iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 Issue: XI Month of publication: November 2023

DOI: https://doi.org/10.22214/ijraset.2023.57053

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue XI Nov 2023- Available at www.ijraset.com

Efficient CAD Systems for Automated Detection of Breast Cancer Malignancy: An Overview of Recent Advancements

Ardra Mariya Joseph[1], Grace John M[2], Anto Sahaya Dhas[3]
[1]PG Scholar, [2]Asst.Professor, [3]Professor, Dept Of E&C,Vimal Jyothi Engineering College, Kannur, Kerala, India

Abstract: Computer- Aided Diagnosis (CAD) systems have importance in medical field since it helps to diagnose and detect many deadly diseases in its primary stages. Breast cancer is considered as one of the major causes of non-accidental death in women worldwide. Early detection and diagnosis of the disease let the doctor to administer suitable treatment, and can improve the patient's chances of survival. Many researches were conducted for early detection of breast cancer. This review aims at providing an outline concerning recent advances and developments of CAD systems for mammogram interpretation in breast cancer analysis, pointing to act as a primer for specialists and scholars in the field. The paper investigates studies of many researchers in this field and briefly explained all the methods they have adapted in every stages of their works. This work can be utilize to study existing efficient techniques and help to develop more versatile CAD system for the detection of breast cancer.
Keywords: Computer-Aided Diagnosis (CAD), Micro Calcification Clusters (MCC), Optical Density Co-occurrence Matrix (ODCM), Radial Local Ternary Patterns (RLTP), Local Ternary Patterns (LTP), Markov random field (MRF), Support Vector Machine (SVM), Twin Support Vector Machine (TWSVM), Diverse- Adaboost SVM (DA-SVM), Artificial Neural Network (ANN), Cellular Neural Network (CNN), GA (Genetic Algorithm), Pulse Coupled Neural Network (PCNN)

I. INTRODUCTION

Breast cancer is the most frequently diagnosed cancer in females globally and the major reason of cancer death among women in the current scenario. Since the cause is still remains as a question, early detection of breast cancer increases the treatment options and the survivability of patient. Mammography is currently the most effective tool for the early detection and diagnosis of breast cancer, by the detection of characteristic masses and micro-calcifications present in the mammogram images. By interpreting mammogram it is possible to identify whether the changes occurred are benign (non-cancerous) or malignant (cancerous). If the results suspects the chances of malignancy, then further tests and treatment can take as soon as possible. Specific abnormalities present in the mammogram images are explored visually by radiologists and physicians. Characteristic masses, clusters of micro-calcifications, and architectural distortions are important indications of breast cancer that experts searching for. However, due to many reasons, the analysis of mammograms by radiologists results in high rates of false positive cases. The problems regarding with the interpretation and thus diagnosis of the breast cancer get solved by introducing computers for biomedical image analysis.

Computer Aided diagnosis (CAD) is a broad concept that incorporates statistics, signal processing and artificial intelligence into computerized techniques that support healthcare professionals in their decision-making procedures. [1] CAD system for breast cancer detection is designed and developed to alert a radiologist to abnormal areas of a mammogram. The tool processes a digitized version of a mammogram and highlight mammographic features which is then examined easily. The goal for CAD is to aid the readers to notice features in a mammogram that might indicate cancer but that they may otherwise miss. To upgrade the accuracy of mammogram interpretation, plenty of CAD systems that uses different methodologies for the analysis have been proposed. CAD systems have become a powerful tool to assist healthcare professionals in achieving high efficiency, due to its capacity to process high volume of images and the large amount of information in less time as compared to the human processing.

CAD has been an active research area in medical imaging for the last two decades. Many researchers worked in this area and proposed different methods to solve the problems regarding the interpretation and diagnosis of breast cancer. Their findings and conclusions in modern medical filed is considered to be substantial and significant in the early detection and diagnosis of the deadly disease. This paper is a detailed study of various contributions by researchers in this area, which analyses performance of various CAD systems. The aim of this review is to present an outline of recent progresses and developments in the field of CAD analysis for breast cancer detection. This can be used as a primer for new researchers in this field.

