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Improved Breast Cancer Detection using Modified ResNet50-Based on Gradient-Weighted Class Activation Mapping

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ABSTRACT

Breast cancer is a prevalent and serious disease that affects many women around the world every year. Detecting breast cancer early is crucial for improving survival rates and treating the illness effectively. Researchers are exploring various methods, including neural networks and machine learning, to assist in detecting the disease. However, due to limited data availability, leveraging pre-trained models trained on diverse image datasets has become a common practice. This article introduces a novel approach to identifying breast cancer that involves the utilization of a deep learning model utilizing the ResNet50 framework, coupled with heat mapping and gradient-weighted class activation mapping (Grad-Cam). The suggested method was primarily assessed using the FDDM dataset of Subtracted Contrast Enhanced Spectral Mammography (CDD-CESM) images. The outcomes from this model were then contrasted with those of five other well-known models: VGG16, VGG19, MobileNetV2, EfficientNet-B7, and standard ResNet50. The newly proposed model yielded an accuracy of 0.8920, which was better than the other models. Additionally, Grad-Cam showed nearly flawless feature extraction in a breast cancer classification assignment. In the discussion section, the suggested method was utilized with the MIAS dataset to ensure thoroughness and scalability, and to allow for comparison with prior research. The results demonstrated the effectiveness of the suggested approach, with an accuracy of 0.9830 achieved on the MIAS dataset, surpassing previous works. This study significantly enhances the improvement of breast cancer detection through the integration of deep learning, the ResNet50 architecture, and visualization methods including heat maps and Grad-Cam.

Keywords:
Deep learning; Modified; Breast cancer; Improved performance; Grad-cam

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1. Introduction

The growth of abnormal cells that invade surrounding tissues in the human body is known as a cancerous tumour. Benign and malignant are the two types of tumours. A non-cancerous tumour consisting of cells that only grow locally and do not spread throughout the body is referred to as an adenoma. [1] In contrast, a malignant tumour is composed of cancer cells that can multiply uncontrollably, spreading to various parts of the body, and invading tissues [2]. Breast cancer (BC) is the most common type of cancer in women, with approximately 12% of women in the United States expected to be diagnosed with it during their lifetime. Every two minutes, one woman is diagnosed with BC in the United States [3,4]. BC is a disease in which breast cells grow uncontrollably. The type of BC depends on which cells become cancerous. BC can start in various parts of the breast, which is made up of three main components: lobes, ducts, and connective tissue. Most BCs start in the ducts or lobules. Early detection of BC is important in increasing patient survival rates [5,6]. High rates of morbidity and the significant cost of cancer-related health care have prompted researchers to develop more accurate models for cancer detection [7]. Mammography and biopsy are the most common methods for detecting BC. A radiologist uses a specific type of breast image to detect early symptoms of cancer in women during a mammogram. Mammography has been shown to reduce mortality rates from BC. Biopsy is another effective diagnostic technique for detecting BC [8] Automatic recognition and localization of tumour cells in BC images is a major challenge because they vary in size, shape, and location. Other abnormalities, such as mastitis, adenoiditis, and granulomas, may be present in BC images, which can degrade the performance of traditional machine learning (ML) techniques, such as preprocessing, segmentation, and feature extraction [9-11]. The recently developed deep learning (DL) method can overcome these traditional challenges. This method can achieve distinct feature representation to solve image classification and object localization problems. Convolutional neural networks (CNNs) are the most well-known DL algorithms proposed in the literature [12] .

This research focuses on enhancing the ResNet50 model based on Grad-Cam to evaluate CDD-CESM (subtracted contrast improved spectral mammography pictures) more effectively. This study extensively investigates well-known models such as EfficientNet-B7, VGG16, and VGG19, and their application in several deep learning tasks associated with medical imaging. The diagnosis of breast cancer strongly depends on CDD-CESM, the dataset that is the primary focus of this study. Our objective is to bridge the gap between the requirements of clinical practice and the constraints of current image processing capabilities by comparing the outcomes of this dataset with those of the MIAS dataset.

Notable accomplishments:

i. Adapting the ResNet50 architecture for CDD-CESM: making changes to the ResNet50 architecture to accommodate the unique visual characteristics of CDD-CESM images, which may differ from those seen in standard datasets used to train conventional models, such as the original ResNet50.
ii. Improved efficiency: The updated ResNet50 outperforms previous designs on the CDD-CESM dataset. This demonstrates how modifications to the model can enhance the accuracy of medical diagnosis based on imaging.
iii. An analysis of the extent to which various deep learning model architectures accurately represent important spectral mammography characteristics enables us to evaluate and differentiate their effectiveness on the CDD-CESM dataset.

iv. During the discussion, we conduct an inter-dataset study to compare the performance of the updated model with prior research that utilized the MIAS dataset. This investigation has comprehensively assessed the effectiveness and versatility of the model in handling various types of mammography images.
v. Identifying the places in mammography pictures that have an impact on model predictions is crucial for the clinical validation and interpretation of model findings. An effective approach to achieve this is through the utilization of Class Activation Mapping (CAM), which enhances the visibility and interpretability of the results.
vi. Assessment in relation to existing optimal methods: To assess the performance of the enhanced ResNet50 models, this stage involves comparing them with other cutting-edge medical imaging models such as EfficientNet-B7.

2. Related work

This section explores previous studies that categorized breast cancer via machine learning methodologies. Extensive research has been conducted on the categorization of breast cancer due to its high prevalence and significant impact on patient outcomes. The limitations of conventional diagnostic methods, such as histopathology investigation, restrict their accuracy and efficiency. Scientists have utilized deep learning and machine learning approaches to enhance the accuracy and efficiency of breast cancer classification. The utilization of deep learning and machine learning approaches in the categorization of breast cancer has yielded favourable effects, facilitating prompt detection, personalized treatment, and enhanced patient results.

