Breast Segmentation and Probable Region Identification for Breast Cancer using DL-CNN

Nagendra Kumar M, Anand Jatti, C K Narayanappa

Abstract--Mammography is one of the key method used for detecting the breast cancer, several researcher has proposed the detection and segmentation method, however absolute solution has not developed till now and they have certain limitation and still it is one of the major challenge for finding the region in masses. Hence in this research work we have developed and design a novel method named as DL-CNN (Dual Layered) architecture CNN. The main intention of the model is segmentation and probable region identification. DL-CNN is based on the Convolution Neural Network. It has two layer first layer is applied for identifying the probable region whereas the second layer is used for segmentation and minimizing the false positive Reduction. In order to evaluate the DL-CNN algorithm by using the In Breast Dataset. Moreover the proposed model is compared against the various model in terms of ROI(Region of Interest), Dice_Index and False positive per Image. Result analysis shows that our model outperforms the existing

Keyword: CNN, DL-CNN, segmentation, Probable Region Identification, Breast Cancer

I. INTRODUCTION

Breast Cancer is one of the leading disease which threatens the life of women worldwide, millions of new cases of invasive and noninvasive cases appears every year and it causes the health burden for several countries mainly underdeveloped countries [1]. Moreover the research in the particular area clearly indicates that early detection of Cancer can provide the better treatment and can be diagonised and thus can improvise the life quality as well as survivalibility.

Hence more focus was given to the particular fields such as breast tomography, ultrasound tomography etc. In total cases of cancer in women, 23% of them suffer from the breast cancer and approximately 1.6 million new cases are observed almost every year. Moreover the early detection of cancer can reduce the death rate and increase the more chances of survival, Breast Cancer is detected as well diagnosed by integrating the several approaches such as physical examination and imaging, the technique used for detecting are known as mammography and the images are firmly known as mammograms[2].

Mammography is one of the screening tool for breast cancer, it helps in diagnosis of particular suspicious lesion through enabling the HR (High resolution)-perception of the given internal anatomy of the breast. It scans the breast from two primary view i.e. Medio lateral oblique view and craniocaudally view [3] [4].

Moreover the mammography tools acquires extra images when it finds the special symptoms such as change in architectural view and abnormality. Moreover, until now FM (Film Mammography) has been used as the reference for screening the breast, however due to the high demand of higher spatial resolution in the field DM (Digital mammography) has been prioritized. However, there are chances of error due to the manifold, hence several time it fails to classify between the benign and malignant and many times fails to identify the Region of Interest. Moreover, due to the restricted information and high risk disease proper model has to develop which can identify the probable region and classify as well. It has been observed that in 70% cases suggested biopsies has benign in the diagnosis phase.

However, these Classic methods had a problem of intrinsic imitation, hence Deep learning concept were introduced. Moreover, In recent years CNN(Convolution Neural Network) has emerged as one of the eminent model for the automatic segmentation of the given image, the advantage of CNN model exist in its deep architecture as it allows the relevant feature learning. Several researcher have worked in this area and tried various approach towards CNN such as [6] proposed a patch based CNN model and fusion model, which classified into subtype of tumor and subgrade of tumor. In this research work, we have proposed a CNN based model named DL-CNN for Probable region Identification and segmentation along with the false positive reduction. The contribution of work can be listed as below.

- We propose Dual Layered architecture CNN model, which helps in identifying the absolute probable region.
- We deployed the Two CNN for producing the absolute region.
- A novel algorithm is presented for identification and segmentation.
- First layer is used for identification whereas second layer is used for segmentation and false positive reduction.
- Reduces the risk of overfitting through generalization
- DL-CNN model is the first ever model with such a novel approach.
- It reduces the false positive reduction and performs better than the other method for segmentation.

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II.   LITERATURE SURVEY

Moreover in recent days deep learning based mass segmentation algorithm has been proposed, [7] presented various CNN based technique on mass segmentation and presented their own, however despite of extensive research not only their specificity rate was high but also false positive was more. Similarly, [8] used the deep learning model FCN for segmentation of breast and CRF (Conditional Random Field) for performing the structured learning. Moreover, adversarial training was employed to improvise the performance of segmentation but this method requires some Image improvisation method and also model is too complex due to multi-step operation.

Hence, [9] proposed a method by combining CRU-Net, Resnet and CRF and tried to solve the issue poor consistency of predicting the pixel labels. Moreover did achieve some good results but failed to solve the issue of inconsistency of intra-class problem.

