ISSN 2249-894X Impact Factor : 3.1402 (UIF) Volume - 5 | Issue - 11 | August - 2016

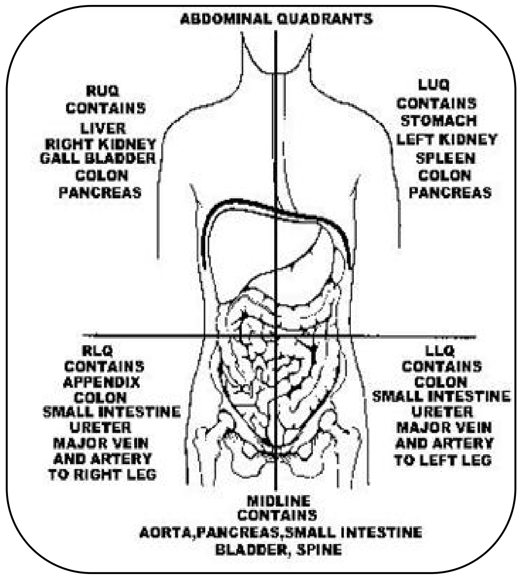
Review Of Research

DIAGNOSIS MODELS FOR ABDOMINAL MASS: PERFORMANCE EVALUATION ON CLASSIFIERS

S. S. Kore[1], S. B. Kadam[2], A. R. Shitre[3] and A. B. Kadam[4]
[1]Research Scholar, Pacific Academy of Higher Education and Research, University, Udaipur, India
[2]Physics Department, LBS College, Partur, Dist. Jalna (M.S.) India
[3]Physics Department, Y. C. College, Tuljapure, Dist. Osmanabad (M.S.) India.
[4]Physcs Department, Jawahar Arts, Science and Commerce College, Andoor
Corresponding Author : shitreanil09@gmail.com

ABSTRACT—
Ultrasound imaging is the most renowned image modality on testing the internal organs, however, the US image processing often tides with complex task because of unwanted noises. Number of detection models is there in the dice with US image. However, only few contributions have been made on abdominal mass detection using US imaging. This paper intends to propose a new abdominal mass diagnosing model with US images. The developed detection approach comprises of two stages: (i) Feature extraction and (ii) Classification. In the feature extraction stage, the texture features are mined or extracted via Adaptive Gradient Location and Orientation histogram (AGLOH). Subsequently, Incomplete Sparse Least Square Regression (ISLSR) model is used to classify whether the given image is normal or abnormal. Further, the performance of developed ISLSR classifier is compared over Neural Network (NN), Support Vector Machine(SVM), K-Nearest Neighbor (K-NN), Naive Bayes (NB) as well as Linear Collaborative Discriminant Regression (LCDRC) with respect to Accuracy, Precision, Sensitivity, False Positive rate (FPR), False Negative rate (FNR), Specificity, False Discovery rate (FDR), Matthews correlation coefficient (MCC), Negative Prediction Value (NPV), and F_1Score, and the superiority of developed approach is proven.

KEYWORDS—*Abdominal Mass Detection; Ultrasound image;LCDRC; Traditional Classifiers.*



I. INTRODUCTION

Generally, the abdominal mass is termed as the extension of any human anatomy, which basically differs by means of its position or location. Often, the occurrence of mass is by the splenomegaly, hepatomegaly, and so on. Moreover, the masses are the unpredictable one, and it could be identified by predicting or by doing certain physical concerns under the abdominal US images. Clinically, this mass formation is analysed as the cyst formation in human organ. In human, Kidney is the organ that normally affects by this mass or cyst. The size of cyst deviates from small to medium tissue.

At first, the evaluation of abdominal mass diagnosis is cmplished by an imaging model termed Plain abdominal Radiographs. Afterwards, radiography has become as the most popular technique to define or determine the location or position of mass with its density. The detection [9] [10] [11] of abdominal mass includes two phases: Extraction of features and Classification. Here, classification is considered as the main phase as it can classify the existence of tumours, and some of them are denoted as teratomas and lithiasis. Certain classifiers are already exist including NN, SVM, Bayes classifier and etc. and that makes a feasible way in accurate diagnosis of abdominal mass. Further, imaging modalities are the most vital aspect, which is used to detect the mass that exist. The common imaging techniques are Computed Tomography' CT Magnetic resonance imaging (MRI) as well as x-rays. the advanced level of imaging modality is US image that analyzes the clear physical characteristics of abdominal images. In fact, there exist many research works on the diagnosis of various cancers like breast cancer, lung cancer, etc. using US imaging. Still, only fewer contributions are there [12] [13] [14] in diagnosing abdominal masses. This paves way for the upcoming researchers to define some advanced work on diagnosing the abdominal mass [15] using US image.