The study's authors provide a way for developing a CAD job that involves identifying and classifying radiological images using the YOLOv4 network and ViT vision [13]. The research utilizes two datasets, Inbreast and CDD-CESM, which include pictures from FFDM (Full-Field Digital Mammography) and CESM (Contrast-Enhanced Spectral Mammography). The utilization of DM-CESM (FFDM) resulted in a commendable global average detection accuracy score (mAP) of 71.65% for the model. The work centred on the analysis of computed tomography (CESM) images obtained from the CDD-CESM dataset [14]. The authors employed a loss function known as Difficulty Weighted Neighborhood Representation (DWNR) to detect anomalies in breast images obtained by CESM. The approach achieved a significantly higher accuracy of 82.91% compared to classic loss functions like focused loss and Cross-Entropy (CE). The authors of this work [15] offer a computer-aided design (CAD) system that combines BI-RADS assessments with pathologies, masses, calcifications, and breast density classifications. The system is designed to be easily understood and used. The CBIS-DDSM and CCD-CESM datasets were utilized. The supplementary tasks in the CCD-CESM dataset achieved an accuracy of 85.0% for pathology, 90.3% for mass, 92.7% for calcification, and 80.0% for breast density.

The technique described by the study's authors [16] consists of two essential components, which are explained in extensive detail. In order to locate the breast tissue and the likely region of interest (ROI) that contains the lesion, the initial step involves utilizing the YOLOX model to extract the ROI. The second function is categorization. The EfficientNet and ConvNeXt models demonstrate high efficiency and accuracy in categorizing Regions of Interest (ROIs) as either benign or malignant. This study utilized mammography pictures from many sources, such as VinDr-Mammo, MiniDDSM, CMMD, CDD-CESM, BMCD, RSNA Highest Accuracy, and Data CCD-CESM Accuracy. The study strategy outperformed earlier strategies in terms of sensitivity, accuracy, ROC AUC, and PR AUC, with an average enhancement of 8.0%.

The study utilized the X-ray mammography data set, which is the largest collection of Convolutional Neural Network (CNN) data. It trained the network using random graduation moment and optimized the configurations for basic learning rate, maximum age limit, and small push indications. The goal was to achieve the highest level of accuracy, as stated in reference [17]. A DCNN consists of seven layers with varying weights. The final three layers consist of the linked groups, while the first four tiers are composed of the Tlavs. Each neuron computes the dot product of the local area weights, which is proportional to the input size. Two steps of assembly are employed to ensure the computation is maintained and flexibility is enhanced. The maximum value from each of the four inputs is allocated to each local region using the assembly layers and the 2x2 pixel filter size. The learning rate in the final Convolutional Neural Network (CNN) class determines the rate at which the weights change over time. The regular images exhibited disorganized tissue structure, calculations, and a concentrated mass in the breast; a breast cancer screening technique based on convolutional neural networks (CNN) utilized pixel intensity characteristics to detect specific categories, such as circumscribed mass identification, resulting in positive outcomes. After conducting ten testing iterations, we obtained an average accuracy of 82%. The objective of [18] is to identify breast cancer (BC) by employing transfer learning techniques that are rooted on deep learning (TL). There are nine different TL models, namely EfficientNetB7, InceptionResNetV2, ResNet, DenseNet, MobileNet, DenseNet121, DenseNet169, DenseNet201, and VGG19, that are employed for the classification of cancer as either benign or malignant. The models underwent 40 epochs of training using the "Adam" optimizer, resulting in improved computing efficiency and precision. The weights were categorized as silhouette and divided into 100 epochs using the MIAS dataset, which consisted of mammography images. The models were represented as input with dimensions of 224 by 224 pixels and 3 colour channels. The accuracy rate of the EfficientNetB7 model was 98%.

This study [19] focused on developing a computer-aided diagnostic system (CAD) that uses MIAS data to accurately diagnose breast masses through mammography. A novel technique was developed which utilized differential noise reduction, active geometric subsistence models with spot partitioning, and a rotating serial filter (ASF) to detect the potential mass. The study properly assigned a unique number to each pixel in the eighty-three photographs, which were evenly divided between instances of malignant and benign masses. This numbering system utilized eight bits. The extensive mass property and location data in the Mini-MIAS database facilitated precise segmentation and evaluation of various retail algorithms. In order to evaluate the efficacy of the created methodology, two sets of publicly accessible data were utilized: The mini-DDSM database has 71 animal X-rays, while the mini-MIAS database contains 83. This enabled the demonstration of the efficacy of the proposed approach across various datasets. The mini-MIAS database achieved a dice coefficient of 95.32%, an accuracy of 97.09%, and a sensitivity of 93.2%.

The experiment utilized two types of data, namely DDSM and MIAS. The DDSM dataset was utilized to train and assess CNN models that were based on particle swarm optimization (PSO). An analysis was undertaken to compare the performance of the PSOCNN model on the DDSM dataset with prior experiments conducted on the same dataset. The MIAS dataset was utilized to analyse the convolutional neural network (CNN) model, which was then fine-tuned using PSO to optimize its hyperparameters. The PSOCNN approach achieved an accuracy of 97.98% on the MIAS dataset. They utilized the particle swarm optimization (PSO) technique to identify the optimal hyperparameters and structure for the CNN model. The utilization of the DDSM and MIAS datasets resulted in accuracy rates of 98.23% and 97.98% respectively, demonstrating the effectiveness of this technique [20]. The study [21] employed mammography to detect breast cancer, utilizing datasets from MIAS, INbreast, and BCDR. Prior to doing probabilistic principal component analysis (PPCA), the input images underwent preprocessing steps including noise removal, smoothing, and normalization. The purpose of this was to identify malignancies in mammograms. The TCNN and Naïve Bayes classifier were employed to categorize the tumour region. The MMFLO and FBGO algorithms were employed to optimize the outputs. The ensemble model combines the Bayes and FBGO algorithms with the TCNN and MMFLO algorithms. The Bayes+FBGO algorithm demonstrated a remarkable accuracy of 96.3% when applied to the MIAS dataset.

The paper presented a systematic approach for analysing the development of a novel lightweight dual-channel attention-based learning model named MOB-CBAM [22]. This model employs the MobileNet-V3 architecture, augmented with a Tlavian block attention module, to accurately forecast the molecular subtypes of breast cancer. The research generated nine distinct data subsets for both coarse and fine predictions. The subsets consisted of mass detection, metastases, mitoses, malignancies, and cancer molecular subtypes, specifically luminal A and luminal B, HER-2 positive, and three negatives. Furthermore, the CMD mammography dataset was utilized to evaluate the effectiveness of the proposed MOB-CBAM model. The MOB-CBAM model demonstrated exceptional precision in distinguishing between benign and malignant tumours, achieving a 99% accuracy rate, call rate, F1 degree, and MCC of 0.98. The model achieved a 98% accuracy in determining mass and clotting for appropriate categorization functions in good/bad situations. The MIAS and CBIS-DSM data sets were mutually validated to assess the performance of the model. The results showed that the model achieved an accuracy of 97% and 98% for the different classification tasks, respectively.

