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Detection and Classification of Breast Cancer from Mammogram Images using Adaptive Deep Learning Technique

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ABSTRACT: Breast cancer has been one of the top causes of death among women in the world and hence early and accurate diagnosis is essential in the process of effective diagnosis and treatment planning. Even though mammogram image is the key in the diagnosis of the aberrant tissue pattern, it is time consuming and subject to human error. To eliminate these challenges, an automated system of detecting and classifying breast cancer based on mammography images is developed using a flexible DL. In order to increase model generalization, data preparation steps such as scaling, data normalization, and data augmentation are undertaken upon the prepared dataset containing labeled images to be classified during preparation and detection bounding box annotations to be identified during preparation. Among the many learning strategies that the framework uses in classification, there are Adaptive CNN, CRNN + LSTM), SVM with (SVM+MLP), Hierarchical Clustering with GLCM, and several parameter transfer learning models such as Xception, EfficientNetB0, and DenseNet121. In order to detect abnormalities, suspicious regions in mammography images are detected with the help of object detection models of the YOLO family, including YOLOv3, YOLOv5, YOLOv8, and YOLOv11. Experimental analysis indicates that YOLOv3 works best with a precision of 71.2 and mAP of 52.4 and also DenseNet121 has 99.8 as its highest accuracy in classification. In addition, explainable AI with Grad-CAM is built to detect discriminative areas that affect model predictions. To report on diagnostic automatically and infer in real time, the trained models are integrated into a web interface based on Flask.

KEYWORDS: Breast Cancer Detection, Mammogram Image Analysis, Deep Learning, Transfer Learning, YOLO Object Detection, Explainable AI, Medical Image Classification, Computer-Aided Diagnosis."

I. INTRODUCTION

Breast cancer is one of the most widespread and fatal diseases that affects women, and to survive, it is necessary to notice it at its initial stages. Early problems with breast tissue may be revealed with mammogram and other diagnostic imaging. In mammography, lumps, tissue densities and other minor changes in structure may be indications of cancer. Hand interpretation of mammogram is time consuming and needs medical expertise. Overlapping tissues, very small lesions and changing imaging quality complicate the process of diagnosis. The highly developed computer systems are required to help clinicians to interpret the mammography images more efficiently and faster due to the tremendous growth in the medical imaging data [1].

The automated approaches based on DL and AI to detect and classify issues within complex medical data are transforming medical image analysis. Mammography pictures can be used to train the ML models that can differentiate between benign lesions, malignant tumors, and normal tissues. The smart approaches enhance the accuracy of diagnostics by minimizing the human factor and speeding up the picture deciphering. DL systems, hybrid networks, and optimization methods have been explored in order to identify and classify breast cancer in medical imaging [2]. Multi-model learning frameworks, in line with the contextual and spatial information in the mammography, are used in the modern analysis of medical images [3].

DNN and hybrid learning can identify breast cancer trends and areas of concern in radiological imaging. Smart models can analyze complex breast tissue morphologies and detect problems by use of the convolutional feature extraction and sequential learning [4]. It has been demonstrated by numerous researchers that DL models enhance the quality of clinical

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decisions and screening early-stage breast cancer [5]. CNN with RNN (hybrid) are more effective in categorization because they extract deeper contextual relationships in medical picture data [6].

New AI models utilize generative models with optimization to enhance the detection of breast cancer patterns in medical imaging [7]. AI algorithms that define how it detects problematic regions in mammography are enhancing the transparency and interpretability of medical diagnostic systems [8]. The advanced classification algorithms and hybrid feature extraction enhance breast cancer screening [9]. DL can be used together with optimization to improve the efficiency and reliability of automated breast cancer analysis [10].

This is aimed at developing a smart system of analyzing mammograms to detect cancer in the breast and provide images of a diagnosis. To be used in automated screening, the technology breaks down photos provided, identifies abnormalities and suggests medical categories with visual representations that can be easily understood. The process of accessibility, screening times, and medical image interpretation is enhanced through an interactive web interface of image processing, report writing, and history record keeping.