II. CAD ABNORMALITY DETECTION IN MAMMOGRAM

The abnormalities or irregularities present in mammogram images can be broadly divided into 2 types: masses or calcifications [4]. A mass is something a little more significant and clearer than a normal lesion. Particularly, a mass has volume and so it inhabit space which is seen in at least two different projections. Masses present in mammogram image are found to be denser in the middle portions as compared to the edges. It may have differences in their margins, shapes, size, location and orientations, and may possess diverse backgrounds. Masses with irregular shapes are much suspected for malignancy. Lobule like masses in the mammogram are more dubious for breast malignancy as compared to purely oval or round shaped ones. Tiny mineral deposits present in the breast tissue which appear as small bright spots on the mammogram images are called as Micro-calcification clusters (MCC). These micro-calcifications are of various kinds and may differ in their allocation.[2,3,4]

A. Detection from Suspicious Mass

Shen-Chuan Tai et al. (2014) [4] presented an automatic CAD system that uses local and discrete texture features for mammographic mass detection. This system segments some adaptive ROIs for suspicious areas. For finding the foreground of concern, Otsu thresholding method is applied to the digital mammogram image firstly. The foreground may contains a breast region and a pectoral muscle region in most Medio Lateral Oblique (MLO) views of mammograms. The entire foreground is then modified by gamma correction with a decoding gamma, to protect the brighter luminance and suppress the darker luminance, thereby enhances the pectoral muscle. The system applied two types of morphological filters to the breast region, such as opening and closing filter, in order to suppress noises and other unwanted information. Hierarchical matching method, which compares three types of templates, is applied to identify the dubious breast masses and the Sech template was employed to match the suspicious area. This work also suggest two complex feature extraction methods based on co-occurrence matrix and optical density transformation to depict the discrete photometric distribution and local texture characteristics of each ROI. The first feature extraction module adopts Gray Level Co-occurrence Matrix (GLCM) features and optical density features. This complex texture feature extraction method take out the details of discrete photometric distribution and local intensity relation. The second feature extraction module used the Optical Density Co-occurrence Matrix (ODCM) in order to distinguish the photometric textures. Finally, the research employs stepwise linear discriminant examination by selecting and rating the discrete performance of each feature in order to classify abnormal regions. Results show that the proposed system achieves satisfactory detection performance. The study concluded that, for the dense breast analysis, the combination of ODCM and optical density features increases the mass detection rate of the CAD system.

Rahimeh Rouhi et al. (2014) suggested [5] two different automated methods to classify benignancy and malignancy by considering masses present in mammogram images. In the primary method, segmentation stage is performed by an automated region growing approach whose threshold is obtained by a trained Artificial Neural Network (ANN). In subsequent method, segmentation is carried out by a Cellular Neural Network (CNN) whose parameters are defined by a Genetic Algorithm (GA). For the noise removal, local area histogram equalization and median filtering is employed. The intensity of image pixels is stretched to extend the contrast in the histogram equalization step. Median filtering is used to reduce “salt and pepper” noise and speckle noise. Intensity, textural, and shape features are extracted from segmented tumours and the suitable features are chosen by GA. lastly, ANN is employed in the classification stage, which categorise abnormal mammogram images into benign or malignant. The sensitivity, specificity, and accuracy rates are obtained as 96.87%, 95.94%, and 96.47%, respectively.

Amal AlQoud et al. (2016) [6] introduced an approach for breast cancer detection system in which the textural features for the classification of mammogram images were extracted by hybrid Gabor based local binary patterns. The pre-processing stage composed of back ground removal and image enhancement by CLAHE. The system used texture analysis to extract features from the mammogram by using 2 techniques, such as Gabor filter and Local Binary Pattern (LBP) techniques, in order to increase features extraction accuracy and get better results. Final classification is done by using ANN classifier which interprets image quickly and effectively.