This paper proposes a new abdominal diagnosing model using US image. The model diagnose whether the given image is normal and abnormal. Two phases are there in proposed abdominal mass detection model. In the first phase, AGLOH is used to extract the features, and in the second phase, ISLSR is used to do the classification process. Finally, the performance of proposed classification approach, ISLSR is compared over conventional models like SVM, NN, KNN, NB and LCDRC.

The rest of the paper is arranged as follows. Section II reviews the literature works. Section III explains the developed abdominal mass detection model. Section IV demonstrates the feature extraction and classification techniques. Section V details the compared existing classifier models. Section VI discusses the results obtained, and Section VII concludes the paper.

II. LITERATURE REVIEW

Related Works

In 2007, Nilavalan *et al*. [1] have presented a patch antenna, which was designed for radiating the frequencies that was in e range of 4–9.5 GHz. The authors have reviewed the antenna in the form of simulation. The real time measurements has posed the broad way of input bandwidth, radiation patterns. The proposed model has proven the superiority of its work on detecting the breast cancer tumor. They have developed a new hybrid approach that involves time of arrival, and have proposed a entropy to remove the artifact as well. The analysis has proven the efficiency of proposed model. They have shown that the proposed minimal cost system was more effective than the expensive VNA with respect to accuracy, and it was more faster in diagnosis.

In 2015, Shradhananda *et al.* [4] have presented an effective model to classify the mammograms for detecting the breast cancer. They have used 2D discrete orthonormal S-transfor (DOST) for the purpose of coefficient extraction. An algorithm, which was on the basis of null-hypothesis test was used for the selection of the most significant coefficients Then, the chosen coefficients were processed for classifying the sevierity. Finally, they have proved the superiority of proposed work. In 2013, Tai, *et al.* [5] have suggested a automatic CADe system, which utilizes both the local as well as discrete texture features to detect the mammographic mass. The system has segmented certain regions of interest (ROIs) under suspicious areas. Further, the authors have developed two feature extraction approaches, which was on the basis of co-occurrence matrix for describing the characteristics of local texture of each and every ROI.

REVIEW

Numerous cancer detection models were reviewed, in which Patch antenna [1] is more suitable for widebrand application, but imaging experimentation has not provided valuable results. C-B-TR-ML [2] effectively removes the artifacts without reducing the quality of image. However, the real time application is quite difficult. Prototype system is proposed in [3], which is low cost and accurate as well. However, some advanced improvement is needed for the clinical application. 2D-DOST [4] enhances the accuracy rate on tumor classification, but the model suffers from increased overhead. An Automatic CAD system [5] effectively identifies the presence of mass. However, additional imaging is required to attain more satisfactory results, which also leads to more execution time. Thus, it is clear that there needs some advanced contribution in detecting the abdominal mass, as all the contributions are mainly focusing on cancer detection.

III. PROPOSED ABDOMINAL MASS DIAGNOSIS MODEL

Fig 1 illustrates the proposed abdominal mass detection model. Two phases are there in this model: Feature Extraction and Classification. Initially, the input US image is processed for extracting the respective features. Here, the texture features are extracted via AGLOH. Then, the extracted features are given as the input to ISLSR classifier, from which the mass that exist in abdominal region is detected.

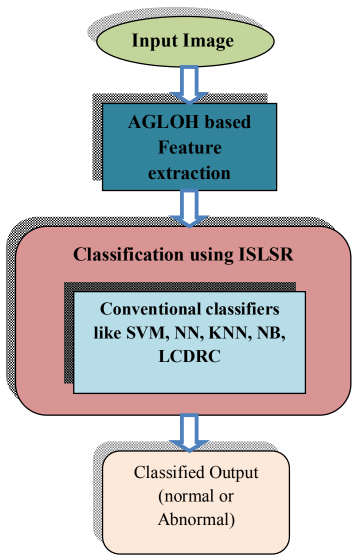


Fig. 1. Architecture of proposed abdominal mass diagnosis model

IV. FRAMEWORK OF FEATURE EXTRACTION AND CLASSIFICATION

AGLOH based Feature extraction

The proposed abdominal mass detection model uses AGLOH [21] mechanism for extracting the features from given input US image, $US_I(x,y)$. This work contributes an adaptive bilinear filtering for the purpose of smoothing the texture of pre-processed image $US_I(x,y)$. Eq. (1) gives the parameter $pa(US_I(x,y))$ is given in Eq. (1).

