Mammography Image Abnormalities Detection and Classification by Deep Learning with Extreme Learner

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***Abstract*—Breast cancer has emerged as a leading killer of women worldwide in recent decades. Mammography is a useful tool for detecting abnormalities and doing screenings. The primary factors in the early identification of breast cancer are the quality of mammogram image and the radiologist's appraisal of the mammography. The extensive use of deep learning (DL) as well as other image-processing technologies in recent times has tremendously aided in the categorization of breast cancer images. Image processing and classification methods may help us find breast cancer earlier, increasing the likelihood of a positive outcome from therapy and the likelihood of survival. employ picture segmentation methods on the datasets to draw attention to the area of interest, and then classify the findings as malignant or benign. In an effort to minimize the mortality rate from breast cancer among females, this research seeks to discover novel approaches to illness classification and detection, as well as new strategies for preventing the disease. In order to correctly categorize the results, the best possible feature optimization is carried out utilizing deep learning technology. The Proposed deep CNN (Convolutional Neural Network) is improved using two classification models such as SVM (Support Vector Machine) and ELM (Extreme Learning Machine). In the proposed deep learning model, the feature extraction with AlexNet is accomplished using deep CNN. Subsequently, different parameters are fine-tuned to enhance accuracy with various optimizers and learning rates.**

Keywords*—Breast cancer; mammography; deep learning; CNN; extreme learning

I. Introduction

Cancer is a lethal disease with an expected 10 million fatalities and 19.3 million cancer diagnoses in 2020. Breast tumours are the fifth largest cause of death among women, and the second most common malignancy in women behind lung cancer [1], [2]. In 2020, there were 684,996 breast cancer-related fatalities and 2.3 million additional cases were recorded among women in developing nations [3], [4], [5]. In these nations, breast cancer is the main reason why women die. A lump or mass is formed as a result of the cells inside the breast tissues changing and dividing into many copies of themselves. The lobules or ducts that are attached to the nipples are where cancer first begins to form. The majority of breast lesions are benign, which means that they do not cause cancer. Benign breast masses may cause fibroids, region enlargement, or lumps. When breast tumours are tiny and curable, they frequently lack symptoms. Initially, breast cancer develops gradually, but it eventually spreads to distant organs. Mammography, ultrasound, MRI, mammographic tomosynthesis are mostly a handful of the diagnostic procedures that can assist detect breast cancer [6], [7]. Mammography is the most advised test at a preliminary phase. Mammography is a low-cost, low-radiation technique preferred for breast cancer premature detection [8]. It is possible to save lives with these treatments if they are started quickly enough. If found early, the rate of survival is 90% in richer nations, 66% in India and 40% in South Africa. Because of limited resources, early detection and treatment are especially important in low-income nations to preserve the lives of women. In recent years, there has been lot of focus on creating deep learning techniques for analysing mammograms. Due to advancements in machine learning and computer vision algorithms, a robust categorization strategy is now available, capable of producing very high rates of accuracy. As a cutting-edge technique, deep learning is increasingly being used to recognise and categorise visual patterns. One of the most well-known and often used deep learning methods is the application of convolutional neural networks (CNNs). Not only does it aid in categorising the image of a cancer, yet it also helps in extracting key features from it. The best accuracy in a system may be achieved by the application of deep learning, which offers a variety of strategies and algorithms for learning the features, extracting, and classifying [9], [10]. Several of these features enhance the representation of data. Instead of manually crafted features, DL techniques use powerful algorithms to uncover hierarchy-based features which best represent the data at current time. Rapid advances in image processing have facilitated the development of rapidly evolving cutting-edge technology . The importance of image processing has increased, especially in the healthcare field [11]. DL is a technique that enhances performance and saves a lot of time when compared to prior methods. Although conventional techniques can only process images with a single layer, DL can process images with multiple layers exceptionally well. The fact that deep learning can interpret pictures in a single pass without needing any input of variables from the user is perhaps the most significant advantage it offers. The objective of this study is to prepare the basis for the application of deep learning to the task of analyzing and classifying images of breast cancer [11], [12], [13], [14], [15], [16], [17].