The authors of the paper [23] described their methodological approach. The MIAS dataset was used to classify breast cancer patients by employing FuNet transfer learning and an extreme learning machine (ELM). A feature fusion technique is utilized to enhance the precision of feature extraction and classification for breast cancer. The quantitative genetic binary Gray Wolf optimizer (Q-GBGWO) improves the ELM parameters to better the overall performance inside the ELM framework. The model has excellent sensitivity and specificity rates for each category, as well as high classification accuracy rates of 96.54% for benign cases, 97.24% for malignant cases, and 98.01% for normal cases. These results indicate the model's ability to accurately identify various subtypes of breast cancer.

A classification study was conducted to classify breast cancer based on mam myography images [24]. The researchers implemented a multi-feature deep information bottleneck approach for breast cancer classification, achieving promising results. However, the study had some limitations, primarily due to the limited number of available images for this method. The researchers utilized ResNet18 as the backbone network for feature extraction in their proposed model. To demonstrate the generalizability of their approach, they also employed other networks such as VGG19, ResNeXt, WRN, and Res2Net for the classification task. Notably, the multi-feature deep information bottleneck approach achieved an accuracy of 97%, indicating its effectiveness in accurately classifying breast cancer cases. Also, Michael *et al.,* [25] introduced an optimized framework for breast cancer classification utilizing machine learning techniques. Their study focused on ultrasound images and proposed a computer-aided diagnosis (CAD) system capable of automatically generating an optimized algorithm. To classify malignant and benign breast tumours, they employed five different machine learning classifiers. The experimental findings demonstrated the effectiveness of Bayesian optimization with a tree-structured Parzen estimator for 10-fold cross-validation. Among the five classifiers used, the LightGBM classifier outperformed the others, achieving an impressive accuracy of 99.86%. Also, [26] conducted a research study focused on breast cancer detection using mammograms with the implementation of a convolutional neural network (CNN). The MIAS dataset was utilized as the basis for their experiments, resulting in an achieved accuracy of 65%. It is worth noting that an accuracy rate of 65% in breast cancer detection using mammograms may be considered relatively modest. Further examination of the study’s methodology, potential limitations, and avenues for improvement is necessary to enhance the accuracy and reliability of breast cancer detection utilizing CNNs and mammographic data.

In another study, [12] conducted an in-depth study on breast cancer classification and lesion localization using deep learning techniques ap- plied to MR images. They specifically investigated the effectiveness of a 3D deep convolutional neural network (CNN) for diagnosing breast cancer. The CNN model was trained with image-level supervision to automatically classify images and accurately localize the lesions. The experimental results demonstrated that their proposed model achieved an impressive accuracy of 83.7%. These findings highlight the potential of deep learning and CNN-based approaches for breast cancer diagnosis and lesion localization using MR images. The utilization of such advanced techniques can contribute to more accurate and efficient detection and treatment planning, ultimately improving patient outcomes in breast cancer care. [27] conducted a machine learning study on the classification of breast cancer types. They analysed RNA-Sequence data from breast cancer tumour cases obtained from The Cancer Genome Atlas. The study evaluated four different classification models, namely Support Vector Machines, K-nearest neighbour, Naive Bayes, and Decision tree. These models were trained using selected features at various threshold levels to classify the two types of breast cancer. The experimental results revealed that the Support Vector Machine algorithm outperformed the other models in accurately classifying breast cancer types, achieving an accuracy of 90%. This finding highlights the effectiveness of the Support Vector Machine approach in breast cancer classification based on RNA-Sequence data. The study contributes to the growing body of research exploring machine learning techniques for improved breast cancer diagnosis and treatment.

Moreover, [28] conducted a comprehensive study on breast cancer classification utilizing ultrasound images. Their research focused on developing a novel framework based on probability-based optimal deep learning feature fusion. The proposed framework consisted of five key steps, including data augmentation, employing a pre-trained DarkNet-53 model, fine-tuning the model using transfer learning techniques, extracting features from the global average pooling layer, and utilizing two enhanced optimization algorithms called reformed differential evaluation (RDE) and reformed grey wolf (RGW). Additionally, a new probability-based serial approach was employed for classification using machine learning algorithms. To evaluate the performance of the proposed framework, experiments were conducted on an augmented Breast Ultrasound Images (BUSI) dataset. The results demonstrated an outstanding accuracy of 99.1%. Comparative analysis with recent techniques showcased the superior performance of the proposed framework in breast cancer classification. These findings underscore the potential of probability-based optimal deep learning feature fusion in enhancing breast cancer classification accuracy and signify a significant contribution to the field of medical image analysis.

Furthermore, [29] conducted a pioneering research study that employed a deep learning model for the automatic detection and classification of breast cancer, utilizing the transfer-learning technique. The study utilized the mammographic image analysis- society (MIAS) dataset and employed pre-trained convolutional neural network (CNN) architectures, including Inception V3, ResNet50, Visual Geometry Group networks (VGG)-19, VGG-16, and Inception-V2 ResNet. Six evaluation metrics were employed to assess the performance of the proposed model. The experimental results demonstrated that the transfer learning (TL) approach utilizing the VGG16 model exhibited exceptional capabilities for breast cancer diagnosis, effectively classifying mammogram breast images with an accuracy rate of 98%. It is important to highlight that the utilization of deep learning models and transfer learning techniques in breast cancer detection holds immense promise for improving diagnostic accuracy and enabling more effective and efficient clinical decision-making.

Also, [30] conducted a study with the objective of enhancing the performance of transfer learning without fine-tuning for breast cancer histology images. They specifically focused on dissimilarity-based multi-view learning techniques and compared the effectiveness of different feature extractors, including one handcrafted feature extractor and five transfer learning feature extractors based on deep learning architectures. The results revealed that the deep learning networks pretrained on ImageNet demonstrated superior performance compared to the commonly used handcrafted features for breast cancer histology images. The findings from Cao *et al.,* study underscore the effectiveness of deep learning networks pretrained on ImageNet for achieving improved performance in breast cancer histology image classification. These results contribute to the growing body of literature exploring advanced machine learning methods to enhance the accuracy and reliability of breast cancer diagnosis. Further investigation and validation of these techniques hold promise for significant advancements in medical imaging and have the potential to improve patient outcomes. [31] conducted an advanced research study aimed at enhancing the classification of breast cancer using an improved convolutional neural network (CNN). The novel modifications made to the CNN architecture were specifically designed to enable accurate classification of breast cancer samples into three distinct categories: malignant, benign, and healthy patients. The experimental findings revealed an accuracy rate of 89%.