Hitiksha shah (2015) [7] also presented a CAD system for automated classification of breast cancer by considering masses presented in mammogram. The digital mammogram is pre-processed by 2D-median filter, connected component labelling method, and morphological functions for breast extraction. Wavelet transform is used for enhancement of mammogram and triangular mask is used for pectoral muscle suppression. Morphological functions such as opening, closing, erosion, dilation and reconstruction are used for the segmentation of mammogram to extract ROI. From ROI, intensity histogram based texture features are extracted. Extracted features are classified by neural network which is applied for two levels.

In the first level, neural network classify the segmented ROI into normal (without tumour) and abnormal (with tumour) ROI. Second level neural network classify abnormal ROI into malignant and benign masses.

Fatemeh Moayedi et al. (2010) [8] have experimented Contourlet-based automatic mammography mass classification with the aid of Support Vector Machine (SVM) family. Segmentation phase composed of removing pectoral muscles by histogram stretching & logarithmic methods, contrast enhancement by intensity adjustments and ROI segmentation by thresholding. Contourlet coefficients are obtained from feature extraction by contourlet transform, which is followed by feature selection stage by the genetic algorithm. More discriminative and compact feature set is extracted by this stage, which improves the robustness and accuracy of the classification. At the final phase, classification is accomplished by performing successive enhancement learning (SEL) weighted SVM, support vector-based fuzzy neural network (SVFNN), and kernel SVM. The system proposed in this work is tested on mammogram images from MIAS database. Accuracies of classification determined over an efficient computational time by SEL weighted SVM, SVFNN and kernel SVM are 96.6%, 91.5% and 82.1% respectively. The final results of the experiment demonstrated that an efficient, powerful and practical method for the automatic breast mass classification of mammograms is the contourlet-based feature extraction combined with the state-of-art classifiers construct

*Chisako Muramatsu et al. (*2016) [9] presented radial local ternary patterns based breast mass classification on mammograms. Apart from shape and margin features this study investigated an ROI based feature, specifically, radial local ternary patterns (RLTP). This approach takes the direction of edge patterns with respect to the centre of masses for benign and malignant mass classification. The paper further analyse and compare ANN, SVM and RF classifiers with those of the regular LTP (local ternary patterns), RIU2 (rotation invariant uniform) LTP, GLCM texture features and wavelet features. Performance analysis was done with 376 ROIs containing 195 benign and 181 malignant masses.

B. Detection from Micro-calcification Clusters

In their study Dong Wang et al. (2010)[10] employed three methods of feature selection to acquire an effective classification of breast micro calcification clusters (MCC) in mammogram. A neural classifier, a clustering criterion and a combined scheme are used in this stage. Performance evaluation of these 3 feature selection approaches is done by applying a same neural classifier with selected features and compare the classification results. In the neural network based feature selection approach, a BPNN (back propagation neural network), with an input layer, a hidden layer and an output layer were employed. To ascertain the performance of designed neural classifier, each of the 39 features is applied as input to it. In the clustering method, mean value and standard deviation of all the samples in benign and malignant group are extracted and an overall rank of each feature was determined.[16] Based on the obtained rank the samples can splits into corresponding two groups. Then a combined scheme is proposed on the basis of feature selection results from clustering rules and NN. Primarily, for the selected features from NN and clustering rules, a score within [1, 39] are assigned to each feature sequentially according to its decreasing discriminative ability. Then, an overall rank is acquired for each feature as the sum of two scores assigned. In further classification primary priority will be given to the feature of lower overall rank. 748 MCC samples got selected from DDSM database, which contain 633 benign and 115 malignant in nature. For each of the sample 39 features are extracted in which 15-20 selected features counts for best classification rate.

