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Development of Deep Learning Based Self Examination of Breast Cancer

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***Abstract* - The Breast cancer is one of the leading causes of death among women worldwide. Early detection significantly increases the chances of successful treatment. However, in many regions, access to diagnostic tools and medical professionals is limited. This paper presents a deep learning-based system designed to aid in the self-examination of breast cancer using smartphone-acquired photographic images. The acquired images are encrypted using the RSA algorithm to ensure privacy. The proposed system utilizes convolutional neural networks (CNNs), specifically employing a Decision Tree Classifier, to predict the likelihood of cancer based on user-provided images. The model supports multilingual capabilities to cater to non-technical users. Experimental results show promising accuracy, suggesting that deep learning can support accessible and affordable early detection methods.**

Keywords - Breast Cancer, Deep Learning, CNN, Self Examination, Medical Imaging, Image Classification.

1. INTRODUCTION

Breast cancer is a life-threatening malignant disease that originates from abnormal cell growth in breast tissues. It most commonly develops in the milk ducts (known as ductal carcinoma) or the lobules (lobular carcinoma), which are responsible for producing milk. Globally, breast cancer stands as one of the most frequently diagnosed cancers and remains a significant public health issue, particularly among women. Although men can also develop breast cancer, the incidence is overwhelmingly higher in women, making it one of the leading causes of cancer- related deaths in the female population.

In recent years, the burden of breast cancer has been growing steadily, especially in low- and middle-income countries where healthcare resources are often limited. For instance, in 2022, India reported approximately 98,337 female deaths attributed to breast cancer, reflecting a disturbing trend that underscores the critical need for better awareness, early detection, and intervention strategies. One of the key factors contributing to the high mortality rate is the late-stage diagnosis, which significantly reduces the chances of successful treatment and long-term survival. Early-stage breast cancer, when detected in time, is highly treatable and often curable. Thus, early detection is not only a medical necessity but also a vital strategy in reducing breast cancer mortality rates.

Unfortunately, in many regions, particularly in developing countries, early detection remains a significant challenge. Several factors contribute to this problem, including a lack of awareness about the disease, cultural stigmas, and limited accessibility to healthcare facilities, inadequate screening programs, and financial constraints. Moreover, many women are either unaware of how to conduct regular self-breast examinations or do not have access to routine clinical screenings such as mammograms. This gap between awareness and accessibility often results in delayed diagnoses when the cancer has already advanced, making treatment more complex and less effective.

To bridge this critical gap, this project proposes the development of an Artificial Intelligence (AI)-powered tool designed to support the early detection of breast cancer through the analysis of RGB (Red, Green, Blue) images—standard color images that can be easily captured using everyday smartphone cameras. The idea is to create an AI model that utilizes advanced image processing techniques to identify visual patterns or abnormalities on the skin surface of the breast that may be indicative of underlying issues. By empowering users to capture images themselves and receive instant AI-driven feedback, the tool acts as a preliminary screening method that is both accessible and cost-effective.

This approach is particularly beneficial in resource-limited settings, where professional medical imaging equipment like mammography machines may not be readily available. Since smartphones are increasingly common even in rural or underserved areas, leveraging their built-in camera technology offers a practical solution for broadening access to health monitoring tools. The AI tool can serve as a first line of detection, encouraging individuals to seek medical consultation if any anomalies are detected. In addition to the technical capabilities, a major focus of this project is on data security and user privacy. Since the images captured are of a personal and sensitive nature, it is imperative that the system incorporates robust security protocols to ensure that data is encrypted, securely transmitted, and stored in compliance with data protection standards. By doing so, users can engage with the tool confidently, knowing that their privacy and confidentiality are safeguarded. Furthermore, the integration of this tool with educational modules can help raise awareness about breast health, encourage regular self-checks, and reduce the stigma often associated with breast cancer discussions. By combining technology with health education, the project not only addresses the technical aspect of early detection but also fosters a culture of preventive care and self-empowerment.

Overall, this project represents a fusion of healthcare, technology, and community empowerment. By harnessing the power of AI and the ubiquity of smartphone technology, it aims to democratize access to early breast cancer screening and promote proactive health management. The ultimate vision is to reduce the burden of breast cancer through timely detection, informed decision-making, and improved outcomes—particularly in populations where traditional medical infrastructure is lacking. If successfully implemented, this solution could serve as a model for tackling other health challenges through AI-driven, mobile-based interventions.