$$pa(US_I(x,y)) = i_{11}xy + i_{10}x + i_{01}y + i_{00} \qquad (1)$$

Thus, the altered filter image FI_I is the resulting image, from where the features are mined via GLOH descriptor. Moreover, descriptor grid of GLOH includes RI circular ring that centres the feature points. These rings comprises of re regions that are constantly contributed with D directions. Consider the region as RG_{uv}, $RG_{u,v} \in FI_I$ with $u = 1,2,....,RI$ and $v = 0,1,....,D-1$.

Further, Eq. (2) determines the block histogram, where, $\oplus$ indicates the concatenation operator. The final descriptor vector, VT is acheived by concatenating histograms, and that is given in Eq. (3). Further, the length of descriptor is given in Eq. (4).

$$BA_h(i) = \begin{cases} i & if \quad i < \frac{l}{2} \\ h - i & otherwise \end{cases} \qquad (2)$$

$$VT_{u,v} = \mathop{\oplus}_{r=0}^{D-1} b_{u,v}^{[v+r]D} \tag{3}$$

$$h = RI\left(RID + 1 + (D-1)\Psi(VT)\right) \tag{4}$$

The descriptor circulation δk is attained by the accomplished factor that is defined in Eq. (5). In Eq. (5), $\delta k = \frac{2\pi}{D}$ consistently, where $VT_{0,k}$ is $VT_{0,k} = \mathop{\oplus}_{r=0}^{D-1} b_{0,v}^{[r+k+v]D}$.

$$VT_{\delta k} = \begin{cases} \mathop{\oplus}_{r=0}^{RI} \mathop{\oplus}_{t=0}^{D-1} VT_{r,[k+t]D} & if \;\; \Psi(VT) = 1 \\ VT_{0,k} \mathop{\oplus}_{r=1}^{RI} \mathop{\oplus}_{t=0}^{D-1} VT_{r,[k+t]Q} & otherwise \end{cases} \tag{5}$$

Eq. (6) defines the distance among features, VT and $\overline{VT}$ is where $\hat{DS}^{T}\left(VT,\overline{VT}\right)$ denotes the evaluation of usual distance. Thus, the features that are extracted from the input abdominal images is represented as $GLOH^{F} == [F_1, F_2 \cdots F_K] \in \Re^{x \times y}$ where TO indicates the total features.

$$\hat{DS}^{T}\left(VT,\overline{VT}\right) = \min_{k=0,1,\ldots,S-1} DS^{T}\left(VT,\overline{VT_{\delta k}}\right) \tag{6}$$

Classification via ISLSR

For the classification purpose, this model uses ISLSR [22] classifier. The input to this classifier is the extracted features $GLOH^{F}$ and produces the classified output (normal or abnormal). The features are defined in the matrix format and every column in $GLOH^{F}$ is indicated as the feature vector that comprises of features. The entities be $E_i = [f_{1i}, \ldots\ldots\ldots\ldots f_{di}]^{US}$ that takes either 0 or 1, which is given in Eq. (7).

$$f_{jk} = \begin{cases} 1, \; if \;\; h_i \; belongs \; to \;\; j^{th} \;\; class \\ 0, \;\; otherwise \end{cases} \tag{7}$$

If $GLOH_0^{F} \in \Re^{n \times N}$ is concerned as the another data matrix with undetermined class labels, the ISLSR approach evaluates the parameter of ISLSR, and the unknown or undetermined abdominal label matrix is indicated by $LA_o \in \Re^{d \times N}$ in terms of $GLOH_0^{F}$ matrix that is on the basis of $GLOH^{F}$, $GLOH_0^{F}$ and LA data matrices. In Eq. (8), RE denotes the regression coefficient matrix.