II. RELATED WORK

Mammography-detected breast cancer results in lower mortality and improved therapy, thus research has been conducted on the topic. Many computer algorithms can autonomously process mammograms and better and more accurately detect abnormal tissue. DL methods are also favored in the medical image analysis because they can automatically identify visual appearance in large datasets. This method reveals subtle patterns of mammography that cannot be detected by human analysis. Developed segmentation and classification models have been researched to improve automated diagnosis of breast cancer. Dhanalaxmi, Venkatesh, et al. suggested a DL-based method of breast cancer mammography segmentation and classification. They grouped questionable areas of medical images into diagnostic categories. DNN collected important visual data and also enhanced categorization meaning that DL has the potential to enhance breast cancer screening [11]. Nour and Boufama applied the active contour and DL in the segmentation and classification of mammography lesions. Observing the abnormalities of the breast tissue is observed through the contour-based segmentation and DNN. We enhance localisation of areas in mammography images and classification of tumour forms [12].

Agrawal, Singh, and others developed a DL model to categorize breast cancer using the mammogram at the image level with better image reduction. They did this in order to enhance the depiction of features by removing unnecessary information in image form whilst maintaining structural patterns. The DL model improved the mammography diagnosis by detecting anomalies in the breast tissue following the image processing [13]. The proposed capsule network design, which is explainable and developed by Alhussen, Haq, et al., is intended to perform mammography breast cancer screening using AI. They apply region-of-interest segmentation and relevance-aware algorithms to find areas in which they make classification decisions. DL systems can be made more interpretable by showing physicians the way the algorithm locates problematic mammography locations [14]. Niranjana, Ravi, and others have created the hybrid DL model, IEU Net++, that would classify the mammograms into several categories. Picture analysis happens through deep structural elements to examine hierarchical picture features with a view to finding abnormalities in the breast. The hybrid network features several techniques of extracting features to identify the mammography data well [15].

Thakur and Kumar provided a credible multi-phase stacked ensemble learning framework to detect and classify breast cancer. Multiple DL models facilitate accuracy in the categorization and stability of prediction. The ensemble architecture has strong learning algorithms that identify the presence of aberrant tissue during mammography [16]. The technique that was developed by Gupta, Kubicek et al. combines DBT feature fusion, mammography, and DL into the diagnosis technique. The equipment employs multimodal imaging in order to detect complex breast tissue issues. Multimodal feature fusion enhanced automated breast cancer diagnosis by relying on additional visual information [17]. Sabre, Elbedwehy, et al. proposed a meta-heuristic ensemble learning framework to diagnose and classify the breast cancer using optimisation and multi-classification. Meta-heuristic optimization improves the mammography cancer detection and the selection of model parameters [18].

According to Chowdhary, Sankaran, and colleagues, the breast image analysis was enhanced by the suppression of the pectoral muscle of images of the mammography equipment. The pectoral muscle can introduce errors in the extraction of features and disrupt the automated analysis. This section is eliminated in order to assist with the DL analysis of mammography and make the architecture of the breast tissue easier to comprehend [19]. Bani Ahmad and Alzubi, along with others, developed a hybrid heuristic DL system that can identify breast cancer with the help of thermography

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photos. They apply heuristic optimization and DL to detect the patterns of heat in breast tumors. DL and optimization enhance breast cancer in the medical analysis of images [20].