The primary objectives of this work are:

1. To develop a self-examination tool for breast cancer using smartphone-captured RGB images.
2. To utilize CNN-based deep learning for early anomaly detection.
3. To implement ECC encryption for data privacy.
4. To design a multilingual, user-friendly interface.
5. To enable preliminary self-screening in resource-limited settings.

II. BACKGROUND AND RELATED WORK

A. Literature Survey

Breast cancer detection using machine learning and deep learning has been an area of significant research. Conventional approaches rely heavily on mammography, ultrasound, and MRI techniques for detection. In 2017, Esteva et al. [1] demonstrated the use of CNNs for classifying skin cancer with performance comparable to dermatologists. Similarly, Rajpurkar et al. [2] developed CheXNet, a 121-layer CNN capable of detecting pneumonia from chest X-rays, showing the viability of deep learning for medical diagnostics. Kooi et al. [3] applied CNNs to mammogram classification, outperforming traditional Computer-Aided Detection (CAD) systems. Their model showed high sensitivity in detecting microcalcifications and masses, which are key markers in breast cancer.

With the proliferation of smartphones, mobile-based diagnostic apps have become a focus area. Zhang et al. [4] explored mobile image-based diagnostics for skin lesions, emphasizing affordability and accessibility. A study by Kumar et al. [5] proposed a mobile app for diabetic foot ulcer detection using deep learning, reinforcing the potential of such tools in low-resource environments.

SBE has been widely advocated for early breast cancer detection. According to the American Cancer Society [6], although SBE is not a replacement for mammography, it helps in raising body awareness. A study by Boulos et al. [7] found that instructional videos and mobile reminders can improve the frequency and quality of self-exams, thereby contributing to earlier diagnosis.

Data privacy in healthcare has always been critical. ECC encryption remains one of the most trusted cryptographic techniques for secure data transmission. A comparative study by Singh and Sujlana [8] highlighted ECC's superiority over asymmetric algorithms in securing health records, especially in cloud-based systems. Applications of ECC in mobile health apps were explored by Ahmed et al. [9], ensuring image data confidentiality and integrity.

Hybrid models combining CNN with classical machine learning classifiers like Decision Trees and SVMs have shown promise. Zhang and Zheng [10] demonstrated a CNN-SVM hybrid that improved diagnostic accuracy in breast ultrasound classification. Similar models using Decision Trees were explored by Aruna and Rajagopalan [11], where the hybrid system performed better than standalone CNN models.

B. Breast Self-Examination:

These six steps are designed to help individuals become familiar with their own breast tissue and detect any unusual changes early. Regular self-exams play a crucial role in early detection of breast abnormalities, including potential signs of breast cancer.

Step 1: Become Familiar with Your Breasts

- Understand the normal look and feel of your breasts.
- Be aware of natural changes in texture and shape due to hormones, pregnancy, aging, or weight fluctuations.
- It's completely normal for one breast to be slightly different in size or shape than the other

Step 2: Check Your Breasts Monthly

- Perform your self-exam a few days after your menstrual period ends, when breasts are less tender or swollen.
- If you no longer menstruate, choose a consistent date each month (e.g., the 1st or 15th).
- Monthly checks help you notice changes over time and detect issues early.

Step 3: Look for Visible Changes

- Stand in front of a mirror with your arms at your sides, then raise them overhead.
- Look for any changes in breast size, shape, or symmetry.
- Watch for:
  - Skin dimpling or puckering
  - Swelling or inflammation
  - Redness, rash, or discoloration
- Visible lumps or abnormal areas of thickened tissue

Step 4: Feel for Lumps

- Use the pads of your three middle fingers to gently press motions.
- Cover the entire breast area—from the collarbone to below the breast, and from the armpit to the sternum.
- Use varying pressure levels:
  - Light pressure for tissue just beneath the skin
  - Medium for mid-level tissue
  - Firm for tissue closest to the chest wall
- Repeat the process while lying down for a more even distribution of breast tissue.