In past several method were proposed by the researcher over the world for finding the probable region and mass segmentation, some of the important work has been discussed in this section.[10] used the texture model for extracting the mammographic appearances in the breast region. This is achieved through the SDC(Statistical Distribution) and PDP(Parenchymal Density Patterns, [11] used the OT(Optimal thresholding technique) for the main criteria to dense region and bifurcate fatty in the breast, another review paper was presented by the [12] which discussed the various breast mass density detection by using the FROC and ROC curves.

In [13] Combination of level set and watershed algorithm were used for improvisation in segmentation technique, moreover in order to avoid he over segmentation noise reduction technique were used , despite of that the model fails to achieve the accuracy.

[14] used the combined method of nearest neighbor clustering and local thresholding for region detection; they used method of wavelet enhancement for detecting the cancer in the breast. Moreover, their intention was to improvise the mammogram, extract the feature, and find the tumor area with the help of DWT along with SVM classifier.

[15] used the pixel-based information for cancer detection; this approach was based on the statistical analysis of the same. Here connected density cluster was observed with the help of spatial information. This method automatically evaluates the breast density by segmenting its given internal parenchyma.

[16] Proposed a methodology for the mass segmentation, which were parted into three different, stages i.e. sensation integration, semantic integration and the verification stage. In each stage, visual rules were used based on the two characteristics i.e. morphological and Gestalt psychology. Moreover, the parameters had to be modified based on the datasets. Similarly, In [17] the method tries to first extract the patches of 128 X 128 pixels from the pre-processed image for the training and for the testing it is extracted from the dense area, these are performed manually. Hence, CAD [18] was presented for abnormality classification where the ROI (Region of Interest) are pointed by the three radiologists and it is cropped into 128X 128 pixel. Moreover, the main issue with these methods were it requires a specialists for the absolute

identification of the particular region and it takes a lot of time since it is manual process.

[19] presented two separate technique for the mass segmentation, first technique was based on the particular region growing and ANN(Artificial Neural Network) were used for growing the threshold and second technique were used for the segmentation purpose named as cellular neural network and   parameter were obtained using the GA (Genetic Algorithm). [20] used the segmentation technique that were based on the Morphological threshold, first it discards the background as well as artifacts in the pre-processing stage and the pectoral muscle removal was done through the modified region growing method. Moreover Image enhancement is preformed through the histogram equalization   and median filter technique, at last morphological operation, watershed transformation and sobel operator were used for the mass segmentation.[21] presented a segmentation technique using the level sets based on the maximum like hood AC(Active Contour) model. Moreover, it computes the segmentation contour, which separates the region using Gamma Distribution.

III.   PROPOSED METHODOLOGY

In previous work while training the masked image for segmentation, the poor masking is observed since it does not consider the real boundaries of that particular object. In other methodology, we have observed the two main drawbacks i.e. either over-segmentation parts or some missing parts. Moreover, boundaries and edges of an object plays an eminent part in getting the Mask. Hence, in this paper we have proposed DL-CNN methodology
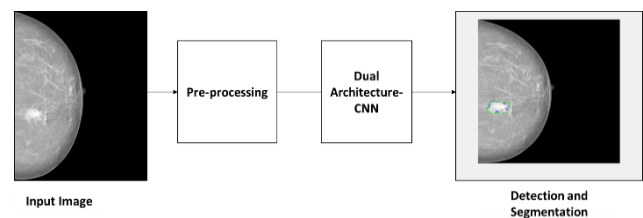
Figure 1 proposed flow work

The above figure shows the proposed flow work where the input is taken as the mammographic original image and then it is pre-processed to the Dual Layered CNN. Then with the help of Dual Layered CNN layer, which is described later in the same section, then through classification the stage of cancer is identified. Moreover, here we do not refer the classification. The main intention is to identify the ROI and find the mass segmentation.

Pre-Processing

In here the breast region extraction is performed through the cropping the unnecessary background, later the mammogram is sub-sampled into the square shape to Improvise the speed.

Dual Layered CNN Architectural Design

CNN is known for its various salient features; here we use the pre-trained CNN model since we use the limited sized   Mammographic dataset. Here we have applied the dual Layered CNN for the detection and segmentation.