III. MATERIALS AND METHODS

An intelligent automated mammography image processing framework helps in the diagnosis and classification of breast cancer. Preprocessing techniques of mammography images are normalization, scaling, and augmentation, which improves the quality of images and ensures consistency of models. These initial steps supplement computer models by detecting interesting structural components of the image of the breast tissue. Intelligent DL systems can be used to make a diagnosis and interpret medical images [21]. Mammogram images are classified under various learning models to analyze tissue properties and classify the disorders in the breast. Some of the classification methods used are the SVM with Multi Layer Perceptron, CNN feature extraction with RNN with LSTM, Adaptive CNN and Hierarchical Clustering with features in the Grey Level Co-occurrence Matrices. The deep transfer learning models, including Xception, EfficientNetB0, and DenseNet121, also improve categorization, including high-level visual representations on the images of mammographies [23]. To detect abnormalities, bounding boxes around probable locations of tumors are formed by object detection models like YOLOv3, YOLOv5, YOLOv8 and YOLOv11. To increase the interpretability and transparency of automated analysis, Grad-CAM uses explainable AI methods to generate visual heatmaps of areas of model predictions [22]. Users use a web interface that is developed with Flask to interact with the system. The interface makes it possible to upload mammography images, automatically analyze them with trained models, visualize the results of detection with highlighted areas, and download diagnostic reports and use them to receive therapeutic help [24].

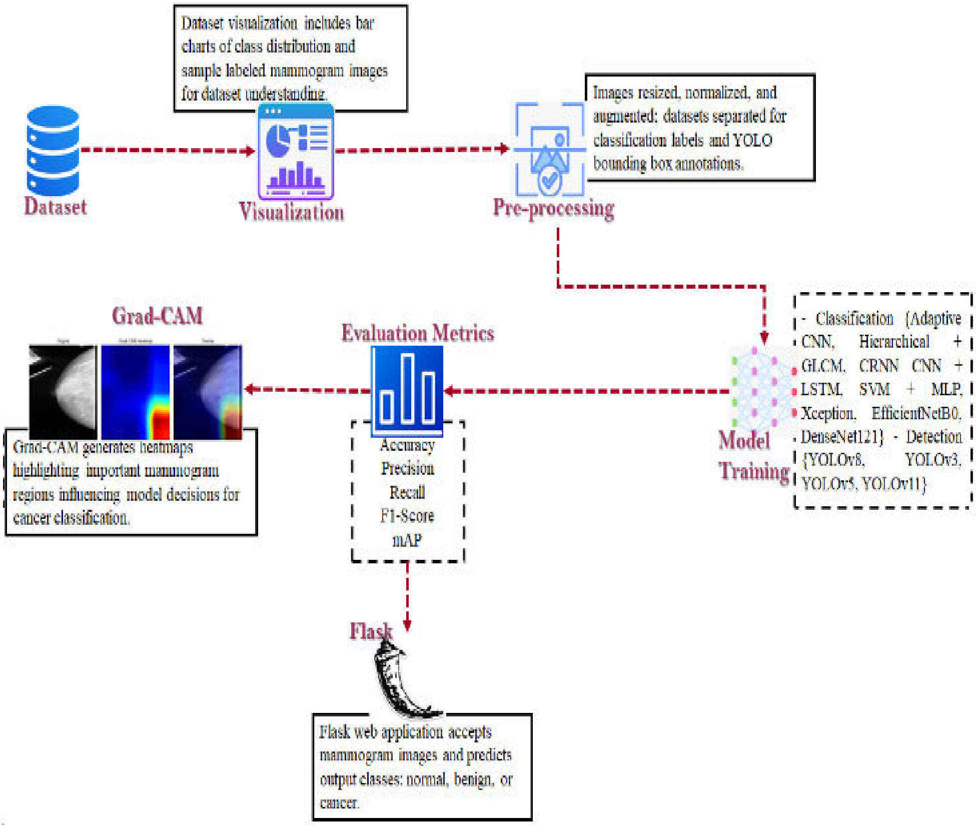

Fig.1. System Architecture

Examples of the steps involved in diagnosing breast cancer and presented in Fig. 1 include data visualization and pre-processing of mammography images. The approach utilizes diverse models in detection and classification both using YOLO. Performance is measured using metrics such as accuracy and mAP, whereas Grad-CAM heatmaps are also used to reveal important areas that influence decisions. Finally, a Flask web application provides its users with user-facing predictions of normal, benign, or malignant classes.