Yanan Guo et al. (2016) [11] introduced an approach for detecting MCCs in mammograms using contourlet transform and non-linking simplified PCNN (Pulse Coupled Neural Network). Three main steps of the method presented in the study are given: Primarily, remove label and pectoral muscle by using the largest connected region marking and region growing method, and then enhance MCCs using the combination of grayscale-adjustment function and double top-hat transform; This is followed by abolition of noise and other unwanted information, and retain only significant data by contourlet coefficients modification using nonlinear function; Final stage employed non-linking simplified PCNN to detect MCCs. The method is checked with MIAS and JSMIT databases and achieved specificity: 94.7%, sensitivity: 96.3%, AUC (Area under the ROC Curve): 97.0%, accuracy: 95.8%, Matthew's Correlation Coefficient (MCC): 90.4%, Proportion of Sample (MCC-PS): 61.3% and comprehensive evaluation indicator (CEI): 53.5%. Authors concluded out that the method presented is simple, fast and high detection rate is achieved.

Sung-Nien Yu and Yu-Kun Huang (2010) [12] investigated detection of MCs in digital mammogram images by combining statistical and model-based textural features. In the primary stage of study, suspicious MCCs were detected using two thresholds and a wavelet filter. Then textural features extracted by MRF (Markov random field) and fractal models. Along with this, statistical textural features based on SRDM (surrounding region-dependence method) were extracted from the neighbourhood of the suspicious MCCs. Classification is done by a three-layer BPNN and its performance is assessed and compared with existing techniques, by FROC (free-response operating characteristic curve).

For the testing and performance analysis of the proposed method 20 mammograms, with 25 areas of MCs, from MiniMIAS database were selected. Experimental results suggests that, for effective detection and characterisation of MCs combined model-based and statistical textural features are suitable. The method achieved a TP rate of 94% at the rate of 1.0 FP per image.

X.Zhang et al. (2012) [13] employed a twin support vector machine (TWSVM) for the detection of MCs. Primarily, film-artefacts in the image got removed by a simple film-artefact removal filter. In the next step, subspace features of each negative and positive samples are extracted by subspace learning algorithms, PCA, LDA, TSA and GTDA. Then to test whether a selected mammogram block has MCs or not, a trained TWSVM is used. The support vectors, which are identified from the samples during training stage, determine the decision function of the TWSVM. The ROC curve illustrated that the proposed method give the best performances.

F. Harirchi et al. (2010) [14] proposed a two-level MC detection algorithm with Diverse- Adaboost SVM (DA-SVM) classifier. Automatic detection of MCs were done by 2 steps; In the primary step, the pixels corresponding to potential MCs are found using a multilayer feed-forward neural network, in which 4 wavelet and 2 gray-level features consist the input and the output is then transformed to potential MC objects using spatial 4-point connectivity. [14] In the final stage, 25 features from potential MCs were extracted [17] and selected with the aid of GLDA are given to the classifiers. Four classifiers, such as NN, SVMP, SVMRBF and DA-SVM, were used and the performance were compared. DA-SVM classifier over performs the other 3 with 90.44% mean TP detection rate at the rate of 1.043 FP per image.

A.Oliver et al. (2012) [15] introduced an automatic MC and cluster detection method for digital mammogram images. The proposed approach is divided in three parts. First, creation of the word dictionary is obtained by convolving patches containing a MC with a bank of filters. This dictionary permits to characterize examples of known MCs and will eventually used to characterize images of unknown. [15] Primarily, the training data is found by convolving positive samples (MC containing patches) and negative samples (patches of other tissues) with the words of the dictionary. Then it is employed as input to the Gentleboost classifier. Now, by this trained classifier new mammogram images got pixel-by-pixel classification. Thus, a pixel-based classification approach is used for the detection problem.

III. ANALYSIS AND DISCUSSION

The performance of detection systems can be evaluated by many factors, such as; the accuracy, sensitivity, specificity, False Positive rate per image (FP/image), area under ROC curve (AUC), Matthew's Correlation Coefficient (MCC), Micro-calcification cluster Proportion of Sample (MCC-PS), Comprehensive Evaluation Indicator (CEI), Free-Response Operating Characteristic (FROC) curve etc. The tables below provides a comparative study of methods and performance of the reviewed papers. CAD systems for automated detection of breast cancer from suspicious mass and MCCs are summarized separately. The values of performance evaluation factors are entered in the table as provided in respective papers. The advantages, drawbacks, solutions to improve performance and future scopes of each papers are also included in the tables, which can be utilized for the developments of future CAD systems.