The dual layer Layered CNN comprises two CNN,

where first layer is for the probable Region identification and second layer is for segmentation and false positive reduction. In DL-CNN at first the sampling is done through the regular mesh $\mathbb{M}$ over the given map $\mathbb{Z}$, later these values are computed though summation which is denoted by $\mathbb{WT}$. Moreover mesh $\mathbb{M}$ is defines the convolution kernel through deconvolution and size. In case of each location $\mathbb{L}_0$ on the given output feature map $\mathbb{U}$ is depicted through the below equation.

$$\mathbb{U}(\mathbb{L}_0) = \sum_{\mathbb{L}_r \epsilon} \mathbb{WT}(\mathbb{L}_\mathbb{p}).\mathbb{Z}(\mathbb{L}_0 + \mathbb{L}_\mathbb{p}) \qquad (1)$$

$\mathbb{L}_\mathbb{p}$ Gives the location in feature map.

$$\mathbb{U}(\mathbb{L}_0) = \sum_{\mathbb{L}_\mathbb{p} \epsilon \mathbb{M}} \mathbb{WT}(\mathbb{L}_\mathbb{p}).\mathbb{Z}(\mathbb{L}_0 + \mathbb{L}_\mathbb{p} + \Delta\mathbb{L}_\mathbb{p}) \qquad (2)$$

$\mathbb{L}_\mathbb{p}$ shows the location in mesh $\mathbb{M}$.

In the dual Layered convolution the mesh, gets augmented with the given offsets $\{\Delta\mathbb{L}_\mathbb{p}|\mathbb{p} = 1, \ldots, \mathbb{p}\}$ where $\mathbb{p}$ is equivalent to $|\mathbb{M}|$, Equation 1 becomes

$$\mathbb{U}(\mathbb{L}_0) = \sum_{\mathbb{L}_\mathbb{p} \epsilon \mathbb{M}} \mathbb{WT}(\mathbb{L}_\mathbb{p}).\mathbb{M}(\mathbb{L}_0 + \mathbb{L}_\mathbb{p} + \Delta\mathbb{L}_\mathbb{p}) \qquad (3)$$

Sampling is on the offset and irregular locations i.e. $\mathbb{L}_\mathbb{p} + \Delta\mathbb{L}_\mathbb{p}$ since the $\Delta\mathbb{L}_\mathbb{p}$ is fractional, hence above equation is written as

$$\mathbb{U}(\mathbb{L}) = \sum_{\mathbb{a}} \mathbb{I}(\mathbb{a},\mathbb{L}).\mathbb{u}(\mathbb{a}) \qquad (4)$$

Where $\mathbb{L}$ is computed as

$$\mathbb{L} = \mathbb{L}_0 + \mathbb{L}_\mathbb{p} + \Delta\mathbb{L}_\mathbb{p} \qquad (5)$$

And $\mathbb{p}$ represents the spatial locations in the given feature map $\mathbb{Z}$. Moreover $\mathbb{I}$ is two dimensional interpolation kernel. Below equation shows two different one-dimensional kernel

$$\mathbb{I}(\mathbb{a},\mathbb{L}) = \mathbb{i}(\mathbb{a}_\mathbb{z}, \mathbb{L}_\mathbb{z}).\mathbb{i}(\mathbb{a}_\mathbb{u}, \mathbb{L}_\mathbb{u}) \qquad (6)$$

Given the size of probable region and input feature map and the input feature map, the probable region parts into bins and gives output on the feature map which is depicted in the below equation.

$$\mathbb{U}(\mathbb{B}) = \sum_{\mathbb{L} \in prm(i,j)} \mathbb{Z}(\mathbb{L}_0 + \mathbb{L})/\mathbb{P}_\mathbb{B} \qquad (7)$$

Let's consider any image $\mathbb{B}$, from the training data, then the identification takes place with the probability $prob$ or if there is no change then it is kept as the probability of $1 - prob$. DL-CNN Identification considers the particular shape region $\mathbb{B}_{reg}$ in the image and random values to the selected area pixels. Let the size of Image be $\mathbb{A} = \mathbb{X} X \mathbb{Y}$ then random initialization of the region is done i.e. $\mathbb{B}_{reg}$ and the range is specified through the min and max. Let there be any central point of the given region denoted as $pt = (\mathbb{E}_{reg}, \mathbb{F}_{reg})$ in the given image $\mathbb{B}$.

Selected region is Initialized between $\mathbb{R}_1$ and $\mathbb{R}_2$ and the size of Selected area is

$$\mathbb{Y}_{reg} = \left(\mathbb{A}_{reg}\right)^{1/2} \qquad (8)$$
$$\mathbb{X}_{reg} = \left(\mathbb{A}_{reg}/\mathbb{R}_{reg}\right)$$

