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A SURVEY OF RECENT STUDIES INVESTIGATING THE POTENTIAL OF DEEP LEARNING ALGORITHMS FOR IDENTIFYING AND CATEGORIZING BREAST CANCER

Shweta Saraswat[1], Bright Keswani[2], Vrishit Saraswat[3]
E-Mail Id: shwetavrishit@gmail.com, bright.keswani@mygyanvihar.com, vrishit.saraswat@gmail.com
[1,2]Department of Computer Science and Engineering, Suresh Gyan Vihar University, Jaipur, Rajasthan
[3]Department of Interventional Radiology, Medanta Hospital, Gurugram, Haryana, India

Abstract- This paper provides a summary of recent investigations on the use of algorithms based on deep learning for detecting and classifying breast cancer, with the goal of improving timely diagnosis and treatment outcomes. Machine learning has an accuracy of 91% in identifying cancer, whereas human specialists have an accuracy of just 79%. In this study, we analyze and contrast the two most current machine learning algorithms for detecting and classifying breast cancer: RetinaNet and YOLO (You Only Look Once). This study adds support to the theory that machine learning-based technologies may be able to make more precise diagnoses of cancer than human doctors. When compared to other breast cancer screening and categorization systems using prominent public datasets, RetinaNet and YOLO fared the best.

Keywords: Breast cancer, YOLO, RetinaNet.

1. INTRODUCTION

Uncontrolled cell division and the development of a tumor are the first indicators of cancer. It doesn't take long for cancer to invade neighboring organs and tissues. Malignant and benign are the two primary categories of tumors. The collected cells in a benign tumor are not malignant, and the tumor itself does not spread beyond its original site. Malignant tumors are composed of cancerous cells that may proliferate forever and metastasize to other parts of the body. Breast cancer, which is among the most frequent forms of the disease, is a major threat to the well-being of women worldwide.

Early discovery, precise diagnosis, and effective preventative actions are essential for lowering female mortality rates. Since breast tissue tends to develop together, the most frequent and typical kind of lesion, masses, may be difficult to detect. Most breast lesions take the form of masses.[1] However, certain breast cells might seem like lumps and be misdiagnosed as such. A false positive occurs if a patient's mass is incorrectly identified. The next step is potentially distressing testing, such as a biopsy and rescreening. After a patient's mass has been properly detected, a true positive result has been attained. A second reading by either human professionals or a Computer- Aided Diagnosis (CAD) system is recommended to further increase the accuracy and precision ofbulk identification, segmentation, and classification. A fresh look at the image could provide the answer.

No research has been done on developing an approach that can find, divide, and sort at the same time. This could mean that there are fewer false positives and false negatives. By using mass segmentation, it is hard to improve overall accuracy and reduce the number of false positives and false negatives. This is because masses often have irregular shapes, sizes, locations, levels of contrast, and fuzzy edges. When attempting to eliminate a mass which has spread to other parts ofthe body, problems may arise. But these methods still have a long way to go prior to being called successful, particularly as it pertains to managing huge scales of segmentation automatically.

Deep learning models may use raw data to discover helpful high-level hierarchy factors that can be utilized for mass segmentation, providing an alternative to more conventional techniques of segmentation. Convolutional Neural Networks (CNNs) are becoming more popular for solving image interpretation issues including breast cancer detection and categorization. As compared to traditional segmentation techniques, deep learning models represent a significant improvement.

In order to address the drawbacks of traditional mass detection models, researchers have turned todeep CNNs. CNN's stellar scores on the toughest item recognition challenges are solely responsible for this. If breast cancer is suspected, a patient might benefit from a mammogram, which serves as both a detection and diagnostic technique. Several studies were spurred by CNNs' undeniable success in standard item identification tests. Mammography and other forms of breast cancer screening are used to diagnose and treat the illness. The first procedure involves compressing and pressing the breast between two thin plates, the

second involves exposing the breast to a mild X-ray dosage that is directed straight through it, and the third involves capturing an image that used a two- dimensional (2D) panel detector. [2]This is the most useful resource for diagnosing, evaluating, and keeping tabs on patients that doctors now have at their disposal.
The rest of the article is categorized as follows: The most common public datasets and their main distinctions are mentioned in the datasets section. The corresponding research and evaluation piece following the dataset section provides classification and detection performance measures to assess the suggested model's accuracy. [3] This article continues the dataset part. This section concludes the suggested model. This section includes metrics, definitions, and calculations. In the following part, we will compare and contrast the latest breast cancer detection and classification studies from 2020–2022, as well as previous research. The process comprises data gathering, cleansing, and augmentation.[4] They then discuss their cancer classification and diagnosis approach. This section includes the final paragraph, which concludes the article.

