. CONCLUSION**

The highest overall classification accuracy 85.0% is achieved by GLCM Mean features at inter-pixel distance d = 1, 2 and 3. However, it is worth mentioning that these features yield reasonable ICA for HEM and FNH with 93.3% and 76.7% for inter-pixel distance d=1, 93.3% and 76.7% for inter-pixel distance d=2 and 90.0% and 80.0% for inter-pixel distance d=3. So in the future, the performance of other features for differential diagnosis between HEM and FNH cases shall be explored.

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