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A) Dataset Collection:
The dataset to be used in analyzing mammography images is found in the Kaggle medical imaging repository. Image analysis algorithms are trained and tested using automated image analysis algorithms trained on the images of mammograms of various states of the breast. Such images classify the breast tissue as belonging to benign, malignant or normal. The dataset has structured medical images that are used in image classification and the detection of aberrant areas. Preparation of ML is done thoroughly through digitally collected, and class-labeled photographs. Mammogram images that have labels of diagnosis category are used in classification analysis. The algorithm of learning is able to observe visual features of each case and distinguish between normal tissue and unusual images due to labeled photographs. Annotations of the dataset that are given in the format of the bounding box of detections are presented in the YOLO format. Regarding the regions within the mammography image, object identification algorithms allow locating the areas in the image as the text files that accompany the image provide object coordinates and object classes. The order of samples is split 90: 10 on the training and validation subsets to evaluate the model accurately. In the evaluation part, this division allows models to acquire visual characteristics in the training set and examine their performance on the unseen image.

B) Pre-Processing:
Pre-processing in medical image analysis is a very important stage where raw pictures of the mammography are prepared to be efficiently trained in models. It improves quality of data by standardizing image sizes, removing discrepancies and bringing out visual patterns. Scaling, normalization, and augmentation is used to make the images friendly to learning algorithms and make the models more accurately identify anomalies and meaningful tissue structures during classification and detection processes.

Visualization: Visualization is essential prior to the commencement of model training in order to understand the distribution and structure of the mammography dataset. To begin with, the distribution of classes is done using visual tools such as bar charts, which indicate the number of photographs that are available in each category. This ensures that learning models are adequately represented by every label of the diagnostic and helps in finding the balance of classes. To understand the differences in the pattern of tissues in the normal, benign and malignant groups, visual inspection of the photographs of the samples labeled is also done. These sample photos enable the researchers to understand the visual characteristics that ought to be acquired by the models during the training process. An annotated image visualization that is used in detection activity also illuminates the identification of problematic spots on mammograms. The accuracy of the annotations can be verified by drawing questionable areas in the photos by using bounding boxes. Such visual representations help to make the distribution patterns, accuracy of the labels, and the structure of the datasets more visible, which can be used to better plan and create reliable analysis.

Processing: ML and DL models need to be processed, so that they can utilize mammography images and annotations being used. To ensure that the dimensions of the inputs across the dataset are the same, the first step will be to scale photos to a uniform resolution. Scaling pixel values then follows and this stabilizes model training and improves convergence. Some data augmentation methods include rotation, flipping and scaling to create diversity in the datasets to increase the ability of the model to generalize to various visual patterns. Each picture is assigned a label which is based on the diagnostic category to classify the pictures. Detection analysis is performed by creating annotation files in the YOLO format, the text files include object coordinates and class identities, which are the areas of anomaly on the picture. Also, a configuration file is generated to define the names of classes and directories of data required to train the detection. These processes ensure that detection and classification datasets are properly structured in order to learn the model.

C) Algorithms:
Adaptive Convolutional Neural Network: An adaptive CNN is a DL model that is designed to automatically extract hierarchical spatial data of picture data. To obtain patterns such as edges, textures and structural differences slowly, it has convolution layers, activation functions, pooling layers and fully linked layers. To represent features better, adaptive learning processes change the parameters based on features of the input. To be able to differentiate between the normal structure and the aberrant patterns of the breast tissue, the model will analyze the medical pictures to detect even the slightest changes in the tissue.

Hierarchical Clustering with GLCM: Hierarchy Clustering based on GLCM is a classical technique of analyzing medical images based on their texture. GLCM characterizes the textural properties such as contrast, homogeneity, energy and correlation through computing statistical correlations between neighboring pixel intensities. These features are structural patterns of mammogram pictures. Hierarchical clustering is the method applying hierarchical clustering to

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images and group them into nested clusters based on the similarity of the gathered feature vectors. The procedure differentiates the images that exhibit aberrant structural patterns and normal mammography images through the analysis of such clusters and detection of prevalent tissue characteristics.