TABLE I
CAD SYSTEMS FOR DETECTION OF BREAST CANCER FROM SUSPICIOUS MASS

Authors & Year	Database	Methodology Adopted	Evaluation of Performance	Remarks
Rahimeh Rouhi et al.[5] (2014)	MIAS & DDSM	1. Segmentation with combined region growing and CNN. 2. Classifier: ANN	Sensitivity: 96.87% Specificity: 95.94% Accuracy: 96.47%	1. Diagnosis strength of malignancy is higher compared to benign. 2. Variability of the results on DDSM & MIAS databases, which can overcome by adopting better pre-processing techniques.
Shen-Chuan Tai		Two feature extraction methods; 1. GLCM + optical	1st method: AZ = 0.981 Sensitivity: 90.3% FP rate: 4.8	1. Both methods achieves satisfactory detection sensitivity with an acceptable FP rate. 2. 2nd method is better for detection in

et al. (2014) [4]	DDSM	density features. 2. ODCM + optical density features	2nd Method: AZ = 0.976 Sensitivity: 90% FP rate: 4.9	dense breast.
Amal AlQoud et al. (2016) [6]	MIAS	1.Fused Gabor and LBP texture features 2.Classifier :ANN	Accuracy : 98.59% Sensitivity: 97.20% Specificity: 97.51%	1. Combination of features improved detection probability 2. Future work: Deep NN classifier
Hitiksha shah (2015) [7]	MIAS	1. Preprocessing: Median Filter, wavelet transform 2. Segmentation: Morphological operations 3. Feature Extraction: Texture features using intensity histogram 4. Classification: NN	1st level classification: Accuracy: 95.37% Specificity: 96.07% Sensitivity: 94.73% 2nd level classification: Accuracy: 85.18% Specificity: 91.66% Sensitivity: 80%	1. Classification in second level get affected by misclassification in the first level. 2. Future Improvements: extraction of new features and proper feature selection method.
Fatemeh Moayedi et al. (2010) [8]	MIAS	1.Preprocessing: histogram stretching 2.Segmentation: Adaptive Histogram Equalization 3. Feature Extraction: Contourlet transform, 4. Feature selection: GA 5. Classification: SEL weighted SVM method	Accuracy: 96.6%	1. Best accuracy with minimum standard deviation is achieved by using SEL weighted SVM. 2. SEL weighted SVM is also more robust when compared to the other classifiers.
Chisako Muramatsu et al. (2016) [9]	Clinical dataset for research	1.Feature extraction: RLTP 2.Classifiction: ANN, SVM, RF	AUC Values; 1. RLTP: 0.90 2. LTP: 0.77 3. RIU2-LTP: 0.78 4. GLCM:0.83	1. Time conserving method, since precise segmentation is not required for ROI based features. 2. The system provide consistent results for lesions overlapped with fibro-grandular tissue where automated segmentation is challenging. 3. Future scope: Feature extraction with a combination of RLTP, DWT and GLCM should apply.