2. DATASET

Here you can discover the most widely used datasets for detecting and categorizing breast cancer using mammography. There are five provided datasets, and they are the MIAS, DDSM, BCDR, CBIS-DDSM and INbreast.

2.1 DDSM Dataset

The online Digital Database for Screening Mammography (DDSM) is used by algorithms to find and classify breast cancer [5]. This breast cancer database screens women. It's typical size is 3000 by 4800 pixels, its resolution is 42 microns, and its 16 bits indicate real breast data. The DDSM database has 2,640 film mammography scans arranged into 43 volumes. Two mediolateral oblique (MLO) and two cranial-caudal (CC) breast images are taken in each case. Expert radiologists can recognize and classify mammography masses as benign or malignant.

2.2 CBIS-DDSM Dataset

The Curated Breast Imaging Subset of DDSM (CBISDDSM) [6] is a modernized and standardized version of the Digital Database for Screening Mammography (DDSM). A professional mammographer hand-picked and maintains the data in this collection from the DDSM. There are a total of 6789 studies in the CBIS-DDSM. After decompressing and converting to DICOM, the images may be seen. Pathologic diagnoses and updated areas of interest (ROI) segmentation are included in the training data set.

2.3 MIAS

The Mammographic Imaging Analysis Society is a British organization comprised of research groups interested in learning more about mammograms. Digital mammograms have been gathered by them into a database. Images of mammograms may be seen at the PEIPA(Pilot European Image Processing Archive), which is housed on the University of Essex's campus. The database contains 322 digitized films, which may be viewed through a 2.3 GB 8 mm (ExaByte) disk. Each image has been resized to have pixel edges of 200 microns and the database has been padded and clipped to a resolution of 1024 x 1024 pixels.

2.4 INbreast Dataset

There are 410 complete digital mammograms included in this set. After evaluating a mammogram, a radiologist gives each lesion, including masses, a BI-RADS category according to the standardized Breast Imaging-Reporting and Data System (BI-RADS) classification [7].

2.5 BCDR Dataset

The Breast Cancer Digital Repository is a database of anonymized Breast Cancer patient cases annotated by expert radiologists with clinical data which includes BIRADS, detected anomalies, classification, breast

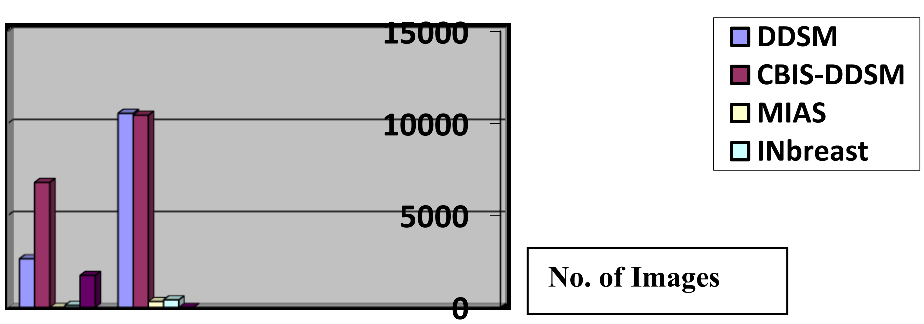

Fig. 2.1 Represents the common used and publicly available datasets in respective of number of cases and images

density etc., lesion outlines, and image-based attributes computed from CC and MLO mammography image stances. Finally, fig. 2.1 gives the main characteristics of the mentioned common used and public datasets for breast mammograms.

3. COMPARATIVE ANALYSIS OF THE EVALUATION MEASURES AND DATASETS USED

Detection of anomalies, classification, and segmentation are all areas where research is advancingrapidly. Well before CAD system can evaluate images for malignancy, important preprocessing is required for the Mass detection phase. Breast mass segmentation is crucial for extracting exclusionary form data of specific mass regions while excluding surrounding tissues.

Initially, the metrics used to evaluate a proposed breast mass identification and classification algorithm are provided, together with the techniques to establish the intended use of each statistic. Second, from the perspective of the data preprocessing used by each methodology, a contrast willbe performed among a few of the most recently described breast cancer identification and classification strategies. Finally, a comparative analysis demonstrating the efficacy of the different classification and detection models is shown.