The related work mentioned in the provided text reviews various studies that have utilized machine learning techniques for breast cancer classification. These studies highlight the potential of machine learning and deep learning techniques in improving breast cancer classification accuracy and supporting medical professionals in diagnosis and treatment decision-making. However, it's important to consider the limitations and potential areas for improvement in each study, such as the size of available datasets, the need for further validation, and the exploration of other machine learning algorithms or models.

3. Methodology

The proposed method consists of four main stages: data collection, data processing, model training, and model evaluation. The first stage involves obtaining a dataset for the challenge [32] Due to the difficulty of obtaining results on this dataset and processing the data, data augmentation methods were used to generate additional images. It also includes resizing, standardization, and data augmentation. Getting to the Model Training Step This step is essential to improve the model's performance. Therefore, work was done to improve ResNet50 based on Grad-Cam and Grad-Cam++ to improve the accuracy of the model for breast cancer detection. In this stage of model training, pre-processed images are used to train the chosen model. During the training process, images are provided to the model and parameters are modified to improve the model's performance. The final stage involves evaluating the model using metrics such as precision, precision, recall, and F1 score. Thus, the proposed method uses deep learning techniques to analyse breast cancer MRI images and accurately classify and diagnose the disease based on optical features. Fig. 1 shows the proposed architecture of this work.

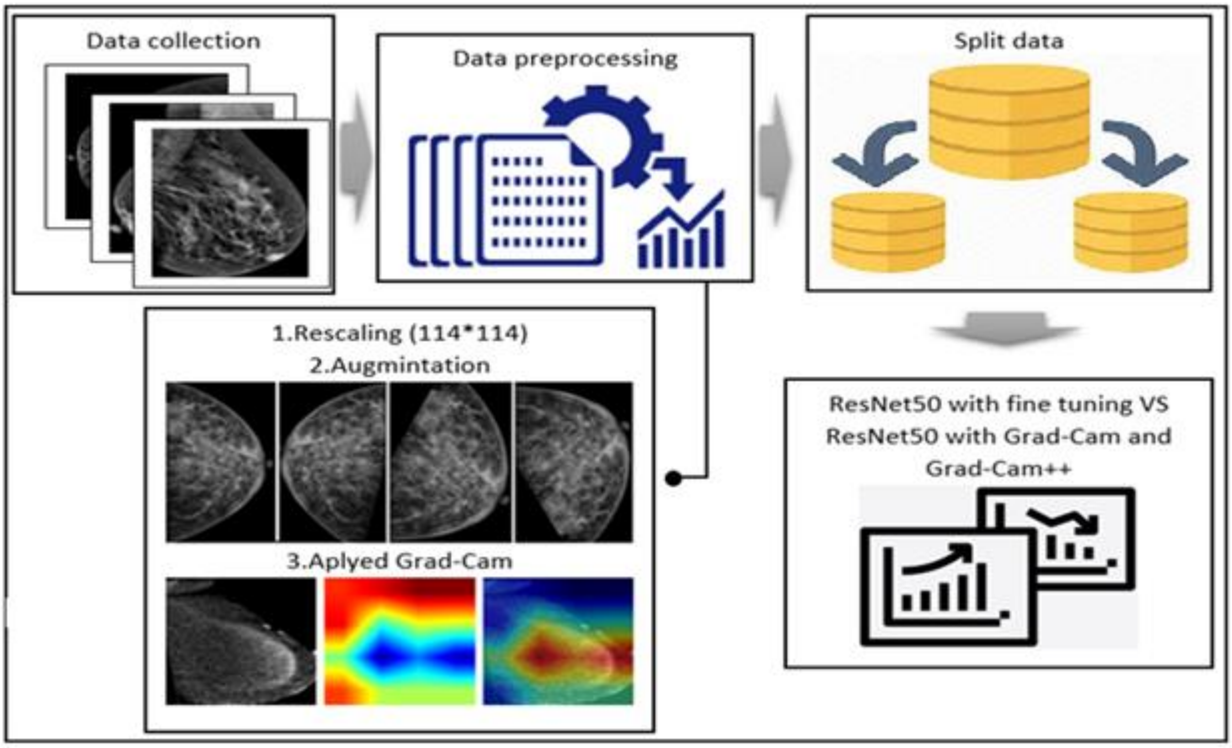

Fig. 1. Proposed architecture of methodology

3.1 Data Description and Collection

The dataset obtained from Subtracted Contrast Enhanced Spectral Mammography images (CDD-CESM) [32] that were collected from the Department of Radiology, National Cancer Institute, Cairo University, Egypt during the period January 2019 to February 2021. All images are high the average resolution is 2355 x 1315 pixels. Data were obtained from 326 female patients, ranging in age from 18 to 90 years. Contains 2006 images with CC and MLO displays (1003 FDDM low power images and 1003 CESM subtracted images) In this research, FDDM is used for classification and a binary system were used to distinguish between normal and cancerous breasts.

3.2 Reprocessing

Pre-processing is important in the field of computer vision, and it is spread over the images to make them suitable for the proposed model and prepare them for training. In addition, some of them were found to increase the accuracy of the model, and the following are the steps used for pre-training treatment.

3.3 Rescaling and Augmentation

The default size for ResNet50 is (224, 224) but resize to (112, 112) to save memory size. Augmentation used on images to comply with the large data volume needed by the deep model and to increase accuracy. The ways used are horizontally flip 50% of the images, vertically flip 50% of the images, rotate the images by a random degree between -20 and 20 and shear the images by a random degree between -16 and 16. Fig. 2 show example of augmentation methods. The account of images after augmentation was 2046 for normal images and 1986 for images that contain tumour.