TABLE III
CAD SYSTEMS FOR DETECTION OF BREAST CANCER FROM MCCS

Authors & Year	Database	Methodology Adopted	Evaluation of Performance	Remarks
Dong Wang et al. (2010)[10]	DDSM	Classification: 1. NN Classifier 2. Clustering Criterion 3. Combined scheme	Combined method perform well compared to the other schemes	1. Effective feature selection provides data redundancy and improved classification. 3.Future scope:For further reduction of false alarms and to deal with the unbalanced data issues, apply combination of classifiers.
Yanan Guo et al. (2016)[11]	MIAS & JSMIT	1. Preprocessing: region marking and region growing method, Contourlet transform 2. Classification: non-linking SPCNN	Specificity: 94.7% Sensitivity: 96.3% AUC: 97.0% Accuracy :95.8 % MCC :90.4% MCC-PS: 61.3%	1.Simple and fast method 2.High detection rate 3. Better performance to fatty breasts. 4.Experimented with a limited sample database 5.Future scope: large dataset
Sung-Nien Yu (2010)[12]	MIAS	1.Detection : Wavelet filter 2.Feature extraction: MRF model & fractal model 3.Classifier:3 layer BPNN	TP rate: 94% (FP/image: 1)	1. Consolidated model-based and statistical textural features are appropriate for distinguishing MCs and fit for supporting an effective and reliable MCs discovery. 2. Require improvement in FP rate.
X.Zhang et al. (2012)[13]	DDSM	1.Preprocessing: film-artifact removing filter 2.Feature extraction: subspace learning algorithms (PCA, LDA, TSA & GTDA)	Sensitivity: 94.417% FP rate: 8.327% AZ: 0.968	1.TWSVM classifier with GTDA has high detection rate 2. Four time faster than SVM. 3. Relatively lower generalization error 4. TSA & GTDA methods perform better with the compact sample size issue; 5. PCA & LDA is better with a large amount of samples 6. Faces problem with greater no of training sample for GTDA
F. Harirchi et al. (2010)[14]	Clinical dataset (University Hospital of Nijmegen, the Netherlands)	1.Feature selection: GLDA 2.Classification: DA-SVM	Sensitivity; 90.44% FP/image: 1.043	1. DA-SVM over-perform other classifiers (NN, SVMP& SVMRBF) 2. DA-SVM provides higher generalization accuracy 3. Produce best TP percentage even in low amount of FP per image [14]
A.Oliver et al.	MIAS & a non-	1.Dictionary creation: by convolving patches containing a MC with a bank of filters	Az: 0.918 1 FP/ image at a sensitivity of	1. Reliable since tested with large dataset. 2.Require improvements in sensitivity and FP rate 3. Computational time and cost are

(2012)[15]	public database	2.Classification: Gentle Boost Classifier	80% 4 FP/image at a sensitivity of 90%	relatively high.

By analyzing the tables, it is clear that even though many methods produced high accuracy rates of order 90%, it requires further improvements in FP rates. Since the system is related with human life, it definitely requires precise results. A minute error may leads to wrong diagnosis, complications in the treatment and even the death of patient at the extreme case. So the future CAD systems needs to be work on this area.

Another fact to consider for the future studies is that most of the existing methods used MIAS database (Mammographic Image Analysis Society) or DDSM database (Digital Database for Screening Mammography) for their experiments. Only few had choose real time clinical datasets. Using real time mammogram images in the training as well as testing phase increases reliability and acceptance of CAD system for the breast cancer detection by the medical field. These points will be considered in the future development of fully automated CAD system for early detection of breast cancer.

IV. CONCLUSION

Breast cancer can be successfully diagnosed with the aid of CAD system. This study briefly explained some of the recent advances in CAD systems proposed by researchers in the breast cancer detection field. They have adopted various methods for different stages of CAD system: 1.pre-processing, 2.segmentation, 3.feature extraction, and 4.feature selection and 5.classification stages. Even though CAD system is accepted by the medical field, it is still acting as a second reading aid and didn't replace human readers. The comparative analysis provided in this study reveals that, an effective CAD system with increased accuracy is still required to develop. By comparing the different methods for each stages of detection, an efficient fully automated CAD for early detection of breast cancer can be developed in the future. The main goal of future CAD systems must be to increase diagnostic accuracy, reduce computational speed and calculation errors, with the advanced mathematical and computational techniques.