A. Motivation

Radiography is used in mammography; however, it is a special technology developed for women's breasts. Its purpose is to identify anomalies as quickly as possible when symptoms or something incorrect is noticed, such as a skin changes, palpable nodule, inflammation, discharge, etc. [18]. An X-ray beam is sent through various breast tissues, and the attenuation of this beam creates the mammography image. The chemical composition of the tissues that this beam passes through has a significant impact on the amount of attenuation that it experiences. Actually, the grease is indeed a radio accessible zone because of its low physical density. This causes it to look extremely black on a mammography. Mammary lesions consist primarily of fibro granulation tissue and calcium, both of which can be seen clearly in radiographs as "opaque" zones [19]. A mammogram [19] is typically taken from a few distinct angles, or occurrences. For the best results, spread the breast tissue out as far as feasible on the X-ray plate to maximise its visibility. Different ramifications are employed based on the area of the breast is being inspected. Face, or Cranio Caudale (CC) incidences, oblique external, or Medio-Lateral Oblique (MLO) incidences, and profile occurrences are the most common types of incidences (Fig. 1) [20].

B. GAP in Previous

- In previous work ignore the non-linear features mapping.its increase the overlapping of features.
- Increase the class overlapping by using linear features and increase over fitting by using polynomial features.

C. Contribution

1) Reducing features overlapping by using deep learning based CNN.

2) Investigate the effect of extreme learning on classifier optimization in the last block of CNN.

3) Apply various activation functions and dropout to the performance analysis of the suggested work.

4) Reducing the overfitting by using extremenlearner by combination of linear classifier.

This research paper is divided into three sections: Section I is a discussion of the basic introduction, Section II is a review of previous literature, and Section III is a proposal for future work. In Section IV, result analysis, comparison with existing approaches, and the last conclusion section, this work is concluded.

II. Related Work

The potential application of deep learning in the detection of breast cancer has generated considerable interest. Several DL algorithms have subsequently been offered as diagnosing aids for breast cancer, enabling doctors to make informed treatment decisions. This section contains several works that appear to be directly related to this research.

Thappa et al. (2022) use a Patch-Based Classifier (PBC) in conjunction with DL architecture to improve the precision with which breast cancer scans can be classified. The Deep Convolutional Neural Network (DCNN) used in the suggested system contributes to improving and boosting classification accuracy. By employing the PBC, this is accomplished. Images are first processed through convolutional layers utilizing the max-pooling layer, the hyperbolic tangent function, the SoftMax function, and the drop out layers before being classified using CNN's entirely distinct layers. Additionally, the output is fed into a PBC that uses the output from patch-wise categorization as the basis for majority voting. For cancer scans that are gathered from breast-histology databases, the outcomes are obtained during the classification step. The suggested technique reduces processing time from 0.45 seconds to an average of 0.2 seconds while increasing classification accuracy from 87% to 94% for images that contained benign, normal, in-situ, or incurable cancer. Zahoor et al. (2022) intend to look into ways to prevent diseases and new ways to classify them in order to lower the chance that women will get breast cancer. The important feature optimization is done to accurately classify the results. False-positive rates have been cut down, which has made the CAD system more accurate. The Modified Entropy Whale Optimization Algorithm (MEWOA) is suggested as a fusion-based deep feature classification and extraction algorithm. For computation, the recommended method employs fine-tuned Nasnet Mobile and MobilenetV2. The features are extracted and then optimized. MEWOA serves to merge and improve the features that have been optimized. Lastly, the optimized deep features are used tell ML classifiers how to put the breast cancer image data into groups. Researchers take the information from three public databases to find features and classify them: MIAS, CBIS-DDSM, and INbreast. INbreast data source has 99.7% highest accuracy, MIAS data source has 99.8%, and CBIS-DDSM has 93.8%. Hashmi & Malebary (2021) recommend BMC, an innovative Breast Mass Classification. It has an enhanced structure using a pairing of RNN and Long Short-Term Memory, k-mean clustering, CNN, RF, and boosting methods to categorize malignant, normal, and benign beast masses. Utilizing two publicly accessible data sources of mammographic images, the suggested The BMC system is however evaluated by comparing to classifications that already exist. The specificity, sensitivity, accuracy, and F-measure of the proposed BMC system are 0.98%, 0.97%, 0.96%, and 0.97% for the DDSM dataset and 0.98%, 0.97%, 0.95% and 0.97% for the MIAS dataset, respectively. Additional Area Under Curve (AUC) rate of a recommended BMC system ranges among 0.94 and 0.98 for the MIAS dataset and among 0.94 and 0.97 for the DDSM dataset. The BMC method performed relatively better than previously developed mammogram classification systems. Krithika et al (2021) aims to develop an automatic CAD [2] model that can identify malignant or benign breast cancer by locating the area of mitotic cell growth. The researchers have come up with a model that uses mammogram images and a fully supervised convolution model. The model was trained with benign and malignant cancer image datasets. This model utilizes the MIAS dataset and hospital-collected datasets containing screening mammography images available for detection of breast cancer as samples. Utilizing techniques for image segmentation on the datasets, designers illustrate the area of interest, and then classify the outcomes as malignant or benign using classification methods. The designed model enables us to generate 97.96% accurate results from the dataset. Altan (2020) came up with a CNN model based on simple feature learning and then a sophisticated classifier model to tell the difference in both healthy and cancerous mammograms. Utilizing CNN, the suggested DL-based model assessed the applicability of different feature-learning models and improved the learning capability of DL models for operative diagnosis of breast cancer. The mammograms were sent to the DL so that the categorization performance of the various CNN models could be evaluated in line with mammography screening. Sensitivity, Accuracy, specificity, and precision rates for the proposed Deep model were 95.30%, 92.84%, and 96.72%, respectively. Gnanasekaran et al. (2020) emphasizes a CNN-based CAD system that employs DL to classify mammogram images as malignant, normal, or benign. The proposed CNN model, which includes eight convolution layers, two fully connected layers, and four max-pooling outperformed the pre-trained VGG16 and AlexNet networks. The suggested framework illustrates the viability of incorporating CNNs into medical image processing methods for breast mass classification. The results have also been compared to a cutting-edge ML classifier that functions similarly to KNN. Experiments are run using three different datasets. The Mammographic Image Analysis Society (MIAS) dataset and the digital database for screening mammography (DDSM) are both accessible to the public. The suggested model had accuracy scores of 92.54, 96.47, and 95 for MIAS, DDSM, and the internally generated dataset, respectively, and an Area under the ROC curve score of 0.85, 0.96, and 0.94. Zhuang et al. (2019) propose an improved DenseNet neural network model, known as the DenseNet-II neural network model, for the precise and efficient classification of benign and malignant tumours. The mammographic images are first prepared. Image normalization reduces light interference, and data improvement reduces over-fitting brought on by limited data sets. In order to substitute the first convolution layers of the DenseNet model for neural networks with the Inception architecture, a new model for neural networks called DenseNet-II called DenseNet-I is designed. The pre-processed mammogram datasets are then fed into the VGGNet, AlexNet, DenseNet, GoogLeNet, and DenseNet-II neural network models, after which the experimental results are examined and contrasted. Table I review some latest work of research.