In order to make the abdominal feature selection in a well realized form, there presents a respective way to do some columns RE to zero. At last, the given Eq. (8) is revaluated by prompting a norm penalty $f_{2,1}$ with respect to RE onto the objective function. The function entry shrinking, which means, the entries of RE column shrink to zero, in which $f_{2,1}$ determines summation of f_2 norms of RE. Hence, the related features are used for detecting the abdominal mass. Further, the revaluated ISLSR model is determined in Eq. (10), where $LA_o > 0$ refers to all LA_o entries as non-negative, 1 specifies the vectors with total entries and λ is the 'trade-off' parameters.

$$\arg\min_{RE,LA_o} \| [LA\ LA_o] - RE[GLOH^F,\ GLOH_0^F] \|_H^2 \quad (8)$$

$$\arg\min_{LA_o,RE} \| \{LA\ LA_o\} - RE\{GLOH^F\ \ GLOH_0^F\} \|_H^2 + \lambda \| RE \|_{2,1}$$
$$so\ that.LA_o^{US} 1 = 1, LA_o \geq 0 \quad (9)$$

this classification process classifies whether the given input image is normal or abnormal.

V. CONVENTIONAL CLASSIFIERS

This section details various conventional classifiers namely SVM [18], NN [19], KNN [17] , Naïve Bayes [16] and LCDRC . Further, this work compares the performance of proposed ISLSR with all the other conventional classifiers.

SVM

SVM [18]is basically the machine learning model, which has the capability of interpreting subtle patterns even in noisy dataset and difficult datasets. Firstly, the designing of SVM is done for doing binary classification.

Eq. (10) defines the primal equation of a soft margin SVM, where ve specifies the normal vector of hyper plane splitting in feature space and the regularization parameter is indicated by PA. This controls the penalty for misclassification.

$$\min_{ve} \left\{ \frac{1}{2} \| ve \|^2 + PA \sum_i \xi_i \right\} \quad (10)$$

NN classifier

NN [16]approach is a multilayer feed forward network that is trained for doing the process of classification. Eq. (11), (12) and (13) defines the network model. In all the mentioned equations, i refers to the hidden neuron, $W_{(Bli)}^{(HI)}$ specifies the bias weight to i^{th} hidden neuron, nu_i indicates the number of input neurons, nu_{HI} specifies the number of hidden neurons, $W_{(B\,\mathrm{Im})}^{(o)}$ refers to the output bias weight to m^{th} layer, $W_{(im)}^{(o)}$ represents the output weight from i^{th} hidden neuron to m^{th} layer, NF refers to the activation function. Eq. (34) defines the network output, $\hat{O}_m$, where O_m refers to the actual output.

$$N^{(HI)} = NF\left(W_{(Bli)}^{(HI)} + \sum_{j=1}^{nu_i} W_{(ji)}^{(HI)} (Input\ Features) \right) \quad (11)$$

$$\hat{O}_m = NF\left(W_{(B\,\mathrm{Im})}^{(o)} + \sum_{i=1}^{nu_{HI}} W_{(im)}^{(o)} e_i^{(HI)} \right) \quad (12)$$

$$W^* = \arg\min_{\{W_{(Bli)}^{(HI)}, W_{(ji)}^{(HI)}, W_{(B\,\mathrm{Im})}^{(o)}, W_{(im)}^{(o)}\}} \sum_{m=1}^{nu_o} O_m - \hat{O}_m \quad (13)$$

K-NN

The working strategy ofK-NN [17] is as follows: It assess the distance between training and testing samples, which exist in given dataset. the model grants the k closest samples. Eq. (14) defines the projection function pf, where po_j is the j^{th} column vector of PO, $PO_{\langle i \rangle}$ indicates the sub matrix of PO and $KE^{(ba)}(\cdot)$ indicates the kernel function with ba bandwidth.

$$pf = \frac{KE^{(ba)}\left(l_i, po_j\right)}{\sum_{j' \in po} KE^{(ba)}\left(l_i, po_{j'}\right)}, j \in PO_{\langle i \rangle} \quad (14)$$

Naives Bayes

The mentioned Naïve Bayes classifier [16]is basically a probabilistic model for doing the classification process. For the unclassified object $OJ = \left(oj_1, oj_2, ...oj_n\right)$, the NB classifier predicts the OJ category (in which category where it falls). More suitably, the classifier classifies OJ object into CT_i category, if and only if it satisfies the constraint of posterior probability, which is defined in Eq. (15). $PP\left(CT_i \mid OJ\right) > PP\left(CT_j \mid OJ\right)$ for all $j \neq i$ (15)