Step1: Input the Given Image, Area of the image, probable region, weight coefficient
Step2: Initialization of $pt_1 \leftarrow RS(0,1)$
Step3: If$(pt_1 \geq P)$ then go to step10
Step4: else
while True do
$\quad \mathbb{A}_{reg} \leftarrow RS(s_l, s_h)XS,$
$\qquad \mathbb{R}_{reg} \leftarrow RS(\mathbb{R}_1, \mathbb{R}_2)$
Step5: $\mathbb{Y}_{reg} \leftarrow (\mathbb{A}_{reg}X \mathbb{R}_{reg})^{1/2}$
$\qquad \mathbb{X}_{reg} \leftarrow (\mathbb{A}_{reg}X \mathbb{R}_{reg})^{1/2}$
Step6: $\quad p_{lu} \leftarrow (\max(1, \mathbb{E}_{reg} - \mathbb{X}_{reg}(0.5), \max(1, \mathbb{F}_{reg} - (0.5)\mathbb{Y}_{reg}))$
$\qquad p_{lu} \leftarrow (\min(\mathbb{X}, \mathbb{E}_{reg} + \mathbb{X}_{reg}(0.5), \min(\mathbb{Y}, \mathbb{F}_{reg} + (0.5)\mathbb{Y}_{reg}))$
step7: $\mathbb{E}_{reg} \leftarrow RS(1, \mathbb{X})$
$\qquad \mathbb{F}_{reg} \leftarrow RS(1, \mathbb{Y})$
step8: $\mathbb{B}_{reg} \leftarrow (p_{lu}, p_{rb})$
step 9: $\mathbb{B}(\mathbb{B}_{reg}) \leftarrow \lambda.RS(0,1) + (1 - \lambda.).\mathbb{B}(I^*)$
Step10: $\mathbb{B}^* \leftarrow \mathbb{B}$
Return $\mathbb{B}^*$
Step11: end

$$\mathbb{U}(\mathbb{B}) = \sum_{\mathbb{L} \in prm(i,j)} \mathbb{Z}(\mathbb{L}_0 + \mathbb{L} + \Delta\mathbb{L}_\mathbb{p})/\mathbb{P}_\mathbb{B} \qquad (9)$$

Generalization

In order to achieve the detection accuracy we have considered the

$$f(\mathbb{U}_d) = \begin{cases} \mathbb{U}_\mathbb{d} & if \ \mathbb{U}_\mathbb{d} < 0 \\ \mathbb{C}_\mathbb{d} \ \mathbb{U}_\mathbb{d} & if \ \mathbb{U}_\mathbb{d} \leq 0 \end{cases} \qquad (10)$$

$\mathbb{U}_d$ is the input from the on the channel and $\mathbb{C}_\mathbb{d}$ is the coefficient, $\mathbb{d}$ indicates the varying on the various channel by using the activation function, since our model shares the properties of non-linear. Moreover, our designed CNN introduces the number of extra parameters to avoid the overfitting. DL-CNN adopts the channel-shared variant which helps in sharing the Coefficient this is given through below equation.

$$f(\mathbb{U}_d) = \max(0, \mathbb{U}_\mathbb{d}) + \mathbb{C}_\mathbb{d} \min(0, \mathbb{U}_\mathbb{d}) \qquad (11)$$

Optimization

Moreover, dual Layered CNN is trained and optimized in both the layers, the above equation is updated by the chain rule and gradient of $\mathbb{C}_\mathbb{d}$ for the first layer is

$$\frac{\partial \varepsilon}{\partial \mathbb{C}_\mathbb{d}} = \sum_{\mathbb{U}_\mathbb{d}} \frac{\partial \varepsilon}{\partial f(\mathbb{U}_\mathbb{d})} \frac{\partial f(\mathbb{U}_\mathbb{d})}{\partial \mathbb{C}_\mathbb{d}} \qquad (12)$$

ε is the OF(Objective Function), Moreover the gradient of the layer is given in the below equation.

$$\frac{\partial f(\mathbb{U}_\mathbb{d})}{\partial \mathbb{C}_\mathbb{d}} = \begin{cases} 0 & if \ \mathbb{U}_\mathbb{d} > 0 \\ \mathbb{U}_\mathbb{d} & if \quad if \ \mathbb{U}_\mathbb{d} > 0 \end{cases} \qquad (13)$$

Moreover the $\sum_{\mathbb{C}_\mathbb{d}}$ is formed over all position $\mathbb{L}_0$ on the given feature Map and the gradient of $\mathbb{C}_\mathbb{d}$ is computed using the below equation.

$$\frac{\partial \varepsilon}{\partial \mathbb{C}_\mathbb{d}} = \sum_\mathbb{d} \sum_{\mathbb{C}_\mathbb{d}} \frac{\partial \varepsilon}{\partial f(\mathbb{U}_\mathbb{d})} \frac{\partial f(\mathbb{C}_\mathbb{d})}{\partial \mathbb{C}_\mathbb{d}} \qquad (14)$$

DL-CNN algorithm

Where $\sum_{\mathbb{d}}$ sums over both the layer, however we consider the momentum given in below equation is considered while updation of $\mathbb{C}_{\mathbb{d}}$

$$\Delta \mathbb{C}_{\mathbb{d}} = \alpha\Delta\mathbb{C}_{\mathbb{d}} + \in \frac{\partial \in}{\partial\mathbb{C}_{\mathbb{d}}} \tag{15}$$

α indicates the momentum and $\in$ is rate of learning.