III. Proposed System

Proposed approach mainly deal with two gaps: one is feature mapping in non linear space, and second its consequence come during learning like classes overlapping by ELM which improve learning.In this research need non linear features because its increase domain knowledge classwise.

A. Dataset

The research has focused on a broader range of tumor abnormalities comparatively including benign and malignant-based breast tumors using mammogram images. In this research work, the Mammogram Image Analysis Society (MIAS) database and Digital Database for Screening Mammography (DDSM) is utilized to test the performance of the proposed methods. MIAS database contains the 322 pictures (161 sets of both left and right) taken at 50- micron goals in "Portable Gray Map" (PGM) group and related information. Different datasets which are acquired from DDSM which contains 2,620 examinations. A total of 600 images are acquired from the database. The obtained data were categorized, and the system's validation was done based on presenting the images for training and testing as mentioned in Table II.

The breast-tumour based abnormality classification system categorizes the input images into normal or abnormal, and benign or malignant using the extracted features from the segmented region of the preprocessed mammogram images. Fig. 1 shows the entire work of the proposed system for breast tumour detection using mammogram image. In the proposed system, various methods were combined and steps have been employed to attain more classification accuracy. This chapter estimates the performance of the proposed and existing methods for malignant tumour detection at an early stage.

The efficiency of every filtering approach for an image optimization procedure was assessed for the input mammography pictures using the current filters and the proposed filtering technique. Mammogram images are used for the tumor segmentation study to evaluate the effectiveness of the suggested visual saliency segmentation method. The currently used techniques, multilevel Otsu thresholding. Apply a convolution network with SVM and ELM after segmentation. A 3-tier, multi-channel CNN architecture built on AlexNet is presented. For the three Conv1D channels, kernels sizes of 11, 5, and 3 are used depending on the AlexNet filter sizes to enable extraction of features at various resolutions. Each convolutional block's output is then sent through a series of max-pooling layers to recapitulate previously learnt features in order to reduce their size while maintaining accuracy. As a regularization strategy in this model, Standard Dropout and Spatial Dropout strategies are used to stop the model from overfitting. The suggested model for CNN generalization uses an exponential linear unit (ELU) activation function (Fig. 2).