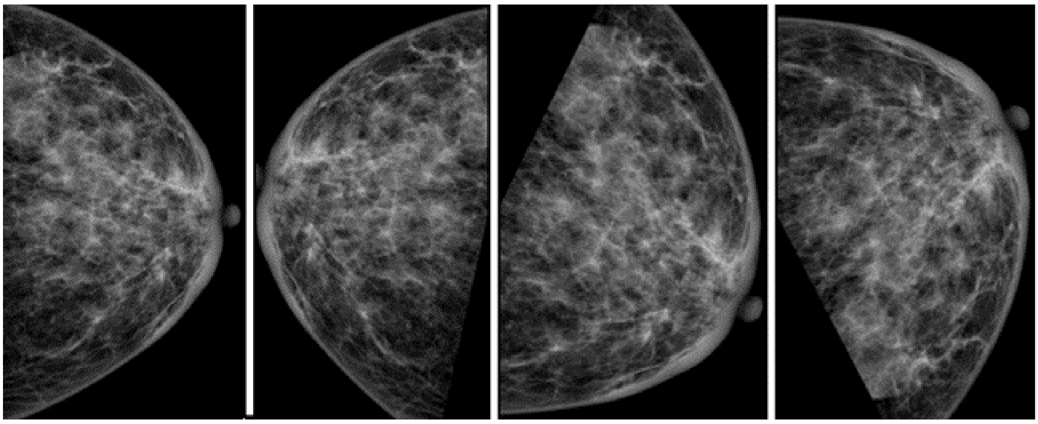

Fig. 2. An examples of augmentation methods

3.4 Gradient-Weighted Class Activation Mapping (Grad-Cam)

The proposed technique known as Grad-CAM (Gradient-weighted Class Activation Mapping) [33] seeks to increase the transparency of CNN-based models by visually highlighting the significant input regions used for making predictions. By utilizing class-specific gradient information, Grad-CAM identifies and emphasizes the image areas that play a crucial role in the model's decision-making process. Through the integration of these localization maps with existing visualizations, such as Guided Grad-CAM, a novel and detailed visualization is generated, enabling a deeper understanding of CNN-based models, including those employed in image captioning and visual question answering tasks. The efficacy of Grad-CAM is assessed based on its ability to distinguish between different classes, instil confidence in human observers, and its alignment with occlusion maps. Overall, Grad-CAM represents a valuable approach for providing visual explanations and improving the interpretability of CNN-based models [1]. Fig. 3 show the effect of applying Grad-Cam on image.

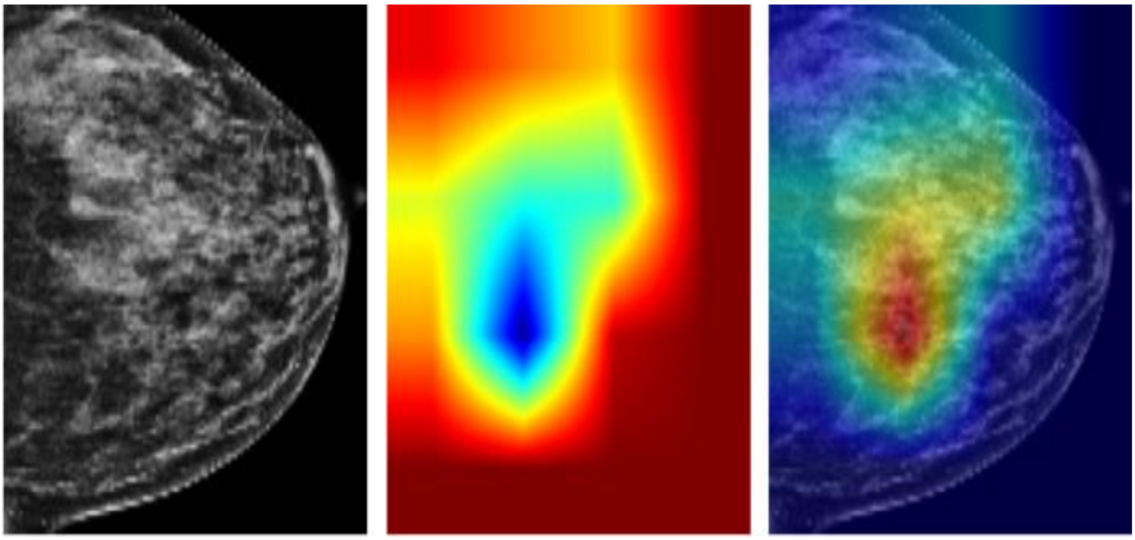

Fig. 3. Effect of Grad-Cam on image

3.5 Residual Network 50 (ResNet50)

ResNet50 is a deep convolutional neural network architecture, and it takes up the challenge of training very deep neural networks by using residual learning. The main idea behind ResNet50 [34] is the input of residual blocks, which allows the network to learn the residual functions by referring to the inputs of the layer. This means that instead of directly trying to figure out the key mapping required, the network learns to set the remainder between the input and output for each block. This formula helps mitigate the vanishing gradient issue and enables training of significantly deeper networks. ResNet50 has 50 layers, including convolutional layers, pooling layers, fully connected layers, and residual blocks. The architecture features skip connections that bypass some layers, allowing gradients to flow more directly during training. These skip connections enable the network to learn and propagate information efficiently, even in the presence of deep layer stacks. ResNet50 achieved impressive performance on several image recognition tasks, including the ImageNet dataset. It has been widely adopted as a powerful infrastructure for such tasks as image classification, object detection, and image segmentation. [35] In a nutshell, ResNet50 is a deep convolutional neural network architecture that uses residual learning and connection skipping to enable training of very deep networks. It has shown excellent performance on image recognition tasks and serves as a basic building block in computer vision applications.

3.6 Visual Geometry Group (VGG-NET)

The VGG16 and VGG19 architectures have emerged as prominent methodologies [36] in the field of medical image analysis, particularly for breast cancer classification. These models have demonstrated remarkable effectiveness in accurately distinguishing between normal breast tissue and tumour affected regions within medical images. Leveraging their sophisticated deep convolutional neural network structures, these models excel in extracting intricate features from breast cancer images, facilitating precise and well-informed classification decisions.

By virtue of their ability to handle high-resolution images and capture intricate patterns, VGG16 and VGG19 represent invaluable tools for aiding medical professionals and researchers in the early detection and diagnosis of breast cancer. Harnessing the capabilities of these architectures empowers healthcare practitioners to gain valuable insights into tumour presence, enabling prompt and accurate treatment decisions [37].