First step: Parameter Initialization

A model has to be initialized in such a way that there should be no hampering of non-linear model, hence here we develop a modified Initialized model, and this helps in discarding the obstacle. Here the idea is to generate the response from each layer,

$$\mathbb{U}_d = \mathbb{WT}_{idx}\mathbb{K}_{idx} + \mathbb{vb}_{idx} \tag{16}$$

Here $\mathbb{vb}$ is a given vector that denotes the co-located pixel in the given input channel, $\mathbb{fs}$ is the filter size of the layer, $\mathbb{U}_d$ indicates the response at output layer, the number of connection to the response is computed using the below formula

$$\mathbb{O} = (\mathbb{fs})^2 \mathbb{ICH} \tag{17}$$

$\mathbb{ICH}$ is input channel. Moreover $\mathbb{WT}$ represents the weights and represented through $\mathbb{N} \, X \, \mathbb{O}$ matrix, $\mathbb{E}$ indicates amount of filter used.

$$\mathbb{K}_{idx} = \mathbb{func}(\mathbb{U}_{d_{idx-1}}) \tag{18}$$

Where $\mathbb{func}$ is the parameter function. And Input channel layer is $\mathbb{ICH}_{idx} = \mathbb{O}_{idx-1}$

Initialized $\mathbb{WT}_{idx}$ to be independent, if $\mathbb{WT}_{idx}$ and $\mathbb{K}_{idx}$ are mutually independent,

$$\mathbb{E}[\mathbb{U}_{d_{idx}}] = n_l \, \mathbb{E}[\mathbb{WT}_{idx}\mathbb{K}_{idx}] \tag{19}$$

$\mathbb{U}_{d_{idx}}$, $\mathbb{WT}_{idx}$ and $\mathbb{K}_{idx}$ represents the random variable, variance is computed through below equation then the product of all independent variable is computed

$$\mathbb{E}[\mathbb{U}_{d_{idx}}] = n_l[\mathbb{WT}_{idx}] \, \mathbb{E}[\mathbb{K}_{idx}^2] \tag{20}$$

$\mathbb{S}[\mathbb{K}_{idx}^2]$ is Variance of $\mathbb{K}_{idx}$ if $\mathbb{K}_{idx}$ has the mean value of zero else it can be just said as expectation of the squared. Moreover here $\mathbb{K}_{idx}$ does not possesses the value of zero and $\mathbb{S}[\mathbb{K}_{idx}^2]$ is computed through the below equation.

$$\mathbb{S}[\mathbb{K}_{idx}^2] = 0.5 \, \mathbb{E}[\mathbb{U}_{d_{idx}} - 1] \tag{21}$$

Substituting this in the equation 20 we get below equation 22 $\mathbb{U}_{d_{idx-1}}$ is symmetric distribution, tis is substituted in equation

$$?? [??_{??_{\overline{????}}}] = 0.5??_? \, ?? [??_?] \, ??_{??_{\overline{????}-1}}] \tag{22}$$

Now for L layers the below equation is derived.

$$\mathbb{E}[\mathbb{U}_{d_{idx}}] = \mathbb{E}[\mathbb{U}_{d_{idx}}](\prod_{idx=2}^{IDX} 0.5 \, n_l \, \mathbb{E}[\mathbb{WT}_{idx}]) \tag{23}$$

The above product is the parameter initialization
Sufficient condition is given as

$$0.5 n_l \mathbb{E}[\mathbb{WT}_{idx}] = 1 \tag{24}$$

Step2: Error minimization

Gradient of layer is computed through the below equation

$$\mathbb{I}_{idx} = \overline{\mathbb{WT}}_{idx}\mathbb{J}_{idx} \tag{25}$$

$\mathbb{I}$ and $\mathbb{J}$ for simplicity, $\mathbb{J}$ is $\mathbb{p} \times \mathbb{p}$ in the given channel $\mathbb{N}$, $\overline{\mathbb{WT}}$ is cXn matrix, and the filters gets rearranged, $\mathbb{I}$ is CX 1 vector that represents gradient at each pixel of the

given layer. Moreover $\mathbb{I}_{idx}$ and $\mathbb{J}_{idx}$ are considered to be th independent. Variance calculation in the below equation

$$\Delta\mathbb{U}_{d_{idx}} = f'(\mathbb{U}_{d_{idx}})\mathbb{I}\,\mathbb{K}_{idx+1} \tag{26}$$

f' derivative of f

$$\mathbb{E}[\Delta\mathbb{K}_{idx}] = \overline{\mathbb{O}}_{idx}\mathbb{E}[w_l]\,\mathbb{E}\,\Delta\mathbb{K}_{idx+1}] \tag{27}$$

Performing scalar operation on the equation we get the equation with the L layers.