IV. Experimentation Results and Discussion

A. Tumour Classification Accuracy

The proposed algorithm was executed for accuracy assessment for the hundred trials and the mean consequence was measured to obtain the accuracy of normal, benign, or malignant. The proposed algorithm accuracy was estimated through several learning kernels. The accuracy comparison of the proposed method BORN for various learning functions utilized has been summarized in Table III. Table III has demonstrated that the high accuracy attained 99.4% with the sigmoidal function for the BORN method in the given MIAS dataset. The proposed BORN's accuracy and the sigmoidal learning function have been calculated with arbitrarily selected hidden neurons given in Table III. Table IV clearly shows that the sigmoidal learning along with 150 neurons has a maximum accuracy of 99.5% in classifying different stages of breast cancer.

The mammogram's tumour classification accuracy depends on the tumour cells detected and classified correctly out of total breast cells presented in the mammogram image. The performance level of the proposed classifier in tumor detection is analyzed through its accuracy level. The proposed classifier has a higher accuracy level compared to existing classification methods, such as SVM, FF-ANN, RF-ELM, and DWT-RF, in

TABLE I. LITERATURE REVIEW FOR DL-BASED MAMMOGRAPHY

Ref	**Year**	**Aim**	**Techniques**	**Clinical Features/Classifier**	**Dataset**	**Findings**
[9]	[2022]	Classification of breast cancer using deep learning.	Convolutional neural network (CNN)	Patch-based classifier (PBC)	Breast-histology datasets	The proposed technique aimed to improve the accuracy of breast cancer classification by raising image contrast and decreasing the vanishing gradient.
[10]	[2022]	Breast cancer mammography classification using a deep neural network and an entropy-controlled whale optimization algorithm.	Fine-tuned MobilenetV2 and Nasnet Mobile models, Modified Entropy Whale Optimization Algorithm (MEWOA)	Optimized deep features/ML classifiers	MIAS dataset, INbreast dataset, CBIS-DDSM dataset	By applying the MEWOM, we were able to optimize the features while simultaneously decreasing the amount of time spent computing them. With the help of these techniques, we were able to lower the rates of both true-positive and false-negative outcomes.
[14]	[2021]	extreme learning and Deep learning are used to make an automated system for classifying breast masses.	Breast Mass Classification system: ResNet RNN-LSTM-CNN based network.	Semantic features/RF-boosting method for classification.	DDSM and MIAS	Comparatively, the BMC technique performed better than previous mammography categorization systems.
[15]	[2020]	Breast cancer mammography categorization using deep learning.	CNN	Simplified feature learning/fine-tuned classifier	Heterogeneous image database	The mammograms were placed into the DL in order to assess how well different CNN designs classified the data. High classifier performance rates were attained using the suggested Deep model.
[16]	[2020]	Classification of breast masses in mammograms using a DL algorithm.	AlexNet and VGG16.	5 geometric and 14 textural features/ A kNN classifier	The internally gathered data set is known as the ID dataset, while the combined dataset is referenced to as CD data set.	The suggested model shows that it is possible to classify breast masses using medical image processing methods and CNNs.
[18]	[2019]	DL-based categorization of malignant and benign lesions in mammography images.	VGGNet, AlexNet, DenseNet GoogLeNet, network model and DenseNet-II neural network model	Breast cancer features/ mammogram images classification.	Mammogram datasets	The classification performance of the DenseNet-II model of neural networks is superior in comparison to other network architectures.

TABLE II. RESEARCH DATABASE

	Total		Malignant		Benign	
	Samples	Cases	Samples	Cases	Samples	Cases
Training	420	60	100	30	100	25
Testing	90	55	100	22	100	16
Validating	90	20	50	18	50	12

TABLE III. ACCURACY OF BORN WITH DIFFERENT LEARNING FUNCTIONS

Dataset details	Learning Kernel	Training Accuracy	Testing Accuracy
MIAS	Sigmoid	98.4%	99.4%
	Sine	96.7%	95.4%
	Tanh	95.5%	96.5%
DDSM	Sigmoid	98.5%	99.3%
	Sine	95.4%	95.4%
	Tanh	95.0%	96.3%