V. ACKNOWLEDGEMENT

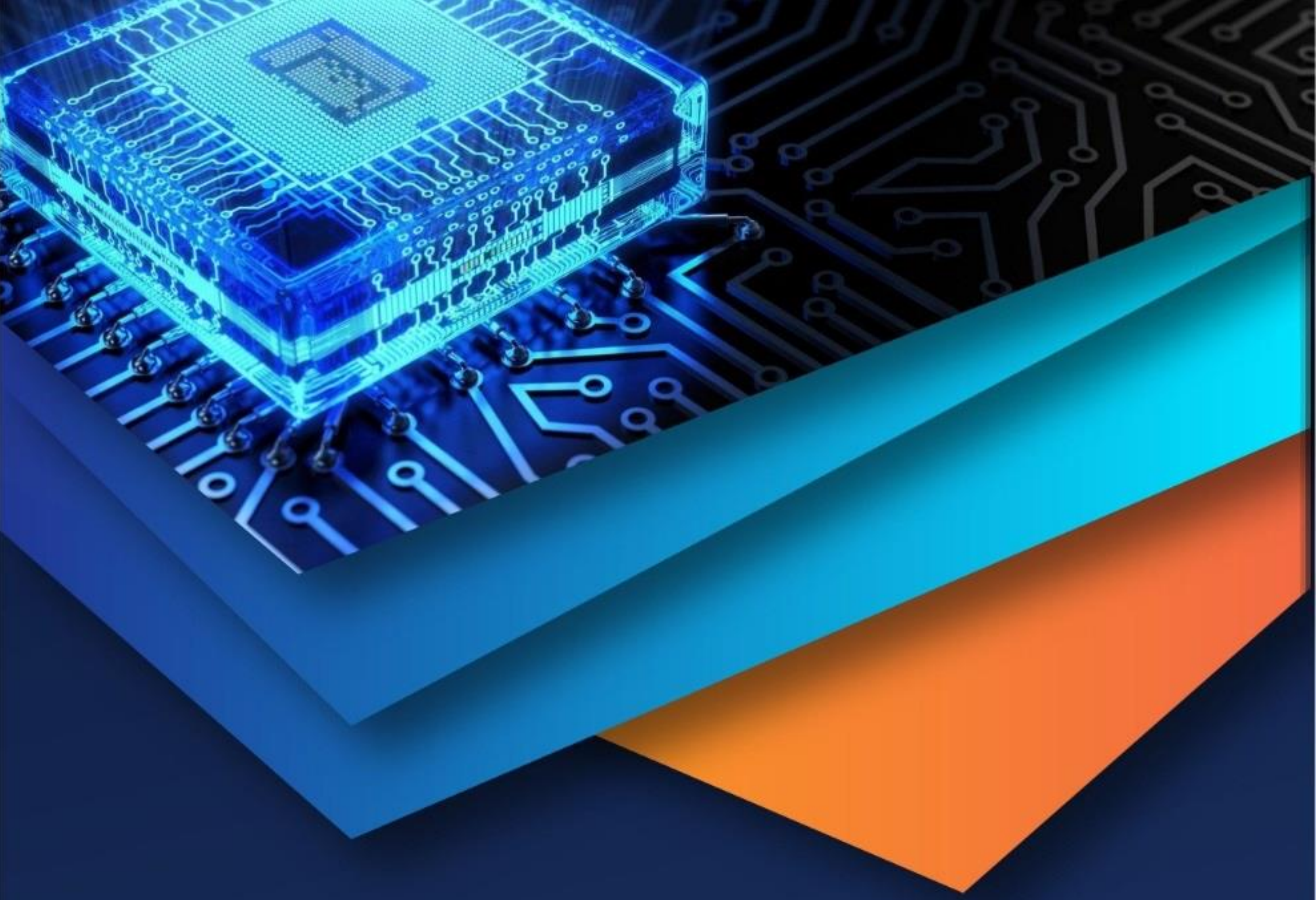
We submit the work in divine feet of God Almighty for blessing us with his wisdom for surpassing every difficulty faced during this work. We wish to thank everyone who supported to fulfil the work successfully.