CRNN CNN with LSTM: CRNN integrate convolutional and RNN in order to elicit spatial and sequential feature associations out of picture input. The convolutional layers can extract spatial patterns based on mammography pictures, which are edges, forms and textures. These feature maps are then sent to the LSTM units which utilize internal memory states to establish the dependencies between the retrieved features. This combination occurs through deeper understanding of complex visual patterns, which helps the system to analyse the relationship among the tissue patterns presented in mammography images.

SVM with MLP: The SVM combines with the Multi Layer Perceptron to form an image classification ML framework. SVM seeks the optimum where the different categories of data are separated by the optimal decision boundaries. The Multi Layer Perceptron consists of the input, hidden and output layers of a feedforward neural network with nonlinear activation functions. These learning processes handle the features of the retrieved images in the analysis of mammography images to determine the patterns present in the structure and differentiate between various conditions of the breast tissues.

Xception: Xception The Xception is a deep CNN that relies on depthwise separable convolutions to augment the usefulness of feature extraction. This process minimizes the complexity of computing and yet has a high representation capacity as it splits channel-wise processing and spatial filtering into two distinct processes. Gradient propagation during training is smoothed out with the help of residual connections. The network examines high resolution medical images of mammograms to identify any small structural variations in the breast tissue. It is richly designed, and that is why complex patterns, including irregular shapes and density variations could be studied.

EfficientNetB0: The CNN EfficientNetB0 design was created by means of compound scaling, in order to balance input resolution, network depth, and width. The architecture progressively scales each dimension instead of increasing one in order to achieve tremendous accuracy using minimal computing resources. In order to enhance the feature representation, the model uses squeezing excitation methods and adjustable inverted bottleneck convolution blocks. EfficientNetB0 is an effective method to find aberrant tissue patterns during mammography analysis, and in it fine-grained visual features are extracted in pictures.

DenseNet121: DenseNet121 is a deep CNN that is characterized by dense layers interconnections. Each layer passes its output to the successive ones, and gets feature maps provided by all the previous layers. This connection is used during the training to increase information flow and reuse features. Transition layers and dense blocks are used to manage computational complexity and dimensionality. In mammography image analysis, the architecture is very useful in portraying small differences in tissues that combine low level features and high level features to give finer visual patterns.

YOLOv3: An object detection network known as YOLOv3 is created to find and identify multiple objects in an image simultaneously. The model makes predictions of bounding boxes and class probabilities after making grid cells on the image. A deep convolutional backbone extracts hierarchical visual features and the multiscale detection layers identify objects of various sizes. To detect suspicious areas of tissues in the mammography images, the YOLOv3 examines the whole image and employs bounding boxes to label these abnormal areas.

YOLOv5: YOLOv5 is a complex object detection system to perform effective and accurate object localization in photos. The network is incorporated with convolutional feature extractor modules, feature pyramid structures and detecting heads. Such factors predict bounding boxes with the respective class probabilities through the visual data analysis at different scales. The model is able to execute images in a single forward pass, which allows it to detect quickly. YOLOv5 is based on the concept of identifying problematic tissue areas during the analysis of mammography through bounding boxes.

YOLOv8: A modern system of object detection named YOLOv8 was developed in order to enhance the accuracy and efficiency of the detection in analysis image tasks. The system includes convolutional feature extraction modules and improved detection heads that study visual patterns of different spatial scales. The feature fusion mechanisms combine the data in a large number of layers in order to detect the objects of different sizes. In the interpretation of mammography images, YOLOv8 studies the entire image and predicts bounding boxes, which represent suspicious regions, which require medical treatment.

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YOLOv11: An advanced version of the YOLO family of object detectors, YOLOv11 will aim at enhancing both the detection accuracy and computing efficiency. The design uses more complex methods of space pattern capture, including deeper convolutional layers and increased methods of feature aggregation. Multiscale prediction layers have the ability to accurately detect objects of different sizes. YOLOv11 is effective at detecting problematic tissue in mammography images since it detects the presence of a suspicious spot by scanning the entire pixel and making predictions based on the scanned image in the form of bounding boxes.