Using Bayes theorem, Eq. (21) is determined as given in Eq. (22).

$$PP\left(CT_j \mid OJ\right) = \frac{PP\left(OJ \mid CT_j\right)PP\left(CT_j\right)}{PP(OJ)} \quad (15)$$

A. LCDRC Classifier

Let [20] $Z = \left[Z_1, Z_2 \cdots Z_K\right] \in \Re^{x \times y}$ be the matrix of whole image with training image, where x refers to the training images' dimension, $Z_i = \left[Z_{i1}, Z_{i2} \cdots Z_{in_i}\right] \in \Re^{x \times y}$, the number of training image from i class is indicated as y_i, and $y = \sum_{i=1}^{K} y_i$, $i = 1,2,3....K$ and K indicates the total classes. Assume a matrix $M \in \Re^{x \times d}$ with subspace and $d < x$. Total u_{ij} must be subjected for learning the subspace by $v_{ij} = M^T u_{ij}$ that lies among $1 \leq j \leq y_i$.

Eq. (16) defines the matrix with training image and for all class; the same is given in Eq. (17)

$$C = M^T Z \in \Re^{d \times y_i} \quad (16)$$

$$C_i = M^T Z \in \Re^{d \times y_i} \quad (17)$$

Eq. (18) and (19) defines the CBCRE and WCRE.

$$CBCRE = \frac{1}{y} \sum_{i=1}^{K} \sum_{j=1}^{y_i} \left\| q_{ij} - \hat{q}_{ij}^{\,\mathrm{int}\,er} \right\|_2^2 \quad (18)$$

$$WCRE = \frac{1}{y} \sum_{i=1}^{K} \sum_{j=1}^{y_i} \left\| q_{ij} - \hat{q}_{ij}^{\,\mathrm{int}\,ra} \right\|_2^2 \quad (19)$$

where $\hat{q}_{ij}^{\,\mathrm{int}\,er} = C_{ij}^{\mathrm{int}\,er} \alpha_{ij}^{\mathrm{int}\,er}$ and $\hat{q}_{ij}^{\,\mathrm{int}\,ra} = C_{ij}^{\mathrm{int}\,ra} \alpha_{ij}^{\mathrm{int}\,ra}$. $C_{ij}^{\mathrm{int}\,er}$ is the C with C_i eliminated and $C_{ij}^{\mathrm{int}\,ra}$ is the C_i with q_{ij} eliminated. Subsequently, $\alpha_{ij}^{\mathrm{int}\,er}$ and $\alpha_{ij}^{\mathrm{int}\,ra}$ is accomplished by Eq. (20).

$$\hat{\alpha}_i = \left(X_i^T X_i\right)^{-1} X_i^T y, \quad i = 1,2 \cdots T \quad (20)$$

Finally, the value of CBCRE and WCRE is determined as in Eq. (21) and Eq. (22).

$$CBCRE = tr\left(M^T e_b M\right) \quad (21)$$

$$WCRE = tr\left(M^T e_W M\right) \quad (22)$$

In order to maximize the CBCRE value and to reduce the WCRE value simultaneously, a Maximum Margin Criterion (MMC) is also employed and it is in Eq. (23), that spotts the maximized EI Eigenvalues and the corresponding Eigenvectorsis is given in Eq. (24), where $\lambda_1 \geq \cdots \geq \lambda_k \cdots \lambda_{EI}$ and $M = [o_1, o_2, \cdots o_k \cdots o_{EI}]$.

$$\max_O J(M) = \max_O (CBCRE - WCRE) = \max_O \left(tr\left(M^T (e_b - e_w) M \right) \right) \quad (23)$$

$$(e_b - e_w) o_k = \lambda_k o_k, \quad k = 1,2 \cdots EI \quad (24)$$

Furthermore, MMC solves the issue named as Small Sample Size Problem (SSSP).