3.7 Proposed ResNet50-Based Model Depends on Heat Maps using Grad-CAM

The ResNet50 architecture has been modified. Where some layers are frozen in the model (not trainable) except for the last 10 layers and any bulk flattening layers, which are set to be trainable. Then a supermodel is created by adding a global mean pooling layer and a dense layer with SoftMax activation, which will act as an output layer. [38] The model was compiled using Adam's optimizer, a binary entropy loss function, and an accuracy scale. The final model is generated by connecting the inputs of the ResNet50 model and the output of the upper model. Then superimpose a heat map on top of the original image. It takes two modes: CAM (camera heatmap). Returns the set of three elements of the original image, the heatmap, and the superimposed image. The function resizes the heatmap to match the dimensions of the original image, converts it to the range 0-255 as an unsigned 8-bit integer, and applies the colour map 'COLORMAP_JET' to visualize the heatmap. The overlay image is created by mixing the heatmap and the original image with equal weights. The resulting overlay is then clipped to the range 0-255 and converted back to the RGB colour space. Then the Grad-CAM (Gradient Weighted Activation Class Mapping) function is executed to generate a heat map that highlights array containing the expected class and heatmap for the CAM (class activation map). The gradients and outputs from the layer are processed to obtain the CAM weights, which represent the significance of each spatial significant regions of the input image for a given class. It takes three arguments: model (ResNet50 model), (input image), and (name of the layer from which the gradient will be calculated). It returns a location in the layer output.

Algorithm 1: Enhanced ResNet50 for CDD-CESM

Input: Dataset: CDD-CESM, Labels: malignant or benign, Input shape: (112, 112, 3) // used (112, 112, 3) instead of (224, 224, 3) to reduce time complexity, Num of classes: 2, Batch size: 16, Epochs: 10

Output: A network model: trained model, Evaluation metrics: accuracy, precision, recall, and F1-score, Class Activation Maps for interpretability

1. Begin
2. //Data Collection:
3. Data <-- Normalization (Data)
4. //Data processing: Data augmentation (rotate, horizontally flip, vertically flip, share) using (TensorFlow. Karas. applications. resnet50.preprocessing. Image)
   Scale all images to (112 × 112)
5. For i = 1 to Number of Training do
6. Data1 <-- Horizontal Flip (Training)
7. Data2 <-- Vertical Flip (Training)
8. Data3 <-- Shift (Training)
9. Data4 <-- share (Training)
10. // Data Augmentation <-- Add (Training, Data1, Data2, Data3, Data4)
11. Split dataset into training, validation, and test sets: 60% training, 20% validation, and 20% testing
12. // Initialize and modify the ResNet50 model
13. base_model = Load_ResNet50_Base (include_top=False, weights='ImageNet', input_shape=input_shape)
14. model = Add_New_Top_Layer (base_model, num_classes)
15. // Set trainable layers
16. model=Set_Trainable_Layers (model, trainable_layers=10, include_batchnorm=True)
17. // Compile the model
18. model.Compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
19. // Train the model
20. Fit the model
21. // Evaluate the model
22. performance_metrics = Evaluate_Model (model, X_test, Y_test)
23. // Generate CAM visualizations
24. Cam visualizations = []
25. for image, true_class in zip (X_test, Y_test):
26. grad_cam_result = Generate_CAM (model, image, 'conv5_block3_out', method='grad_cam')
27. cam_visualizations.append((image, grad_cam_result))
28. // Compare results with other models
29. models_to_compare = ['original ResNet50', 'VGG16', 'VGG19', 'MobileNetV2', 'EfficientNet-B7']

```
    comparison_results = Compare_With_Other_Models (models_to_compare, X_test, Y_test)
    // Output results
    Return trained_model, performance_metrics, cam_visualizations, comparison_results
End
```

CAM is obtained by multiplying the layer output by the CAM weights and applying ReLU activation. CAM values are scaled to the range 0-1 by dividing by the maximum value of the CAM. Finally, the predicted class and CAM heatmap are returned in group form. Finally, a ResNet50-based model is built, heat maps are superimposed on the images, and separation activation maps are generated using Grad-CAM. The steps included in building of proposed model for breast cancer detection are presented in Algorithm. Table 1 shows the deferent between enhanced ResNet50 based Grad-Cam.

Table 1
ResNet50 comparison table

Layer type	Original ResNet50	Enhanced ResNet50
Input layer	Fixed size (224, 224, 3)	Customizable (112, 112, 3)
Output layer	Dense (1000, SoftMax)	Dense (2, SoftMax)
Architecture customization	None	Custom top layers for breast cancer classification
Trainable parameters	All layers potentially trainable	Last 10 layers and Batch-Normalization layers trainable
Integration of CAM	Not integrated	Integrated for specific layers
Data preprocessing	Standardized for ImageNet	Custom for specific dataset
Model Training and Evaluation	Standard training and evaluation	Includes advanced visualization (CAM), custom splits, and evaluation metrics
Model compilation	Standard settings	Custom settings for optimizer and loss function
Special features	None	Methods for generating heatmaps and superimposing CAM outputs

3.8 Performance Measurement

The performance of the deep learning algorithms used in this study was measured through 4 reliable measures, [37] which are accuracy, precision, recall, and F1-score. These measures depend on collecting true positive results (TP), true negative results (TN), and false positive (FP), false negative (FN) based on the confusion matrix, where the following equations show accuracy, precision, recall, f1-score.

$$Accuracy = \frac{T_p+T_N}{T_p+T_N+F_p+F_N} \tag{1}$$

$$Precision = \frac{T_p}{T_p+F_p} \tag{2}$$

$$Recall = \frac{T_p}{T_P+F_N} \tag{3}$$

$$F_1 - Score = 2 \times \frac{precision \times Recall}{Precision + Rrecall} \quad (4)$$

4. Result and Discussion

Based on the evaluation metrics provided, the best model among the options appears to be modified ResNet50 based on Grad-Cam. It achieves the highest precision, recall, F1 score, and accuracy compared to the other models. Precision measures the proportion of correctly predicted positive instances out of all instances predicted as positive. A higher precision indicates that the model has a lower false positive rate, meaning it is more accurate when it predicts positive instances. As shown in 2, ResNet50 with Grad-Cam has the highest precision 0.92, indicating that it has a relatively low false positive rate.