TABLE IV. ACCURACY OF BORN ALGORITHM FOR VARIOUS NEURONS UTILIZED

Dataset details	No of neurons	Training Accuracy	Testing Accuracy
MIAS	10	95.5%	96.5%
	20	96.4%	97.5%
	50	98.4%	97.5%
	75	97.4%	96.5%
	100	98.4%	99.4%
	150	98.4%	99.5%
	200	97.5%	98.5%
DDSM	10	98.5%	99.3%
	20	95.4%	95.4%
	50	95.0%	96.3%
	75	94.4%	95.5%
	100	97.5%	96.4%
	150	98.55	99.4%
	200	97.55%	98.2%

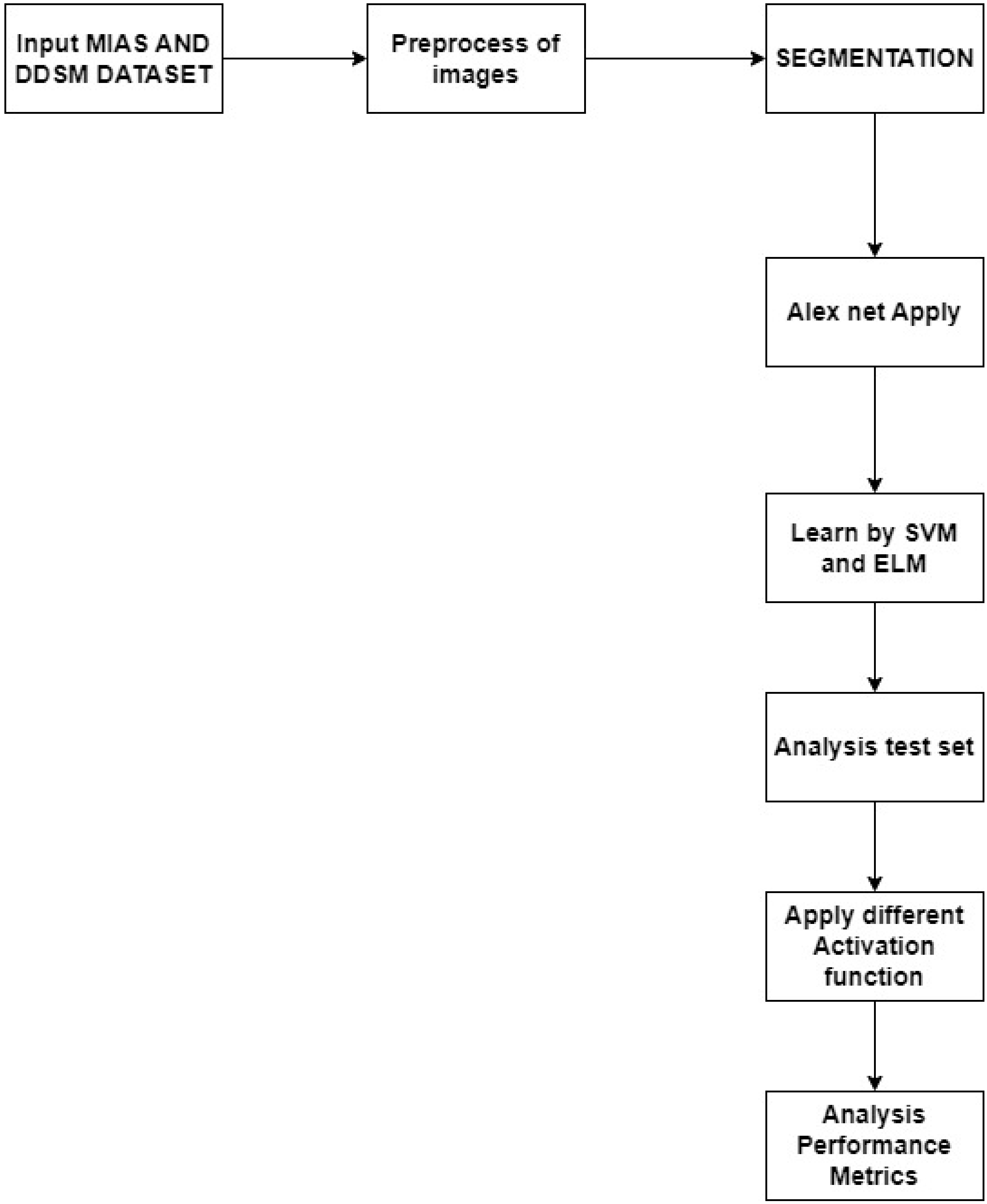

Fig. 1. Proposed system's block diagram.