VI. RESULTS AND DISCUSSIONS

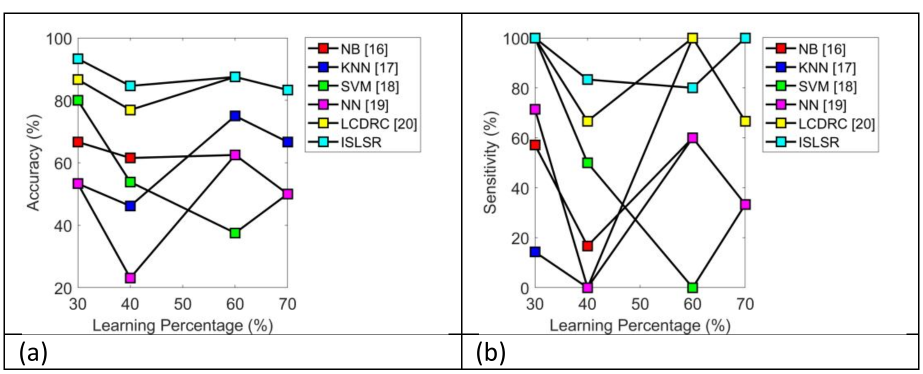
Simulation procedure

The proposed ISLSR was compared to other conventional classifiers like SVM, NN, K-NN, Naives Bayes and LCDRC. The analysis was carried out with respect to measures like accuracy, sensitivity, specificity, precision, FPR, FNR, NPV, FDR, F1-score, and MCC. The model has granted satisfactory results by means of better classification.

Performance analysis

In this section, the performance of proposed ISLSR is compared over certain existing classifiers including SVM, NN, K-NN, Naives Bayes and LCDRC by varying the learning percentage to 30%, 40%, 50%, 60% and 70%. This is evidential from Fig 2. The analysis reviews that the proposed ISLSR attains better accuracy over other methods for all the training percentage (Fig 2 (a)). For 30% learning, the proposed ISLSR is 10.46%, 63.06%, 16.53% and 44.73% better from LCDRC, NN, SVM and NB, respectively. For 40% learning, the proposed model attains high accuracy, which is 4.79%, 70.57%, 41.66%, 41.66%, 41.37% and 30.83% better than LCDRC, NN, SVM, KNN and NB, respectively.

Sensitivity of proposed method (Fig 2 (b)) is also high. For 30% learning, the proposed ISLSR attains high sensitivity, which is 37.29%, 80.59% and 66.80% better from NN, KNN, and NB, respectively. For 40% learning, the proposed method is 32.37%, 52.96% and 76.39% better from LCDRC, SVM and NB, respectively. The specificity of proposed method is high for 30% learning. The proposed ISLSR is 16.93%, 54.85% and 41.24% better from LCDRC, NN and KNN, respectively with high specificity (Fig 2 (c)). For 40% learning, the specificity of proposed method is 97.52% and 51.06% better than NN and SVM. Similar analysis is made for all the residual measures, and it has proven the superior performance of proposed ISLSR with accurate classification.