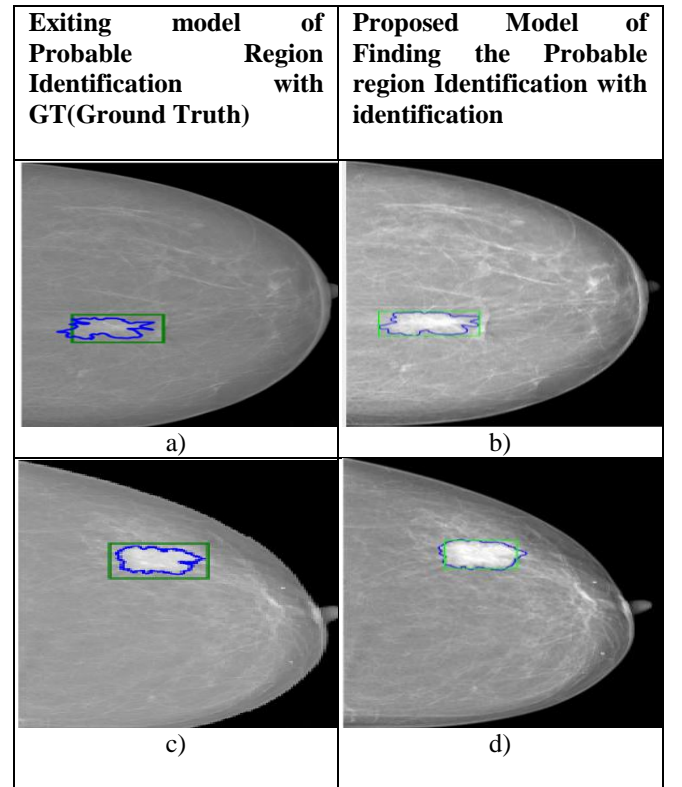$$\mathbb{E}[\mathbb{K}_{idx\,2}] = \mathbb{E}[\mathbb{K}_{idx+1}] \\ \prod_{idx=2}^{IDX} 0.5 \, \overline{\mathbb{O}}_{idx}\mathbb{E}[\mathbb{WT}_{idx}] \tag{28}$$