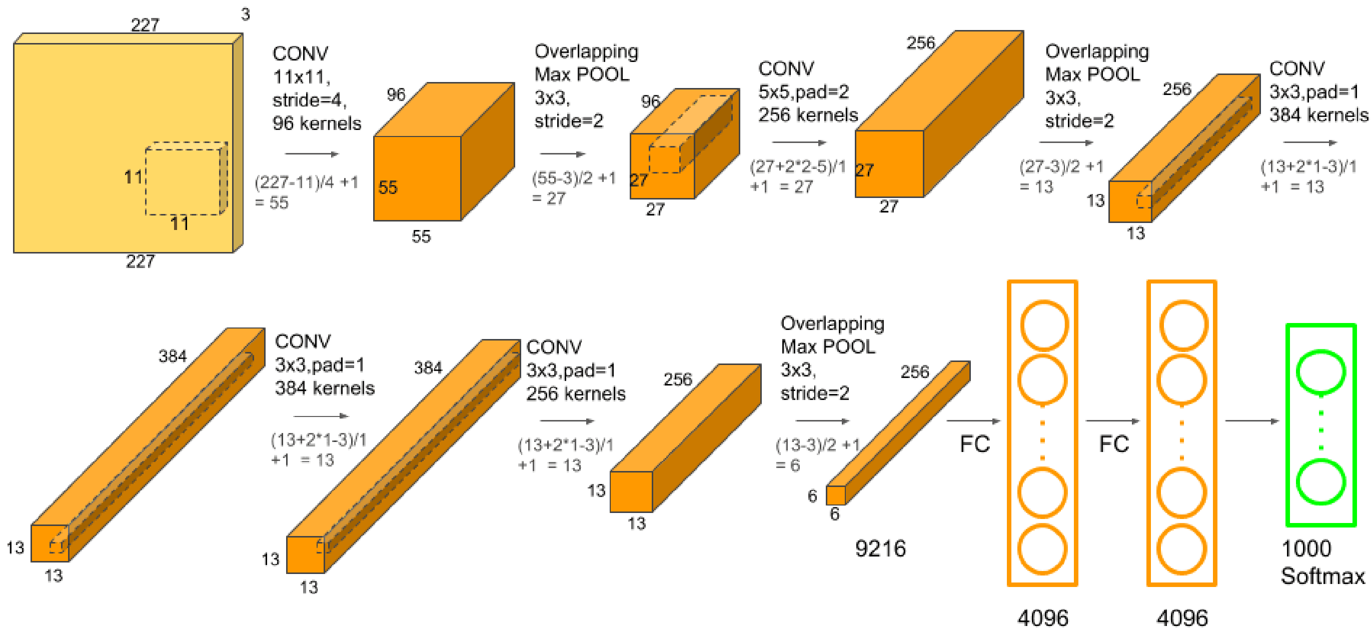

Fig. 2. Alexnet architecture.

detecting and classifying the tumor into normal, benign, or malignant.

B. Deep Convolution Method for Detecting Breast Cancer with Extreme Learning To Machine

The CBIS-DDSM database has been utilized to test and train the benign and malignant classes given in Table V. The 70% of dataset was used for training and 30% of the dataset was employed for testing. AlexNet with the fine-tuned parameters of the proposed method has been estimated with several optimizers like sigmoid, dam, ad delta, and rmsprop. In the experiments, the AlexNet with Adam has given results with high-quality training and testing accuracy summarized in Table V.

TABLE V. Comparisons of Accuracy and Loss for Various Optimizers

Learning Rate	Activation	Training Accuracy	Testing Accuracy	Test loss
0.0001	Adam	100	99.26	0.74
	Sigmoid	99.56	97.36	2.64
	rmsprop	99.76	95.61	4.39
	adadelta	92.34	87.19	12.81
0.001	Adam	99.22	98.56	1.44
	Sigmoid	98.72	96.49	3.51
	rmsprop	99.7	98.24	1.76
	adadelta	91.42	91.4	8.6