D) Integration of XAI & Flask:
EAI is a medical image analysis technique that enhances greater clarity. Grad-CAM is applied to produce visual heatmaps to display the most important areas of mammography images that influence the classification. These heatmaps help to illustrate the interpretation of visual patterns in a picture by DL models. The mechanism of explainability enhances the confidence in machine diagnosing predictions and contributes to the understanding of model behaviour, which points out the relevant tissue areas related to abnormal conditions. Moreover, pictorial descriptions make interpretation of classification outcomes easier.

The Flask framework is integrated to provide an interactive online interface of automated mammography image analysis. The service allows users to post medical photos to the site using a simple web-based form which is processed by the detection and classification algorithms that are trained on the backend. The system displays the studied image and suggested category names, confidence levels and highlighted anomalous regions. The interface also records the history of the analysis to be used in future and enables creation of downloaded reports.

IV. EXPERIMENTAL RESULTS

Accuracy: Accuracy of a test is a property which defines how a test is able to differentiate between the healthy cases and the patients. To estimate test accuracy, we should find out the extent of correct hits and the correct misses in every case evaluated. Mathematically this can be stated as:
"Accuracy=TP+TNTP+FP+TN+FN(1)"

Precision: Precision is the percentage of correctly identified samples or events of those that are identified as positives. Thus the accuracy is obtained by the formula below:
"Precision=True PositiveTrue Positive +False Positive(2)"

Recall: Recall is a ML measure that evaluates the ability of ML model to find all relevant examples of a particular class. The proportion of positive observations which are actually predicted to be positive presents data on the ability of a model to capture instances of a given type.
"Recall=TPTP + FN(3)"

F1-Score: The F1 score is a ML appraisal statistic that measures the precision of a model. It combines the precision and the recall scores of a model. The accuracy measure is used to compute the number of times a model was able to predict correctly across the entire data.

"F1 Score=2*Recall X PrecisionRecall+Precision*100(4)"
mAP: MAP is one measure of quality ranking. It considers the number of recommendations that are relevant and their position at the list. The AP of query or user K is arithmetically averaged to find MAP of query or user K.
"mAP=1nk=1k=nAPk 5"

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"Table.1 Performance Evaluation – Classification"

Model	Accuracy	Precision	Recall	F1-score
Adaptive CNN	0.9762	0.9753	0.9787	0.9768
Hierarchical + GLCM	0.4122	0.2778	0.4453	0.3387
CRNN (CNN + LSTM)	0.9770	0.9770	0.9780	0.9780
SVM + MLP	0.8400	0.8500	0.8400	0.8400
Xception	0.9720	0.9730	0.9740	0.9730
EfficientNetB0	0.9820	0.9830	0.9840	0.9830
DenseNet121	0.9980	0.9980	0.9980	0.9980

On the findings of mammography image analysis using accuracy, precision, recall, and F1-score measures, Table 1 compares the performance of the models in categorizing the findings.

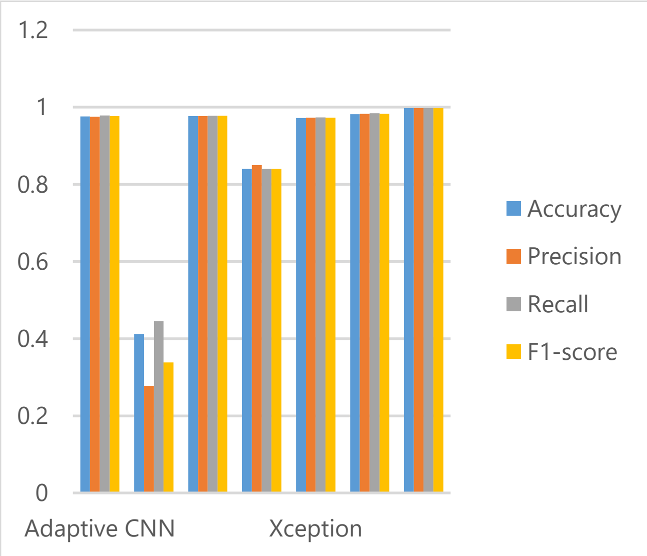

Fig.2. Comparison Graph – Classification

The results of performance metrics of several classification models are presented in Fig. 2, and it turns out that the DenseNet121 is the most precise architecture to work with.