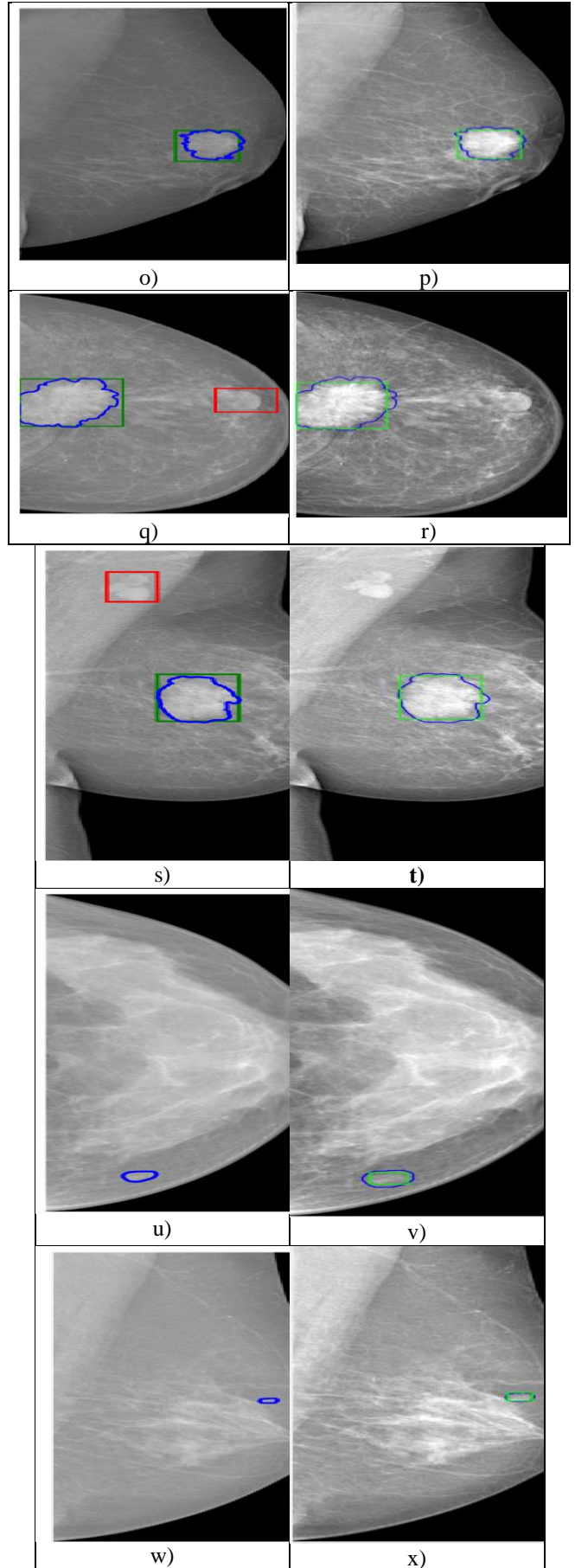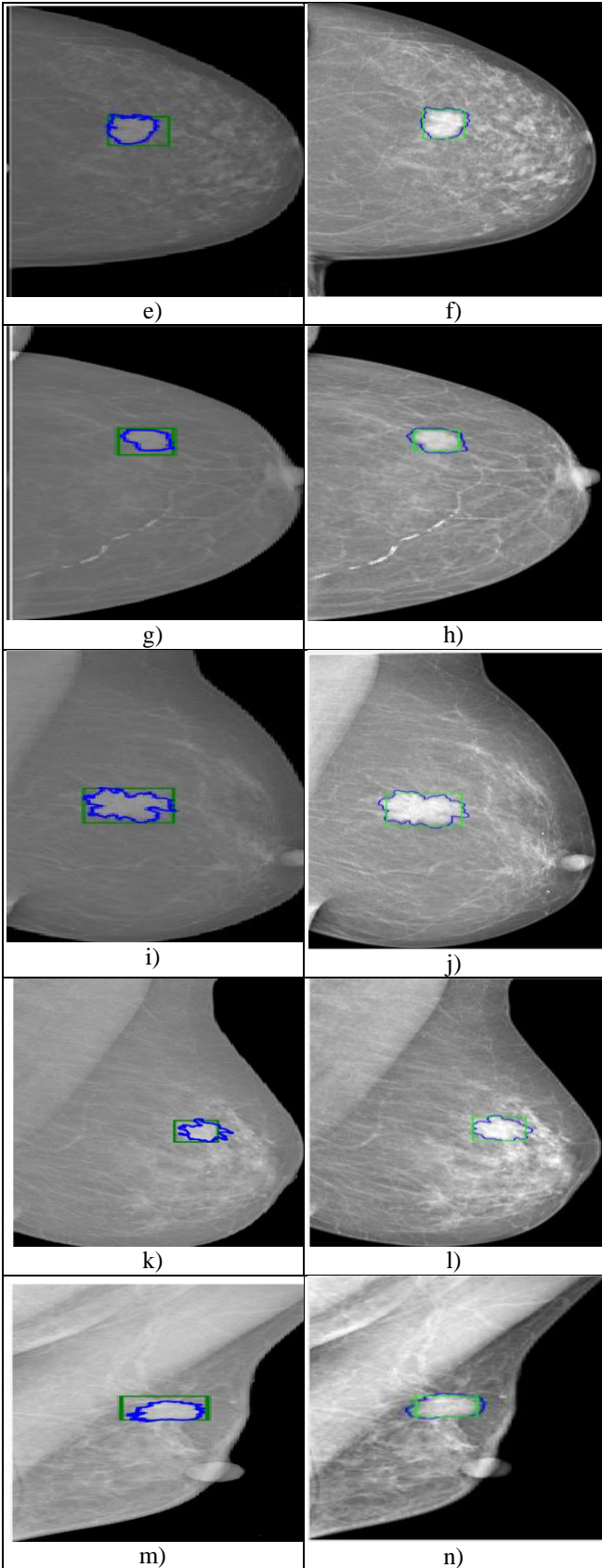$$0.5 \, \overline{\mathbb{O}}_{idx} \, \mathbb{E}[\mathbb{WT}_{idx}] = 1 \tag{29}$$

Moreover, this generates the probable region; DL-CNN is evaluated in the next section.

IV. PERFORMANCE EVALUATION

In order to evaluate the DL-CNN we have used the In Breast dataset, it is publicly available and it contains 115 FFDM cases with the pixel-level ground truth annotation proof for breast cancers. We have performed with the three parameter that helps in evaluating and prove the efficiency of our model. First we find the probable region and compare with the existing technique [22] which is depicted in the Table 1, second Parameter is considered as the FPI (False Positive Per Image) and it is compared with the three best technique available for the segmentation in the research work and depicted in the table 2. Moreover, table 3 presents the comparison of various technique along with the existing technique based on the dice score.