The Tumor classification Accuracy for the learning rate 0.0001 and the classification accuracy for the Learning rate 0.001is given in Table V. It is evident that the Adam optimizer the losses were minimum compared to the other optimizers. The proposed method was compared with existing deep neural network models Mask R-CNN, DCNN with SVM, VGG16 classifier with ResNet, and CNN with Deep Autoencoder The presented deep learning model was trained for 200 epochs while the loss has been decreased more and attained as $2.1287e^{-08}$ for the ELM and 0.0256 for the SVM classifiers. As a result, even the time enhanced, there can be no modifications in the accuracy of the training process. The classification results of AlexNet with SVM can be 97.36 % and the ELM can be100% with the learning rate of 0.0001. The proposed method is compared with existing deep learning methods regarding the accuracy, AUC [Area Under an ROC (Receiver operating characteristic) Curve],sensitivity and selectivity. The comparison of the proposed and existing deep learning methods has been summarized in Table VI.

It is demonstrated that the proposed deep learning model of AlexNet with SVM and AlexNet with ELM have given high accuracy. The AUC during the tumor detection and tumour classification in the mammogram images. The classification accuracy using Local binary features with the histogram yielded 64.35%. The VGG16 with ResNet provided the classification accuracy of 93.5%.The DIResNet 50 model produces the classification accuracy of 94.4.The sensitivity and specificity is improved with Support vector Machine and Local Binary features 98.48% and 92.31% respectively. The first model (AlexNet with SVM) produced the accuracy, sensitivity and selectivity as 97.63%, 98.58% and 93.15%. The second model(AlexNet with ELM) produced slightly higher values of 100%, 99.32% and 95.61% for accuracy, sensitivity and selectivity. An improved deep learning model with AlexNet

TABLE VI. COMPARISON WITH DIFFERENT STATE-OF-THE-ART METHODS

	Models/ Descriptors	Accuracy (%)	AUC	Sensitivity (%)	Specificity (%)
Malebary, S. J. et al. (2021) [14]	CNN+AlexNet	71.19	-	84.40	62.44
Altan, G. (2021) [15]	DCNN+SVM	87	0.94	-	-
Shu, X. (2020) [17]	Deep Autoencoder	92.84		95.30	96.72
Ramesh, Set et al., (2022) [21]	Efficient Net-B0	76	0.934	85.13	85.13
Thapa, A et al (2022) [9]	VGG 16 +Resnet	93.5	0.88	86.1	80.1
Zahoor, S et al. (2022) [10]	DIResNet 50+ SVM	94.4	0.944	98.48	92.31
Proposed Model	AlexNet+SVM	97.36	0.99	98.58	93.15
	AlexNet+ELM	100	1.0	99.32	95.61

and ELM can detect tumours efficiently at an early stage.

V. CONCLUSION

Breast cancer is curable if identified in its early stages. The standard method for identifying this fatal illness is time-consuming and prone to human error. This work offers an end-to-end CAD framework for breast cancer identification in mammography images, comprising of picture pre-processing, ROI extract, and classification processes. The suggested model utilized feature fusing and extreme learning-based DCNN for classification and feature extraction, that is the most crucial aspect of the CAD model. Utilizing feature fusion to extract valuable features from extreme learning and ROIs to categorize ROIs for final prediction The presented scheme can provide a more precise classification of tumours in mammography imaging. Finally, the performance of the proposed deep learning model has been estimated and compared with the existing deep learning methods ResNet, VGG-16, SVM, and CNN with Deep Autoencoder in terms of accuracy and AUC. The proposed deep learning method has taken high accuracy and high AUC during the mammogram image classification from the comparative analysis. Thus, the proposed methods can give more tumour detection accuracy. Limitation of proposed work increase the overlapping of class and take much resources compare to conventional Machine learning approaches

REFERENCES

[1] H. Sung, J. Ferlay, R. L. Siegel, M. Laversanne, I. Soerjomataram, A. Jemal, and F. Bray, "Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries," *CA: a cancer journal for clinicians*, vol. 71, no. 3, pp. 209–249, 2021.

[2] Z. Q. Zhao, P. Zheng, S. T. Xu, and X. Wu, "Object detection with deep learning: A review," *IEEE transactions on neural networks and learning systems*, vol. 30, pp. 3212–3232, 2019.

[3] B. Lauby-Secretan, C. Scoccianti, D. Loomis, L. Benbrahim-Tallaa, V. Bouvard, F. Bianchini, and K. Straif, "Breast-cancer screening-viewpoint of the IARC Working Group," *New England journal of medicine*, vol. 372, no. 24, pp. 2353–2358, 2015.