Table 2
Assessing the effectiveness of our approach

Models	Accuracy	Precession	Recall	F1
VGG16	0.7710	0.7200	0.8200	0.7700
VGG19	0.7200	0.6800	0.7900	0.7300
MobileNetV2	0.6700	0.6900	0.6200	0.6500
EfficientNet-B7	0.6900	0.7000	0.7100	0.7100
ResNet50	0.7196	0.6800	0.7500	0.7100
Enhanced ResNet50 based on Grad-Cam (proposed)	0.8920	0.8500	0.9440	0.8940

Fig. 4 illustrates a comparison between the modified ResNet50 model and other well-known classification models, namely MobileNetV2, EfficientNet-B7, VGG16, and VGG19. The F1-Score, Precision, and Recall serve as the evaluation criteria. The results indicate that the suggested model surpasses the previous models in all aspects, with a recall rate of 0.944 and an accuracy rate of 0.892. The improved ResNet50 demonstrates exceptional proficiency in detecting positive instances and exhibits a minimal rate of misidentifying negative instances. Furthermore, the recall rate of 0.85 indicates that the proposed method effectively identifies a significant proportion of positive cases. The model obtains a high recall rate by accurately identifying and categorizing a significant portion of the true positive events in the dataset. Figure 4 displays the accuracy scores of multiple models.

Overall, the revised ResNet50 performed superiorly compared to the original ResNet50. The utilization of Grad-Cam significantly enhances the performance of the model by emphasizing particular places that play a crucial role in the model's predictions. The results were highly competitive, with a recall rate of 0.82 and a precision rate of 0.72, which were attained by the widely used VGG16 model. This is further corroborated by the F1 score. The enhanced ResNet50 model exhibited a superior F1 score of 0.8940, whereas this model demonstrated a lower F1 score. Although VGG16 may successfully capture a substantial number of positive samples and accurately detect true positives, it is still unable to match the performance of the leading model. Like ResNet50, VGG19 had unsatisfactory performance in terms of recall, F1-score, accuracy, and precision. Although the recall rates of both models were similar, VGG19 exhibited somewhat lower F1 score and precision compared to VGG16.

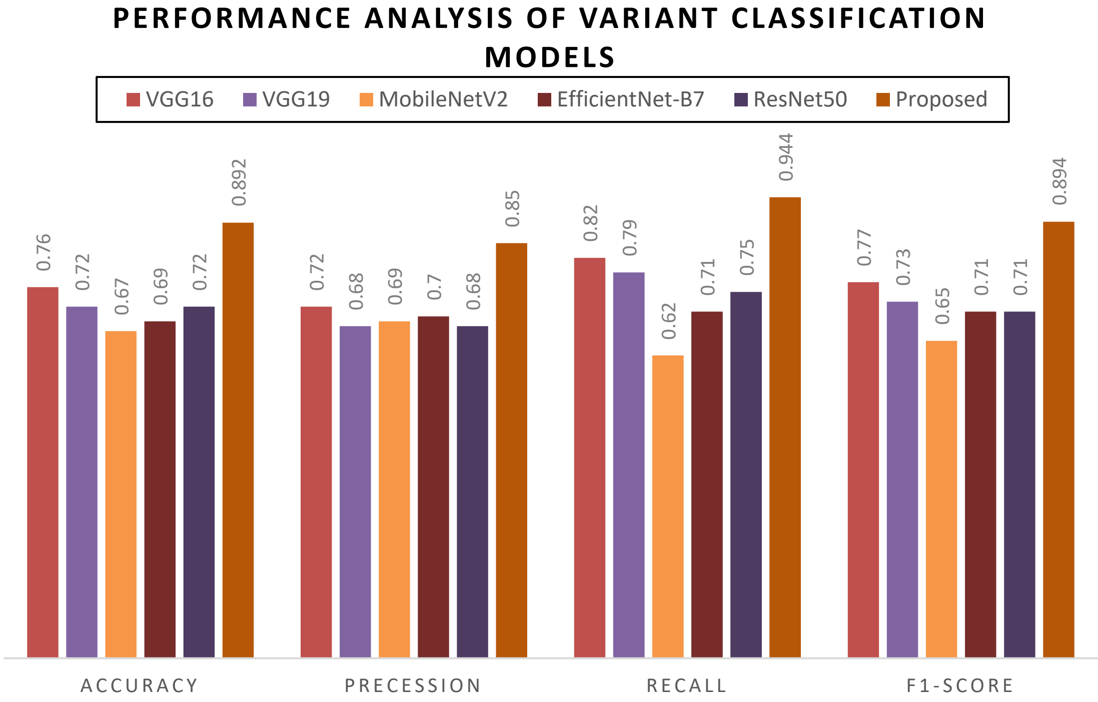

Fig. 4. Performance analysis of variant classification models

Fig. **5** displays a confusion matrix all models. In the improved ResNet50 of breast cancer classification, a confusion matrix can be used to assess the performance of a model in distinguishing between malignant (cancerous) and benign (normal) tumours. There were still 22 false positives, meaning that some normal images were incorrectly classified as cancerous. False positives can lead to avoidable stress and additional diagnostic procedures for patients. Reducing false positives is essential for minimizing unnecessary interventions. False positives, where normal images are misclassified as cancerous can lead to unnecessary biopsies or invasive procedures causing anxiety and additional costs for patients. Minimizing false positives is crucial for reducing the number of unnecessary interventions and providing peace of mind to patients.