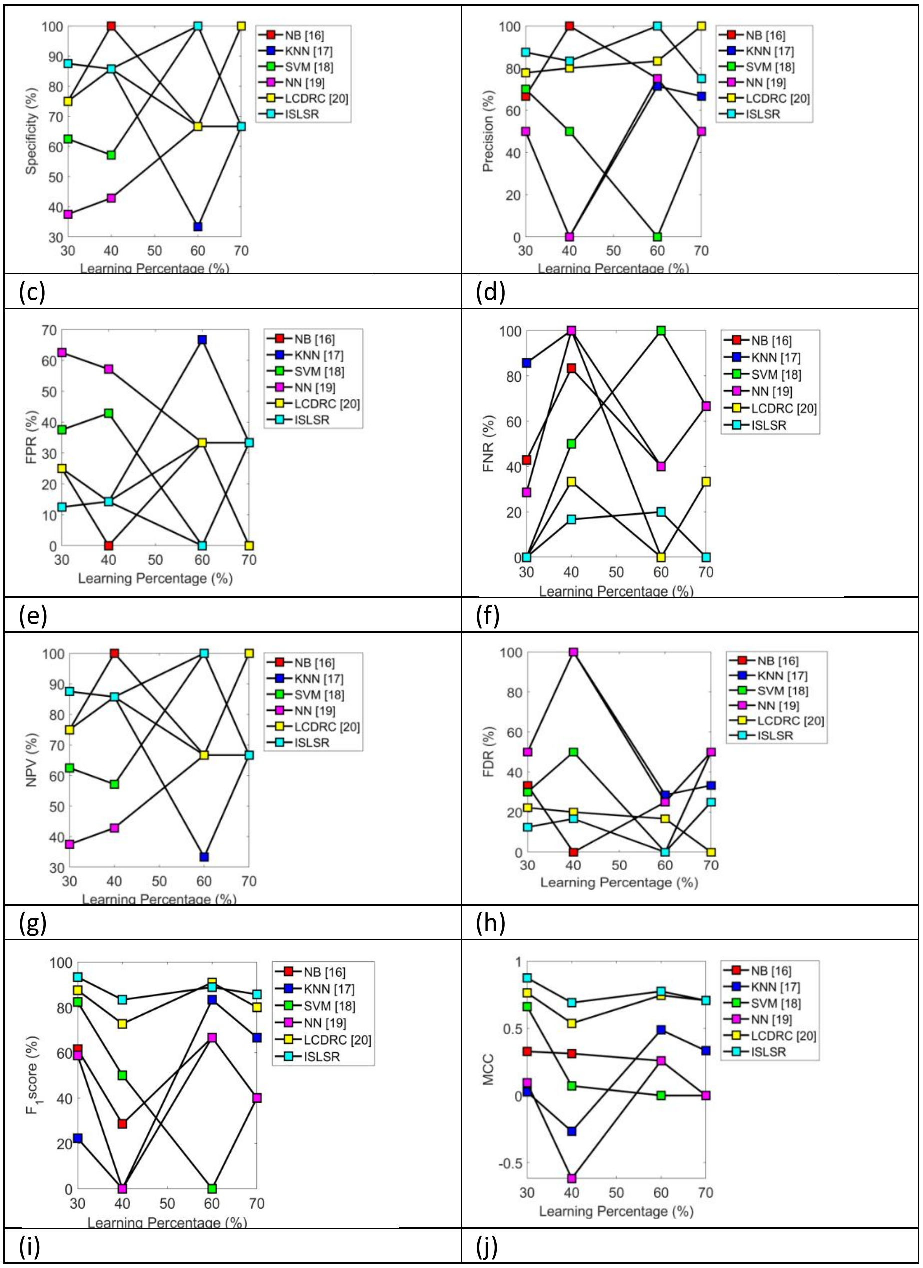


Fig. 2. Performance of developed ISLSR classifier over other classifiers by varying the learning percentage by 30%, 40%, 50%, 60% and 70% (a) Accuracy (b) Sensitivity (c) Specificity (d) Precision (e) FPR (f) FNR (g) NPV (h) FDR (i)F_1Score (j) MCC

Table 1 : Overall performance of proposed ISLSR

Measures	NB [16]	NN [19]	LCDRC [20]	SVM [18]	KNN [17]	ISLSR
Precision	0.66667	0.5	0.77778	0.7	0.5	0.875
Sensitivity	0.57143	0.71429	1	1	0.14286	1
Specificity	0.75	0.375	0.75	0.625	0.875	0.875
Accuracy	0.66667	0.53333	0.86667	0.8	0.53333	0.93333

FDR	0.33333	0.5	0.22222	0.3	0.5	0.125
FPR	0.25	0.625	0.25	0.375	0.125	0.125
MCC	0.32733	0.094491	0.76376	0.66144	0.026207	0.875
NPV	0.75	0.375	0.75	0.625	0.875	0.875
FNR	0.42857	0.28571	0	0	0.85714	0
F1-score	0.61538	0.58824	0.875	0.82353	0.22222	0.93333

The overall performance of proposed ISLSR over other conventional classifiers is given in Table I. In this, it is reviewed that the accuracy of developed approach is 7.69%, 16.66% and 39.99% better than LCDRC, SVM and Nb, 75% better from both NN and KNN. Then, the sensitivity of proposed method is 39.99% superior to NN model. The specificity of ISLSR is 16.66% better than LCDRC and NB, and the proposed ISLSR is 57.14% and 40% better from NN and SVM with high specificity. The precision of ISLSR is higher than other classifiers, which is 12.49%, 75%, 25%, 75% and 31.24% enhanced than LCDRC, NN, SVM, KNN, and NB, respectively. FPR of proposed ISLSR is low when compared to other methods, which is 50% better than LCDRC and NB, 80% and 66.66% better than NN and SVM, respectively. The FDR of proposed method is 43.74% and 58.33% better from LCDRC and SVM, 75% superior to NN and KNN with less FDR. Similarly, the NPV of proposed ISLSR is high, and it is 16.66% better than LCDRC and NB, 57.14% and 40% better than NN and SVM, respectively. Hence, the overall performance reviews that the proposed ISLRC is more efficient than other conventional methods in terms of abdominal mass diagnosis.