[4] E. U. Ekpo, M. Alakhras, and P. Brennan, "Errors in mammography cannot be solved through technology alone," *Asian Pacific journal of cancer prevention*, vol. 19, no. 2, pp. 291–291, 2018.

[5] F. Zahedi and M. K. Moridani, "Classification of Breast Cancer Tumors Using Mammography Images Processing Based on Machine Learning," *International Journal of Online & Biomedical Engineering*, vol. 18, no. 5, 2022.

[6] M. A. Khan, I. Ashraf, M. Alhaisoni, R. Damaševičius, R. Scherer, A. Rehman, and S. A. C. Bukhari, "Multimodal brain tumor classification using deep learning and robust feature selection: A machine learning application for radiologists," *Diagnostics*, vol. 10, no. 8, pp. 565–565, 2020.

[7] M. A. Khan, M. Sharif, T. Akram, R. Damaševičius, and R. Maskeliūnas, "Skin lesion segmentation and multiclass classification using deep learning features and improved moth flame optimization," *Diagnostics*, vol. 11, no. 5, pp. 811–811, 2021.

[8] S. Ramadhani, "A Review Comparative Mammography Image Analysis on Modified CNN Deep Learning Method," *Indones. J. Artif. Intell*, vol. 4, no. 1, pp. 54–61, 2021.

[9] A. Thapa, A. Alsadoon, P. W. C. Prasad, S. Bajaj, O. H. Alsadoon, T. A. Rashid, . . Jerew, and O. D, "Deep learning for breast cancer classification: Enhanced tangent function," *Computational Intelligence*, vol. 38, no. 2, pp. 506–529, 2022.

[10] S. Zahoor, U. Shoaib, and I. U. Lali, "Breast cancer mammograms classification using deep neural network and entropy-controlled whale optimization algorithm," *Diagnostics*, vol. 12, no. 2, pp. 557–557, 2022.

[11] J. Chai, H. Zeng, A. Li, and E. W. Ngai, "Deep learning in computer vision: A critical review of emerging techniques and application scenarios," *Machine Learning with Applications*, vol. 6, pp. 100 134–100 134, 2021.

[12] L. Shen, L. R. Margolies, J. H. Rothstein, E. Fluder, R. Mcbride, and W. Sieh, "Deep learning to improve breast cancer detection on screening mammography," *Scientific reports*, vol. 9, no. 1, pp. 12 495–12 495, 2019.

[13] L. Tsochatzidis, L. Costaridou, and I. Pratikakis, "Deep learning for breast cancer diagnosis from mammograms-a comparative study," *Journal of Imaging*, vol. 5, no. 3, pp. 37–37, 2019.

[14] S. J. Malebary and A. Hashmi, "Automated breast mass classification system using deep learning and extreme learning in digital mammogram," *IEEE Access*, vol. 9, pp. 55 312–55 328, 2021.

[15] G. Altan, "Deep learning-based mammogram classification for breast cancer," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 8, no. 4, pp. 171–176, 2020.

[16] V. S. Gnanasekaran, S. Joypaul, P. Sundaram, and D. D. Chairman, "Deep learning algorithm for breast masses classification in mammograms," *IET Image Processing*, vol. 14, no. 12, pp. 2860–2868, 2020.

[17] X. Shu, L. Zhang, Z. Wang, Q. Lv, and Z. Yi, "Deep neural networks with region-based pooling structures for mammographic image classification," *IEEE transactions on medical imaging*, vol. 39, no. 6, pp. 2246–2255, 2020.

[18] H. Li, S. Zhuang, D. A. Li, J. Zhao, and Y. Ma, "Benign and malignant classification of mammogram images based on deep learning," *Biomedical Signal Processing and Control*, vol. 51, pp. 347–354, 2019.

[19] Z. Jiao, X. Gao, Y. Wang, and J. Li, "A deep feature-based framework for breast masses classification," *Neurocomputing*, vol. 197, pp. 221–231, 2016.

[20] P. Krithika, S. Ramesh, P. R. Satya, and C. D. Preetha, "Segmentation and classification using image processing and supervising learning framework for mitosis detection in breast cancer mammographic images," *Journal of Physics: Conference Series*, vol. 1979, pp. 12 059–12 059, 2021.

[21] S. Ramesh, S. Sasikala, S. Gomathi, V. Geetha, and V. Anbumani, "Segmentation and classification of breast cancer using novel deep learning architecture," *Neural Computing and Applications*, vol. 34, no. 19, pp. 16 533–16 545, 2022.