3.1 Accuracy Metrics for Detection and Classification

This section discusses about the accuracy metrics that were used to judge the work on detecting and classifying breast cancer. They are also used to show how to measure how accurate something is. These are:

Table-3.1 Four Numbers of cases that are used to find Accuracy, Precision and Recall

		Actual	
Predicted		Positive	Negative
	Positive	**True Positive**	**False Positive**
	Negative	**False Negative**	**True Negative**

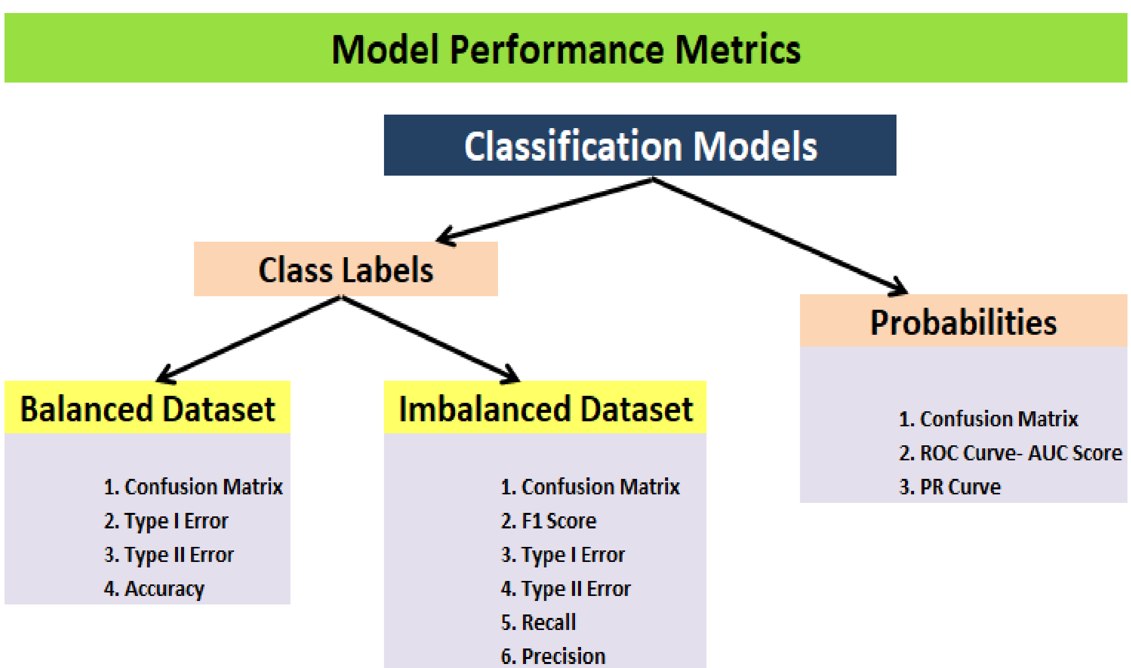

Fig. 3.1 illustrates all the Metrics that may be used to determine whether a Model is Accurate

3.1 Datasets Preparation

In this part, we will analyze and contrast seven of the most up-to-date, comprehensive proposals for detecting and categorizing breast cancer. Researchers examine them from several angles, such as the datasets they utilized, whether or not they performed preprocessing on the data, whether or not they employed data augmentation, and the mammography views they used during training.

Table-3.2 Comparative Study for the Dataset Preparation for the Recent Work in the Breast Cancer Detection and Classification

Ref.	Dataset	Size	Views	Augmentation	Preprocessing
[8]	INbreast	107 M	CC/MLO	Augment mammograms eight times by rotating them with the angles of 45^0	Aconrast-limited adaptive histogram equalization(CLAHE)method is utilized as a preprocessing step for all detected masses
[9]	DDSM	600 M	CC/MLO	Rotating mammograms with 90^0,180^0,270^0	Otsu thresholding technique to generate breast region.Then, multi-threshhold peripheral equalization enhanced peripherals thickness and remove irrelevant information
[10]	DDSM	150 M	CC/MLO	No Data augumentation	Multi-threshhold peripheral equalization to enhance peripherals thickness and remove irrelevant information.
[11]	BCDR-F03	736 M	CC/MLO	To each refined breast lesion,another seven new samples are genereated using a combination of flipping and rotation (π/2, Π and 3π/2) transformations	No preprocessing
[12]	DDSM+ NP	2242 M	CC/MLO	Each ROI was flipped and rotated four times to obtain eight augmented samples	No preprocessing
[13]	DDSM	1820 M	CC/MLO	The selected mammograms augmented by 5 random rotations and sampled 5 random crops for each rotation, thus effectively multiplying the training set size by 25	First extract the mass from the full mammogram by taking a bounding box around the pixel level mask applied to the original image Followed by a fixed padding of 50 pixels all around the mass
[14]	INbreast+ NP	329 M	CC/MLO	Mammograms were flipped, randomly cropped and rotated up to 90^0,180^0 and 270^0	Original Mammograms are divided into small sub-sections which do not require the resizing method

Table 3.2 Ref. column stands for "Reference," the acronym for the cited research publication. The dataset column identifies the dataset used, the size column indicates the size of the dataset used, the views column identifies the views used in the training process (which may be Mediolateral Oblique (MLO) views or Cranio-Caudal (CC) views, or both), the augmentation column identifies whether or not augmentation was performed using the proposed method, and the preprocessing column identifies the preprocessing steps taken. M stands in for mammography throughout the table, whereas NP stands in for "Not a Public Dataset."