"Table.2 Performance Evaluation – Detection"

Model	Precision	Recall	mAP
Yolo V8	0.591	0.526	0.547
Yolo v3	0.712	0.493	0.524
Yolo v5	0.544	0.498	0.472
Yolo v11	0.593	0.474	0.503

Table 2 compares the detection performance of YOLO models using precision, recall, and MAP of anomalous regions localization.

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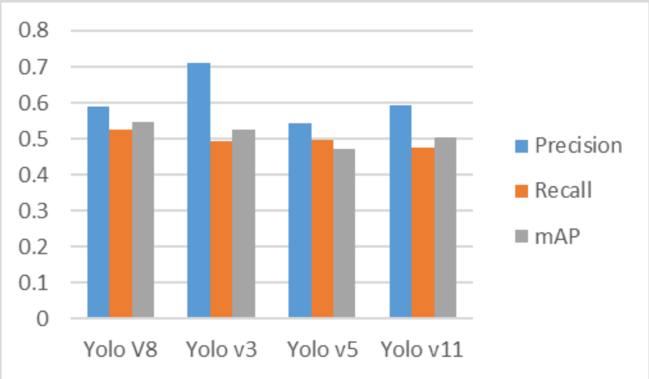

Fig.3. Comparison Graph – Detection

The superiority of recall and MAP of YOLO v8 is evidenced by the improved balance of the two metrics as shown in Fig. 3, showing all the metrics of detections of all variations of YOLO.

V. CONCLUSION

Early and precise identification of the abnormalities of the breast in the mammographic images is a very high probability of successful course of treatment and decision-making in clinical aspects. The effectiveness of the combination of detecting and classifying models to analyze breast cancer in an effective manner can be evidenced by the developed adaptive DL structure. The combination of multiple ML and DL algorithms, structures of transfer learning, and models of object identification makes the methodology possible to accurately control mammography pictures and localize suspicious regions. Data pretreatment, data augmentation and the structured set up of the dataset improve model generalization and stability during the training process. Based on experimental analysis, the DenseNet121 transfer learning model had a higher ability to distinguish between cancerous and non-cancerous patterns of mammograms with the highest classification performance of an accuracy of 99.8, a precision of 99.8, a recall of 99.8, and an F1-score of 99.8. YOLOv3 gave the best results of abnormality localization with a recall of 49.3 and mAP of 52.4 and therefore managed to find the possible location of tumors in the photos with a precision of 71.2. Moreover, explainable AI with the use of Grad-CAM also provides visual heatmaps, which demonstrate the most important areas that influence the prediction, which increases the interpretability and credibility of automated diagnosis. The trained models are further utilized in conjunction with a Flask-based web interface to make real-time analysis, region visualization and the creation of diagnostic reports possible, enabling the useful application in computer-aided medical screening environment.

To increase the generality of the diverse models to different imaging systems and patient populations, future studies can focus on increasing diagnostic strengths by incorporating larger and more diverse multi-institutional mammography datasets. Hybrid CNN-Transformer models and sophisticated transformer-based vision architectures must be explored to be able to detect smaller tissue variation and longer-range spatial connections. By using an in-depth analysis of the patients, integrating the multi-modal medical data, such as MRI, ultrasound and the clinical records, there will be an opportunity to enhance the quality of the diagnostic more. One can also reduce the use of fully annotated datasets with semi-supervised and self-supervised learning methods. The use of lightweight tailored-to-edge or cloud-based clinical models might also enable faster real-time screening. A continuous development of advanced explainable AI schemes may increase clinical assurance and openness in the automated process of breast cancer diagnostics.

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