VII.CONCLUSION

This paper has presented a new abdominal mass diagnosing method with US images. Here, two phases were there. In the first phase, Texture features were extracted using AGLOH approach. ISLSR classifier was used to diagnose the mass that exist in US image. The proposed ISLSR approach was compared to other classifiers like NN, SVM, K-NN, NB and LCDRC. From the results, it was observed that the accuracy of proposed model is 7.69%, 16.66% and 39.99% better than LCDRC, SVM and NB, 75% better from both NN and KNN. Then, the sensitivity of proposed method is 39.99% superior to NN model. The specificity of ISLSR is 16.66% better than LCDRC and NB, and the proposed ISLSR is 57.14% and 40% better from NN and SVM with high specificity. Thus, it was concluded that the developed ISLSR outperforms other conventional method with respect to better mass diagnosing.

REFERENCES

[1] R. Nilavalan, I. J. Craddock, A. Preece, J. Leendertz and R. Benjamin, "Wideband microstrip patch antenna design for breast cancer tumour detection," in IET Microwaves, Antennas & Propagation, vol. 1, no. 2, pp. 277-281, April 2007.

[2] S. Beura, B. Majhi, R. Dash and S. Roy, "Classification of mammogram using two-dimensional discrete orthonormal S-transform for breast cancer detection," in Healthcare Technology Letters, vol. 2, no. 2, pp. 46-51, 4 2015.

[3] S. C. Tai, Z. S. Chen and W. T. Tsai, "An Automatic Mass Detection System in Mammograms Based on Complex Texture Features," in IEEE Journal of Biomedical and Health Informatics, vol. 18, no. 2, pp. 618-627, March 2014.

[4] A. Chatterjee, "Sensitivity and Error Analysis of a Coupled Micro-Resonator Array for Ultra-Sensitive Mass Detection Using Matrix Perturbation Theory," in IEEE Sensors Journal, vol. 16, no. 5, pp. 1304-1309, March1, 2016.

[5] C. B. Top, A. K. Tafreshi and N. G. Gençer, "Microwave Sensing of Acoustically Induced Local Harmonic Motion: Experimental and Simulation Studies on Breast Tumor Detection," in IEEE Transactions on Microwave Theory and Techniques, vol. 64, no. 11, pp. 3974-3986, Nov. 2016.

[6] Q. Li et al., "Direct Extraction of Tumor Response Based on Ensemble Empirical Mode Decomposition for Image Reconstruction of Early Breast Cancer Detection by UWB," in IEEE Transactions on Biomedical Circuits and Systems, vol. 9, no. 5, pp. 710-724, Oct. 2015.

[7] Ronald R.Yager, " An extension of the naive Bayesian classifier", Information Sciences, vol. 176, no. 5, pp. 577-588, 2006.

[8] ZhenyunDeng, XiaoshuZhu, DeboCheng, MingZong and ShichaoZhang, " Efficient kNN classification algorithm for big data", Neurocomputing, vol. 195, pp. 143-148, 2016.

[9] David Meyer, FriedrichLeisch, Kurt Hornik, "The support vector machine under test",Neurocomputing, vol. 55, pp.169 – 186, 2003.

[10] Y. Mohan, S. S. Chee, D. K. P. Xin and L. P. Foong, "Artificial neural network for classification of depressive and normal in EEG," 2016 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES), Kuala Lumpur, 2016, pp. 286-290.

[11] Xiaochao Qu, Suah Kim, Run Cui and Hyoung Joong Kim, “Linear collaborative discriminant regression classification for face recognition,” Visual communication image retrieval, vol. 31, pp. 312-319, 2015.

[12] Y. Liang, L. Liu, Y. Xu, Y. Xiang and B. Zou, "Multi-task GLOH feature selection for human age estimation," 2011 18th IEEE International Conference on Image Processing, Brussels, pp. 565-568, 2011.

[13] Wenming Zheng Minghai Xin, Xiaolan Wang, and Bei Wang, " A Novel Speech Emotion Recognition Method via Incomplete Sparse Least Square Regression", IEEE SIGNAL PROCESSING LETTERS,, vol. 21, no. 5, 2014.