Table-3.3 Comparative Study for the Recent Proposed work in the Breast Cancer Detection and Classification

Ref.	Detection & Segmentation	Classification	Classes	Fine tuned	Accuracy
[8]	YOLO is used for mass detection. Then, they proposed a new full resolution convutional network(FrCN) deep learning model for pixel-to-pixel mass segmentation	AlexNet	B/M	They used the transfer learning method to initialize the parameters of all deep learning models	-Detection accuracy=98.96% -Classification accuracy= 95.64%
[9]	YOLO is used to detect	YOLO	B/M	Fine-tuned with the	-Detection

	the mass			pre-trained weights with a large computer vision ImageNet dataset	accuracy=99.7% -Classification accuracy= 97%
[10]	Adaptive threshold & morphological operations	Deep Belief Network(DBN)	B/M/N	Not fine tuned	-Overall accuracy= 92.86%
[11]	ROIs are first extracted and then Otsu segmentation algorithm followed by morphological operation to refine the mass	Alexnet, GoogLeNet and Shallow CNN	B/M	Pre-trained on a large scale visual database	GoogLeNet AUC=88% & AlexNet AUC= 83%
[12]	No detection and segmentation	DCCN	B/M	Fine –tuned with the pretrained weights with a large computer vision ImageNet dataset	The multitask transfer DCNN was found to have significantly (p=0.007) higher performance generalization compared to the single-task transfer learning DCCN
[13]	No detection and segmentation	Alexnet, GoogLeNet and Shallow CNN	B/M	Fine –tuned with the pretrained weights with a large computer vision ImageNet dataset	The GoogleNet with Deeper Training outperforms the other models with a recall of 0.934 compared to at most 0.901 for the other models
[14]	RetinaNet	No Classification	No Classification	They used RetinaNet50 that is pretrained on the ImageNet dataset for the backbone netw	They did a lot of experiments and they achieved higher true positive rate than the complex model which is average 97%

4. APPLICATION OF DETECTION AND CLASSIFICATION MODELS: A COMPARATIVE ANALYSIS

In Table 3.3, we have a comparison of the same seven approaches with respect to the presence or absence of a detection model, the presence or absence of a classification model, the classes used to train the model (benign, malignant, or normal), and the accuracy (if present). Here's how the numbers shake out: Columns labeled "classification" and "classes" represent the mass classification model, "fine adjusted" and "classes" show if the model has been fine tuned, and the "accuracy" column indicates the model's efficacy. The paper citation may be found in the "Ref." column.

Based on our findings, AlexNet [14], GoogleNet [15], YOLO [9], and RetinaNet [16] are the most popular and up-to-date models for large-scale pattern recognition. Both [9] and [16] include summaries of recent, high-quality studies on breast detection and categorization.

4.1 Models Constraints on Existing Detection and Classification Methods

Despite their shown accuracy, the aforementioned models are not without flaws. The AlexNet model's block-based representation of pictures is highly linked, requiring more Memory than is typically used. GoogleNet was able to solve the problem of redundant data and reduce costs by removing superfluous feature maps, but it was still dependent on weak ties. Although GoogleNet had many benefits, its heterogeneous architecture required frequent fine-tuning as new modules were added. Unfortunately, the representation bottleneck substantially restricts the feature space in the next layer, which may lead to the loss of critical information in certain circumstances. The YOLO model may be adjusted to meet your requirements, but it has certain constraints when it comes to determining how close an item is, such as an inability to correctly pinpoint microscopic items. Hence, the RetinaNet was created to efficiently and rapidly address the limitations of one-shot object detectors like YOLO.

CONCLUSION

In an effort to reduce the number of lives lost to breast cancer, this study compares the most up- to-date diagnostic and classification strategies. We incorporated many publicly available datasets from recent papers, such as DDSM, CBIS-DDSM, and INbreast. These datasets are compared to one another in a number of aspects, including size, views, classifications, and image format. Lastly, we do an extensive analysis of recently reported machine learning-based detection and classification methods. The CBISDDSM is the biggest and de facto standard database since it is an enhanced version of the DDSM. As compared to their more complicated predecessors, the standard CNN networks, the newest models, YOLO and RetinaNet, perform better and more efficiently when used for mass detection and cancer categorization. Models with a more uniform distribution of classes to identify perform better than those with skewed distributions of data.

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