REFERENCES

[1] H.Eren and J.G.Wedster, "Tele-health and Mobile Health", Taylor & Francis Group, Boca Raton, 2016.
[2] A.M. Joseph, G.John M, A.S.Dhas, "Mammogram Image Denoising Filters: A Comparative Study", Proc. IEEE Conference on Emerging Devices and Smart Systems, India, pp.184-189, 2017.
[3] X.Gao, Y. Wang, X. Li et al. "On combining morphological component analysis and concentric morphology model for mammographic mass detection", IEEE Trans. Inf. Technol. Biomed. Vol. 14, Issue.2, pp. 266– 273, 2010.
[4] S.C. Tai, Z.S. Chen, W.T. Tsai, "An Automatic Mass Detection System in Mammograms Based on Complex Texture Features", IEEE Journal of Biomedical and Health Informatics, Vol. 18, Issue.2, pp. 618-627, 2014.
[5] R.Rouhi, ,M.S.Kasaei, P.Keshavarzian, "Benign and malignant breast tumours classification based on region growing and CNN segmentation", Expert Systems with Applications Elsevier,Vol. 42, pp. 990–1002, 2014.
[6] A.AlQoud, M.A. Jaffar, "Hybrid Gabor based Local Binary Patterns Texture Features for classification of Breast Mammograms", IJCSNS International Journal of Computer Science and Network Security,Vol. 16, Issue. 2, pp.16-21, 2016.
[7] H.Shah, "Automatic Classification of Breast Masses for Diagnosis of Breast Cancer in Digital Mammograms using Neural Net-work", International Journal of Science Technology & Engineering,Vol. 1, Issue. 11, pp. 47 –52, 2015.
[8] F.Moayedi, Z.Azimifar, R.Boostani et al., "Contourlet-based mammography mass classification using the SVM family", Computers in Biology and Medicine Elsevier, Vol.40, pp. 373–383, 2010.
[9] C.Muramatsu, T.Hara, T.Endo et al., "Breast mass classification on mammograms using radial local ternary patterns", Computers in Biology and Medicine Elsevier. Vol. 72, pp. 43–53, 2016.
[10] D. Wang, J. Ren, J. Jiang et al., "Applying Feature Selection for Effective Classification of Micro-calcification Clusters in Mammograms", 10th IEEE International Conference on Computer and Information Technology (CIT 2010). Pp. 1384-1387, 2010.
[11] Y.Guo, M.Dong, Z.Yang et al., "A new method of detecting micro-calcification clusters in mammograms using contourlet transform and non-linking simplified PCNN", Computer Methods and Programs in Biomedicine Elsevier, Vol.130, pp. 31–45, 2016.
[12] S.N.Yu, Y.K. Huang, "Detection of micro-calcifications in digital mammograms using combined model-based and statistical textural features", Expert Systems with Applications Elsevier, Vol.37, pp.5461–5469, 2010.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue XI Nov 2023- Available at www.ijraset.com

[13] X.Zhang, X.Gao, “Twin support vector machines and subspace learning methods for micro-calcification clusters detection”, Engineering Applications of Artificial Intelligence Elsevier, Vol. 25, pp. 1062–1072, 2012.
[14] F. Harirchi, P. Radparvar, H.A.Moghaddam et al., “Two-Level Algorithm for MCs detection in mammograms using Diverse-Adaboost-SVM”, International Conference on Pattern Recognition (ICPR) IEEE. pp.269-272, 2010.
[15] A.Oliver, A.Torrent, X. Llado et al., “Automatic microcalcification and cluster detection for digital and digitised mammograms”, Knowledge-Based Systems Elsevier, Vol. 28, pp. 68–75, 2012.
[16] D.Wang, “Digital image processing via combination of low-level and high-level approaches”, University of Bradford, 2011.
[17] P.Xi, C.Shu and R.Gaubran, “Abnormality detection in mammography Using Deep convolutional neural networks”, IEEE International Symposium on Medical Measurements and Applications, 2018.



10.22214/IJRASET

INDEX COPERNICUS
45.98

IMPACT FACTOR:
7.129

TOGETHER WE REACH THE GOAL
IMPACT FACTOR:
7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY