Pink Guardian: A Gateway to Early Breast Cancer Detection

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***Abstract*—Breast cancer (BC) remains a pivotal concern in global health, and existing methods for early detection are often limited by accessibility and diagnostic accuracy. We present "Pink Guardian," a mobile application that offers a significant advancement in the early detection of breast cancer, leveraging a proposed BC-InceptionV3 architecture within TensorFlow Lite for real-time, precise classification of mammogram images. This sophisticated model has been integrated into a user-friendly interface, enabling users to easily obtain diagnostic predictions and corresponding confidence scores. Through rigorous experiments, BC-Inception-V3 emerged as the best model, showcasing superior training and test accuracies, thus signifying a breakthrough in clinical breast cancer screening that could be readily available on users' smartphones. Source code is available at https://github.com/kanchanmaurya95/PinkGuardian.git.**

***Index Terms*—Breast Cancer Screening, Convolutional Neural Networks (CNNs), Mobile Health (mHealth), Healthcare**

I. Introduction

Breast cancer's profound impact on global health necessitates advancements in early detection [1] and precise diagnostics. We aim to leverage the potential of neural networks and deep learning to enhance medical image analysis, delivered through an all-accessible within a cutting-edge mobile application. The core objective is to develop a comprehensive system that detects breast cancer from mammogram scans [2] with high accuracy and provides preliminary recommendations to guide subsequent medical decisions. This initiative involves constructing advanced neural network architectures [3] tailored explicitly for medical image analysis [4] and creating a user-friendly platform for uploading scans, ensuring seamless integration for real-time diagnostic predictions.

Our methodology relies on meticulous data management and the strategic implementation of machine learning principles. We initiate the process by meticulously gathering and refining a diverse dataset of mammogram images. This involves expert annotation, normalization for zero mean and unit variance, resizing to ensure uniformity, and the application of augmentation techniques such as random rotations and flips. The dataset, known as CBIS-DDSM (Curated Breast Imaging Subset of DDSM) [5], sourced from Kaggle, plays a vital role in training our "Pink Guardian" application for precise breast cancer image classification. We explored different neural network architectures, particularly exploring the potential of transfer learning from established models like ResNet50 [6], Xception [7] and Inception models [8] and others, to achieve superior diagnostic accuracy. The development and training of the BC-Inception V3 model focus on fine-tuning hyperparameters and incorporating advanced regularization techniques to prevent overfitting. The model has been optimized for breast cancer image classification. The Pink Guardian app is based on [9], which features user-friendly interfaces, delivering real-time predictions with confidence scores and initial health advisories for informed follow-up actions.

In this paper, we identified several limitations of existing deep models used in the early detection of breast cancer in Table I. We compared results with different ImageNet models, including ResNet-50 [10], ResNet-101 [10], Xception [11], EfficientNet [12], and Inception [13]. We used pre-trained weight and replaced the last fully connected layer with the unit size of two (benign and malignant). Optimal parameters were obtained through a combination of grid search and manual tuning, adjusting learning rates, batch sizes, and epochs based on validation performance to prevent overfitting.

TABLE I: Limitations of Existing Deep Models

Model	Limitations
ResNet-50	Prone to overfitting with small datasets, low accuracy
ResNet-101	Increased complexity and training time; overfitting issues, low accuracy
Xception	Requires large datasets for effective training; computationally expensive
EfficientNet	Complexity in scaling; requires significant computational resources
InceptionV3	High memory usage; complex architecture leading to longer training times

The developed models will be adapted to mobile-friendly formats using TensorFlow Lite and integrated within apps built using Android Studio, ensuring functionality across a diverse range of devices. This strategic deployment across multiple platforms facilitates the early detection of potential tumors in mammograms. By merging advanced AI analytics [14] with accessible, user-friendly designs, we aim to enhance early breast cancer detection markedly, thus improving healthcare practices and patient outcomes globally. The efficacy of this integrated system will be continuously benchmarked against existing methodologies to ensure its reliability and accuracy in practical, real-world settings.

II. Related work

The integration of deep learning (DL) in medical imaging, particularly mammography, revolutionized the accuracy and efficiency of breast cancer detection. The study by Wang [3] highlighted how deep learning-assisted mammography improved sensitivity and specificity by adapting to individual patient factors. Further, research by Shen [15] and Yala [16] demonstrated that convolutional neural networks (CNNs) reduced false positives and enhanced the detection of subtle lesions that human radiologists might overlook. Digital breast tomosynthesis (DBT), which provides three-dimensional imaging, offered higher accuracy and better lesion visibility than conventional mammography, proving especially beneficial for women with dense breast tissue [2] [17].

In the burgeoning field of breast health applications, platforms such as “MBC Connect,” [18], and “Breast Advocate” [19] made significant contributions to breast health management. ”MBC Connect” cultivated a supportive community for individuals dealing with metastatic breast cancer, highlighting the importance of emotional well-being through peer support. ”Breast Advocate” provided informed decision-making with extensive resources and personalized risk assessments, encouraging users’ active participation in their health care. These platforms underscored the dynamic integration of technology and personalized care in breast health management. Our developed “Pink Guardian” emphasizes medical accuracy and straightforwardness for proactive health monitoring.

The role of machine learning extended beyond image analysis to predictive analytics and personalized treatment plans. Articles presented breakthrough methodologies in predicting breast cancer metastasis using gene targeting and the MLISBCP [20] model, addressing issues such as class imbalance [21]. Al-Qazzaz et al. [22] detailed advancements in non-invasive classification systems for metastatic breast cancer, which could revolutionize diagnostic accuracy and patient outcomes [23]. The development of imaging classification apps, inspired by Android app developers’ blogs [24], YouTube videos [25], and other online resources, highlighted the significant potential of mobile applications in transforming breast cancer detection and engaging patients in healthcare management [26].

Models like ResNet-50 and ResNet-101 used residual learning and skip connections to train deep networks for mammogram analysis, with ResNet-101 incorporating additional layers for improved detection accuracy [27]. EfficientNet B0 balanced network dimensions for efficiency [28], while B7 scaled up for higher accuracy in detailed cancer detection [29]. Xception improved feature extraction and computational efficiency through modifications to the Inception architecture, suited for high-resolution imaging [30] [31]. Inception-V3 optimized large-scale image processing with mixed layers [32] [33], and VGG-16 focused on texture and pattern recognition in breast tissue [34]. MobileNet provided a lightweight solution for real-time mobile screening [35], while NASNet-Mobile adjusted its architecture for optimal performance in mobile diagnostics [36] [37]. Our “Pink Guardian” app compared the aforementioned classification model to demonstrate the superiority of our proposed BC-Inception-V3 model in improving the accuracy of breast cancer diagnosis.

III. Methods

A. Dataset Overview:

We utilized the CBIS-DDSM (Curated Breast Imaging Subset of DDSM) [5] dataset, which is available on Kaggle [38]. This dataset is derived from the Digital Database for Screening Mammography (DDSM) and is integral for training our ”Pink Guardian” application to classify breast cancer images accurately. It contains high-resolution JPEG images and includes essential data such as the image modality and annotations necessary for effective training.

Key Features and Specifications:

Dataset Format: Images in the dataset are stored in JPEG format, maintaining the original resolution to capture the detailed nuances essential for accurate diagnosis.

Size and Content: - The total size of the dataset is around 6 GB, making it a substantial repository of medical images. - It comprises 10,239 mammogram images, offering a diverse range of cases for model training and testing.

Dataset Composition:

Participants and Studies: The dataset includes 6,775 studies, each corresponding to a series. A total of 1,566 participants have contributed to the dataset, ensuring a broad representation of cases.

Modality: The primary modality is Mammography (MG), which is critical for screening and detecting breast cancer.

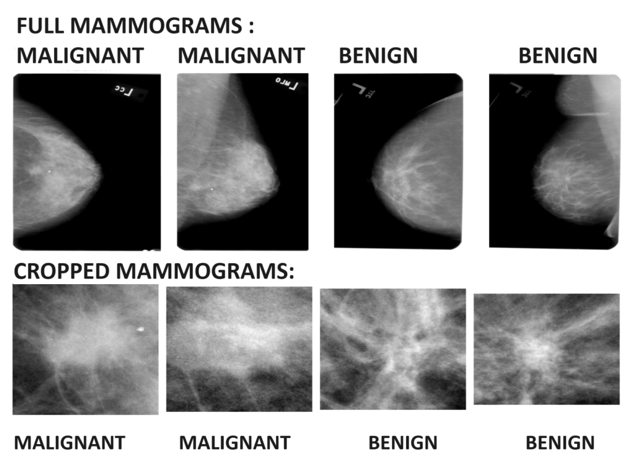


Fig. 1: The Full and Cropped Mammograms Images

Enhanced Features: The dataset has been updated to include DICOM format and improved ROI segmentation, enhancing the usability of the images for machine learning applications.

Standardization and Improvement: CBIS-DDSM addresses the challenge of standardized data in mammography research, providing a curated and well-documented collection of images that aid in developing more effective machine learning models.

Significance in Medical Research: This dataset's comprehensiveness, diversity, and standardization make it an excellent resource for developing robust machine-learning models for breast cancer detection, particularly within the medical imaging domain.

B. Programming Languages and Technologies

The development of the "Pink Guardian" app involves multiple programming languages and technologies, each adding unique capabilities to the app.

Kotlin: was used for Android app development due to its safety, clarity, and support for modern programming features. **Python:** was employed for backend operations or model training, supported by TensorFlow for integrating the BC-Inception-V3 model and utilizing data processing libraries like NumPy and Pandas for data preprocessing. **XML:** was utilized for UI design in the Android environment, allowing for the clear separation of design and functional code and enabling the creation of a scalable and customizable user interface. **Java:** is used for integrating parts of the app with legacy code or certain Android libraries and for backend development.

These technologies provide a robust foundation for developing a user-friendly, efficient, and effective medical image classification application.

C. Model Development:

We explored different ImageNet classification models to optimize breast cancer detection capabilities. Each model has been carefully chosen based on its strengths in handling specific aspects of image processing and classification tasks.

BC-Inception-V3:

In our proposed BC-Inception-V3 architecture for the "Pink Guardian" app, the network begins with an input layer suitable for 224x224 pixel images. It progresses through a series of convolutional layers, with filters ranging from 32 to 192 in size, meticulously engineered to extract a spectrum of features from breast cancer screening images. The detailed architecture is shown in Table II.

Central to the BC-Inception-V3 are the Inception modules, starting with 'mixed0'. These modules contain parallel branches of convolutions and pooling operations, each branch employing different kernel sizes and average pooling strategies to capture an extensive range of image details. The architecture iterates this multi-faceted approach in subsequent Inception modules ('mixed1' to 'mixed10'), allowing for complex feature development and refinement. To synthesize the extracted features into a form suitable for classification, the network adopts global average pooling, which also serves to decrease the model's parameter count and computational demand, consequently reducing overfitting risks. This is followed by a dense layer consisting of 1024 neurons with ReLU activation to interpret the pooled features into a high-level understanding. Our implementation includes detailed tuning of hyperparameters such as learning rate, optimizer choice, batch size, and dropout rate. Specifically, we used an initial learning rate of 0.0001 with the Adam optimizer, and the batch size was set to 8. These hyperparameters were fine-tuned through grid search and manual adjustments to optimize model performance.

TABLE II: Architecture of the BC-Inception-V3 model.

Layer Sequence
Input: 224x224x3
Conv2D: 32 filters - BatchNorm - ReLU Conv2D: 32 filters - BatchNorm - ReLU Conv2D: 64 filters - BatchNorm - ReLU - MaxPooling2D Conv2D: 80 filters - BatchNorm - ReLU Conv2D: 192 filters - BatchNorm - ReLU - MaxPooling2D
Inception Module: mixed0 Branch 1: Conv2D 64 - BatchNorm - ReLU Branch 2: Conv2D 48 - BatchNorm - ReLU - Conv2D 64 - BatchNorm - ReLU Branch 3: AvgPooling2D - Conv2D 32 - BatchNorm - ReLU Branch 4: Conv2D 64 - BatchNorm - ReLU Concatenate
Inception Module: mixed1...mixed10 (Repeating similar structure with different filters and branches)
GlobalAveragePooling2D Dense: 1024 units - ReLU - Dropout Dense: 1 unit - Sigmoid
Output: Prediction

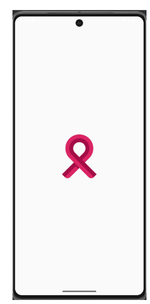


Fig. 2: Launch Screen and Logo of the App

The network incorporates a dropout layer as a regularization mechanism to foster generalization by preventing dependency on individual neurons during training. The culmination of the BC-Inception-V3 model is a singular dense output neuron with a sigmoid activation function, signifying its binary classification goal—to reliably differentiate between malignant and benign findings in mammographic analysis. The BC-Inception-V3's tailored structure not only adapted to performing its critical task with precision but also was optimized for the computational constraints of mobile healthcare applications, ensuring both accuracy and accessibility for users needing reliable breast cancer screening tools.

D. App Details Development

*1) **Android App Development**:* Developed using Android Studio, this mobile app employs TensorFlow Lite [9] for the classification of medical images into "Malignant" or "Benign" categories. The user interface is crafted through XML layout files, which ensure an intuitive navigation experience for users with varying technical proficiency. This includes the main screen, result display, and an optional camera result screen.

Upon initialization, the app loads a TensorFlow Lite model which is adept at recognizing features within medical images to determine tumor status, accompanied by a confidence score to reflect the certainty of its predictions. Users have the flexibility to select images from their gallery or capture new ones via the device's camera, facilitated by Android's activity result contracts for seamless integration. Images are then preprocessed to meet the model's input specifications before classification occurs.

The design and functionality of the app are enhanced by user feedback and usability testing, focusing on easy navigation and effective interaction. The prediction results are displayed through the ResultActivity in a format that users find easy to understand, such as "Malignant (75 percent)." For images taken with the device's camera, a temporary image file is created to aid in displaying predictions, improving user engagement and experience. In medical image classification, the model is particularly well-suited because it can capture intricate patterns and features of images, which is crucial for distinguishing between malignant and benign tumors.

In summary, the model at the heart of this mobile app leverages neural network architectures and TensorFlow Lite to deliver accurate and efficient medical image classification. Its multi-prediction, including classification results and a confidence score, enhances its utility as a diagnostic tool. The model's design ensures that it can be seamlessly integrated into the app, enabling users to make informed assessments of tumor status based on their medical images.

The application exemplifies how advanced programming tools and frameworks can be leveraged to deliver critical healthcare services through mobile technology, reflecting a significant advancement in mobile health applications.

IV. Results

Initially, the user is presented with an interface that prompts them to upload a scan, like a mammogram, by selecting an image either from their device's gallery or directly from the camera. This user-friendly interface is designed to make the upload process as straightforward as possible (see Figure 3a for the main screen, Figure 3b for the image selection functionality, and Figure 3c for the results screen).

Once the user uploads the scan by camera or from the gallery, the application processes the image using the developed BC-Inception-V3 model. Our model can identify patterns that may indicate the presence of tumors. The particular focus of this application appears to be on analyzing scans for signs of malignancy in breast tissue. After the analysis is complete, the application displays the results directly to the user. It provides a diagnosis, categorizing the tumor as malignant or benign, and includes a confidence score expressed as a percentage. This score reflects the algorithm's certainty regarding the diagnosis based on the patterns it has learned to recognize in the training phase. It is important to emphasize that such automated diagnoses are preliminary and should be reviewed by a healthcare professional for accurate medical evaluation and confirmation.

A. Comparison of different models

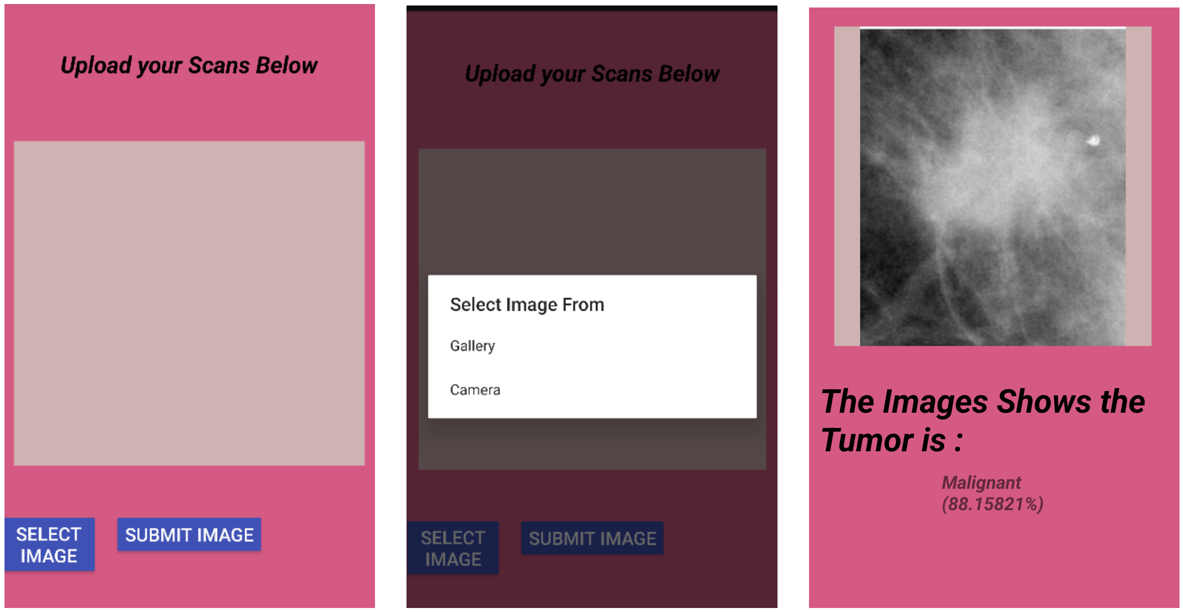
We compared our developed BC-Inception-V3 model with the other nine models as shown in Table. III. Our model achieves a training accuracy of 99.49 % and a validation accuracy of 78.70 %, which highlights not only its capacity to internalize training data effectively but also its proficiency in generalizing to new, external datasets. The superior performance of the BC Inception V3 model suggests that its extensive tuning and sophisticated feature extraction capabilities are particularly well-suited for clinical applications where precision is crucial.

TABLE III: Comparison of Different Models with our BC-Inception-V3 (Acc: accuracy in percentage %).

Model	**Train Loss**	**Train Acc**	**Test Loss**	**Test Acc**
ResNet 50 [10]	0.6895	55.18	0.6986	51.79
ResNet 101 [10]	0.6839	56.53	0.7019	51.79
EfficientNet B0 [12]	0.6887	54.76	0.6943	51.79
Xception [11]	0.4547	77.17	0.7171	65.48
Inception [13]	0.5508	70.85	0.5847	67.26
Fine-tuned Xception [11]	0.5813	69.50	0.6602	62.50
EfficientNet B7 [12]	0.6887	54.76	0.6942	51.79
Nesnet Mobile [39]	0.5134	73.46	0.6881	61.31
Custom Xception [11]	0.5705	71.78	0.6396	64.88
Ours	0.1454	99.49	0.6645	78.70

While the custom Inception V3 model led in terms of performance, other models also demonstrated significant capabilities. ResNet50 and ResNet101, though showing moderate effectiveness, laid the foundational architecture for deep learning in medical imaging. EfficientNet models and Xception provided a balance between computational efficiency and accuracy, with Xception showing strong performance due to its depthwise separable convolutions. Similarly, the Nesnet Mobile and other custom models like Custom Xception adapted well to the specific challenges of mammogram image processing, indicating that tailored modifications to these networks can enhance their diagnostic precision where we hyper-tuned the parameter to adjust and observe changes in the training and testing accuracy.

The results from our study underscore the potential of using a diverse array of deep learning models to improve the accuracy and reliability of breast cancer screening technologies. The success of the Bc-Inception-V3 model on the nuances of medical imaging tasks can lead to significant improvements in performance. This approach not only helps in achieving high accuracy in detecting malignant tissues but also ensures that the models can be effectively integrated into clinical workflows, enhancing their practical utility.



(a) Main/Start Screen of The App (b) Select Image Functionality (c) After Submit Button-Result Screens

Fig. 3: Screenshots of the Pink Guardian app showcasing the user interface flow: (a) the initial launch screen with the app's logo, (b) the start screen where users begin their interaction, (c) functionality for selecting an image for analysis, and (d) the results screen presented after image submission and analysis.

Training and Validation Loss: Figure 4 plots the training and validation loss. There is a noticeable decrease in training loss over time, which is a positive sign. However, similar to the accuracy graph, the validation loss does not show a consistent downward trend and has spikes, which could be a sign of the model not performing consistently across different sets of data. This could point towards the need for better regularization techniques or a review of the model's architecture to improve its generalization capabilities.

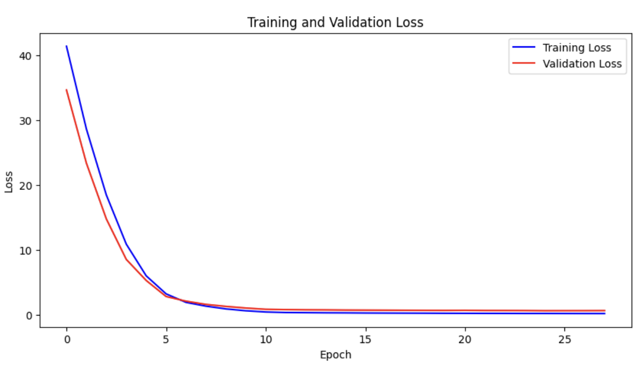


Fig. 4: Training and validation loss.

V. Discussion

A total of 24,637,826 parameters characterize the model deployed for the classification of breast cancer. Within this substantial number, there are 1,050,114 trainable parameters, which undergo modifications during the training process to optimize the model's fit to the dataset. The bulk of the parameters, amounting to 23,587,712, are non-trainable. These are typically associated with layers that have been pre-trained or are frozen from pre-existing models, indicating a complex integration of learned and fixed components within the model.

In the course of developing the "Pink Guardian" mobile app, the integration of multiple advanced neural network models has provided a robust framework for the classification of medical images, specifically mammograms. We compared results with different ImageNet models, including ResNet-50 [10], ResNet-101 [10], Xception [11], EfficientNet [12], and Inception [13]. Our findings indicate that while some models, like the Custom Inception V3 and Xception, performed exceptionally well, others struggled with higher validation losses, suggesting a potential overfitting to the training dataset. This variation underscores the importance of continuous model evaluation and adjustment, particularly in the medical field, where the cost of misdiagnosis can be exceptionally high.

One of our key challenges was the adaptation of the trained model to operate efficiently on mobile devices. The use of TensorFlow Lite played a pivotal role in this context, enabling the deployment of powerful AI models in a format that is both lightweight and optimized for mobile environments. This adaptation not only ensures that the app runs smoothly on a wide range of devices but also helps maintain the accuracy and speed of the image classification process, which are paramount for a good user experience and reliable diagnostics.

With a test accuracy of 78.7%, the app demonstrates robust predictive capabilities, though ongoing development and validation are crucial for enhancing reliability in real-world settings. The app's user interface, designed with user feedback and usability testing, ensures ease of use and fosters user engagement by simplifying mammogram uploads and analysis. Moreover, the integration of multiple models facilitates a comparative analysis framework, boosting confidence in the predictions and providing a robust verification system by leveraging the strengths of various models. This seamless integration of user-centric design with sophisticated technology exemplifies the impact of interactive systems in medical diagnostics. The discrepancy suggests that the model performs well on training data but struggles to generalize to unseen data. To address this, we recognize the need for better regularization techniques and a more diverse training dataset. Additionally, the lower performance of other models, with training accuracies less than 80%, suggests insufficient tuning or inherent limitations in those architectures for this specific task. We have evaluated the robustness of the models under different conditions, including mammogram noises and low contrast regions, using data augmentation techniques and preprocessing steps like histogram equalization and exposure adjustment to simulate various noise conditions and improve image quality.

To address privacy concerns, we currently use open-source datasets to train our models, and we do not store any images that users upload for analysis on our app. In future developments, we plan to implement additional security measures, such as user authentication through login systems and encryption/decryption of data. These enhancements will ensure that when the app is deployed within specific institutions, it adheres to stringent privacy standards and securely handles sensitive medical data. Future work will also add AI components, such as integrating doctor schedules and medication plans based on cancer stages and treatment needs, to further enhance the application's utility.

The "Pink Guardian" app illustrates the potential of advanced machine learning technologies to revolutionize medical diagnostics. By integrating top-tier neural network models into a user-friendly mobile app, we have developed a tool that not only enhances the accuracy of breast cancer detection but also makes cutting-edge health technology accessible to a broad audience. Our app serves as a model for future endeavors in the health tech space, highlighting the importance of adaptability, user-centered design, and continuous innovation in the development of medical diagnostic tools.

VI. Conclusion

The "Pink Guardian" app exemplifies a remarkable integration of advanced deep learning and mobile technology. The integration of proposed BC (breast cancer)-Inception-V3 into the "Pink Guardian" app represents a significant advancement in the field of medical diagnostics, specifically in the detection and analysis of breast cancer from mammographic images. Extensive experiments demonstrated our BC-Inception-V3 achieves state-of-the-art accuracy. The success in integrating the BC-Inception-V3 model with user-friendly mobile technology paves the way for broader applications of AI in healthcare. Future work includes implementing "Pink Guardian" on different platforms and supporting other medical imaging modalities, such as ultrasound and CT scans.

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