Exiting model of Probable Region Identification with GT(Ground Truth)	Proposed Model of Finding the Probable region Identification with identification

a)   b)

c)   d)

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In the above table, i.e. Table 1 shows the pictorial comparison of existing and proposed model along with given ground truth, here a, c, e, g, I, k, m, o, q, s, u, w represents the probable region identification by existing method and b, d, f, h, j, l, n, p, r, t, v, x represents the probable region identification. In observation, it is found that in existing system q and s captures the false region where as proposed system identifies it properly. Moreover, in case of image u and w the existing model FFDM fails to identify masses whereas with DL-CNN the model identify the absolute region.

False Positive per Image (FPI)

FPI is one of the common reference point used for evaluating the DL-CNN, False Positive per Image should be as less as possible, and less FPI indicates the better model performance. In here i.e. Table 2 comparative analysis is done based on the FPI, we observe that [23] possesses the value of 3.67and [24] possesses massive value of 5, such large FPI cannot be acceptable for the real time scenario. However [25] achieves the FPI value of 0.56 and existing achieves 0.58 respectively, but still it is more when compared with the proposed model as DL-CNN achieves the lowest value of all i.e. 0.39706.

Methodologies	FPI(False Per Image)
[23]	3.67
[24]	0.56
[25]	5
Existing System[22]	0.58
Proposed_system	0.39

Dice Index

Dice Index is one of the evaluation metric used for evaluating DL-CNN method, the Dice Index totally depends on the three value TP, FP and FN. TP(True Positive) is recognized as the correct mass pixel categorized. FN (False Negative) is the mass pixel miss-classified as the BG (Background) tissue and FP (False Positive) is the amount of BG-tissue miss-classified as the mass pixels. Table 3 represents the Dice Index (in percentage) comparison of the promising method developed earlier. Here, we observe that except [26] and U-Net all other methods such as in [27], RU-Net, NPnet and [28] achieves DI of 90, 90.16, 90.53, 90.97, and 91.10 respectively. Moreover MNPNet i.e. existing model scores.

Methodologies	Dice Index
[26]	88
U-Net	89.83
[27]	90
RU-Net	90.16
NPNet	90.53
[28]	90.97
MNPNet	91.10
proposed	92.12

V. CONCLUSION

In this paper we developed a methodology named as DL-CNN which is used for finding the ROI(Region of Interest) and segmentation, Proposed met;hodology is Dual CNN where first is used for identifying the region and second is for segmentation and reduction in False Positive per Image. Moreover, by taking the In Breast dataset evaluation is performed on DL-CNN and compared with little best method available for the same. The Comparison analysis is parted into three parts, in first the pictorial comparison is done with the existing technique, observation suggests that in existing system miss identification takes place for few image and sometimes it fails to find ROI, whereas DL-CNN simply excels with the same scenario. In second part, the comparison is done based on FPI (False Positive per Image) and DL-CNN achieves the lowest FPI of value 0.39706. In third part of result, the comparison takes place based on the Dice-Index score and our methodology scores massive percentage of 92.12 outperforming the other method. In future, we will implement the Classification technique to identify the type of cancer.

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AUTHORS PROFILE

Nagendra Kumar M received B.E in Electrical & Electronics from Mysore University in 1996 & M.Tech in Biomedical Instrumentation from Visvesvaraya Technological University in 2002. He is currently working as Associate Professor at department of Electronics & Communication Engg, S J C Institute of Technology, Chickballapura since 2002 with total teaching experience of 20 years. His research interests include Bio Medical Signal Processing, Image processing and Control Systems. He is the member of ISTE, IETE and IE.

Dr.Anand Jatti currently working as Associate Professor in the department of Electronics and Instrumentation Engg. In R V College of Engineering, Bengaluru since 2002.He completed his B.E from Kuvempu University during 1996,M Tech in Bio medical Instrumentation from Visvesvaraya Technological University during 2002 and awarded Ph.D from Visvesvaraya Technological University during2013.He Published /Presented 60 research in National/International conferences and Journals.

Narayanappa C K received PhD from Visvesvaraya Technological University, Belagavi in 2014 and M.Tech in Biomedical Instrumentation from Mysore University in 1996. He is currently working as Associate Professor at department of Medical Electronics, Ramaiah Institute of Technology, Bengaluru since 2000. His researchinterests include Signal & Image processing and Control Systems. He is the memberof ISTE, IETE and BMESI. He is also a fellow at The Institution of Engineers (India).