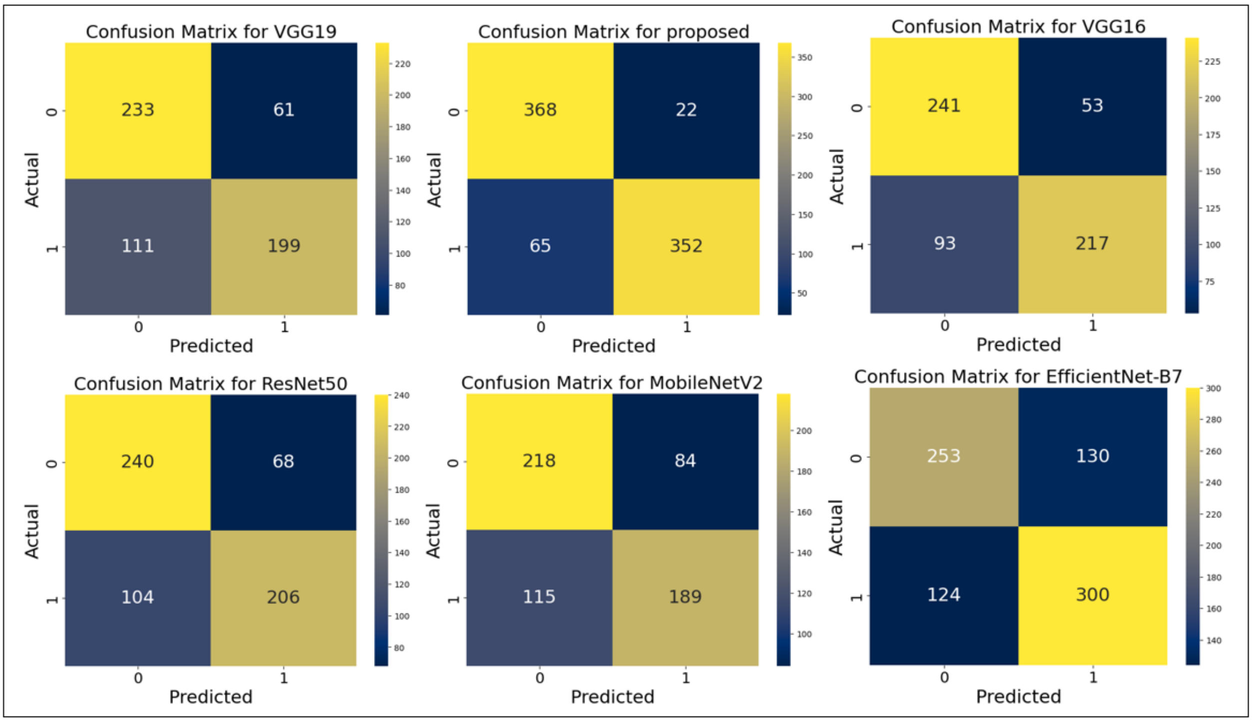

Fig. 5. A confusion matrix all models

The given confusion matrix illustrates the classification results of a breast cancer classification system based on image data. Although the system achieved a high accuracy and demonstrated relatively good sensitivity and specificity, there were still false positives and false negatives present. Further analysis and evaluation of the system's performance, including exploring methods to reduce false positives and false negatives, would be beneficial for enhancing the accuracy and reliability of breast cancer classification using image-based approaches.

5. Discussion

To ensure the scalability and comprehensiveness of our suggested technique, we conducted tests using the MIAS dataset, which is well recognized as a benchmark in medical imaging research. Consequently, we were able to make a comparative analysis of our findings with those of other studies that utilized the identical dataset.

Table 3 presents a concise overview of the outcomes of the comparison analysis. Our Enhanced ResNet50 model, which utilizes Grad-Cam, surpassed our competition in every area. The model yielded a recall of 0.9890, precision of 0.9825, and accuracy of 0.9830. The F1-Score achieved a value of 0.9857. These data clearly show the effectiveness of our technique, beyond that of previous study.

The employment of Efficient-Net-b7 yielded the following results: an F1-Score of 0.9800, an Accuracy of 0.9800, a Precision of 0.9700, and a Recall of 0.9900 [18]. Furthermore, the research conducted by [20] employing PSOCNN had an accuracy rate of 0.9798. Although these findings are satisfactory, our model outperforms them, particularly in terms of Precision and F1-Score. The comparison also encompasses studies employing various methodologies. The research conducted by [21] found that combining TCNN with MMFLO achieved an accuracy of 0.9800, precision of 0.9600, recall of 0.9700, and F1-Score of 0.9700. A MobileNet-V3 backbone with MOBCBAM was employed in another significant study conducted by [16]. The findings demonstrated a high level of accuracy, with a value of 0.9700. Additionally, the Precision, Recall, and F1-Score values were all quite similar, with respective values of 0.9600, 0.9700, and 0.9700. Despite the high quality of these methods, our proposed solution surpasses all evaluation measures.

Table 3
Outcomes overview and comparison result with previous related

Ref.	Dataset	Approach	Accuracy	Precession	Recall	F1-score
[17]	MIAS	Efficient-Net-b7	0.8507	-	-	-
[18]	MIAS	Efficient-Net-b7	0.9800	0.9700	0.9900	0.9800
[19]	MIAS	Diffusion segmentation	0.9709	-	-	0.9532
[20]	MIAS	PSOCNN	0.9798	-	-	-
[21]	MIAS	TCNN +MMFLO	0.9800	0.9600	0.9700	0.9700
[22]	MIAS	MOBCBAM that utilizes the backbone of MobileNet-V3	0.9700	0.9600	0.9700	0.9700
[23]	MIAS	Q-GBGWO_ELM	0.9654	0.9649	0.9602	0.9646
Our	MIAS	Enhanced ResNet50 based Grad-Cam	0.9830	0.9825	0.9890	0.9857
[13]	DM-CESM	YOLOv4+ViT transformer	0.8000	-	-	-
[14]	DM-CESM	TN-pretrained ResNet-18+ DWNR	0.8655	-	-	0.8413
Our	DM-CESM	Enhanced ResNet50 based Grad-Cam	0.8920	0.8500	0.9440	0.8940

Through a comparison with the DM-CESM dataset, we have reaffirmed that our methodology is capable of being scaled. Our Enhanced ResNet50 Grad-Cam model achieved high levels of accuracy, precision, recall, and F1-Score, with values of 0.8920, 0.8500, and 0.9440, respectively. These findings demonstrate a substantial improvement compared to earlier studies that employed YOLOv4+ViT transformer [13] and TN-pretrained ResNet-18+DWNR [14].

The significant improvement in performance indicators on both datasets showcases the robustness and applicability of our proposed technique. We demonstrated the model's ability to effectively process challenging medical imaging datasets by integrating Enhanced ResNet50 with Grad-Cam, resulting in improved classification performance. This comprehensive analysis validates the effectiveness of our technique with the initial dataset and demonstrates its adaptability to different datasets and contexts.

6. Conclusion

In this research, an improvement to the ResNet50 model based on Grad-Cam was presented. The proposed methodology was evaluated using the MIAS and FDDM datasets. The proposed methodology is compared to five more deep learning models, including the widely accepted ResNet50 model used in the industry. The modified ResNet50 model surpasses the other options analysed in every evaluation criterion. The picture categorization abilities are proved by its exceptional recall, F1 score, accuracy, and recall. In general, the enhanced ResNet50 outperforms VGG16, even though VGG16 performs satisfactorily. Utilizing techniques such as Grad Cam to enhance the accuracy of models in image classification tasks is of utmost importance, as demonstrated by the research findings. The enhanced ResNet50 exhibits significant potential for numerous practical applications owing to its exceptional accuracy in detecting positive scenarios and minimal false positive rate. Further research and experimentation can explore novel models and methodologies for image categorization, thereby contributing to the advancement of the field. The development of more dependable and accurate systems will enable several practical applications.

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