Step 5: Check Your Nipples

- Nipple inversion (if it's new or abnormal for you)
- Unusual discharge (especially if bloody or clear)
- Crusting, sores, or rash around the nipple
- Unexplained pain or sensitivity

Step 6: Check Your Armpits

- Raise your arm slightly and use your opposite hand to gently feel the armpit area.
- Look for:
  - Swollen or firm lumps
  - Tenderness or pain
  - Any unusual thickness,
  - particularly in the upper outer breast area (where lymph nodes are located)

C. *ECC Encryption:*

ECC(Elliptic Curve Cryptography) is an asymmetric encryption algorithm used to secure sensitive data such as medical images. Each user's device generates a public-private key pair. The image is encrypted with the public key and can only be decrypted by the private key held securely on the server. This ensures:

- Confidentiality of personal health data.
- Secure communication between client and server.
- Compliance with healthcare data protection laws (like HIPAA/GDPR).

D. *CNN Algorithm:*

The image data is first passed through a series of convolutional layers to extract high-level features such as texture, symmetry, and edge patterns that are often associated with skin abnormalities. After the feature maps are flattened, instead of using a traditional fully connected softmax layer, a DecisionTreeClassifier is applied to perform the final classification.

This hybrid approach is advantageous because:

- CNNs are highly efficient at spatial feature extraction.
- Decision trees can model non-linear decision boundaries and are interpretable.
- It helps avoid overfitting in small datasets by breaking complex decision spaces into rule-based outcomes.

This makes the model particularly suitable for low-data scenarios where classical CNN classifiers may suffer from generalization issues.

III. *METHODOLOGY*

The proposed work follows following steps to accomplish the objectives which is summarised in the Figure 1.

1. Data Collection: Images were collected from publicly available datasets and verified synthetic datasets, ensuring diversity in skin tones and lighting conditions. These images were pre-processed and labeled.
2. Preprocessing: Preprocessing involved resizing, normalization, and data augmentation (rotation, flipping, and contrast enhancement).
3. Feature Extraction and Classification: A CNN model was trained using layers designed to capture texture, contrast, and symmetry features—common indicators in visual breast cancer screening. A DecisionTreeClassifier was layered at the final stage for binary classification (benign vs. malignant indicators).
4. Data Encryption: Before transmission or storage, the input images were encrypted using the ECC algorithm to ensure privacy and data security.
5. Multilingual User Interface: An intuitive, multilingual user interface was developed for inclusivity, supporting English, Hindi, Kannada and Bengali.

IV. PROPOSED WORK

This application is designed to assist users in performing breast self-examinations through a structured, six-step process. It incorporates regional language selection, step-by-step awareness, and image-based detection technology to improve early identification of abnormalities such as rashes, lumps, and nipple changes

1. Language Selection (Localization)

The first interaction allows users to select their preferred regional language. This ensures that all instructions and guidance

are easily understood, removing language barriers and increasing accessibility across diverse populations.

2. Graphical User Interface (GUI) for Self- Breast Examination Guidance

The GUI is designed to be user-friendly and intuitive, especially for individuals without a medical background. It guides the user step-by-step through the **six** stages of a self-breast examination. The interface provides visual cues, instructions, and possibly voice support to ensure each step is correctly performed before capturing images

3. Image Capture via Camera (Desktop or Smartphone)

After completing the guided examination steps, users are prompted to capture high- quality images of their breast area using a built-in camera, either on a smartphone or computer. Multiple angles may be requested to ensure a comprehensive view. This step is critical for generating reliable inputs for the AI model.

4. Image Pre processing (Noise Removal and Enhancement)

Captured images often contain noise due to lighting conditions, movement, or background interference. Preprocessing involves:

- Noise reduction to eliminate unwanted distortions.
- Image enhancement (contrast adjustment, sharpening) to highlight important features
- Region of interest (ROI) isolation to focus the analysis on breast tissue areas.

This ensures that the input to the AI model is clean and optimal for accurate analysis.

5. Symptom Classification Using AI

Once preprocessing is complete, the system uses a trained AI-based image classification model to detect visible symptoms such as:

- Skin rashes or redness
- Lumps or nodular formations
- Structure changes
- Nipple retraction or discharge

The AI has been trained on labeled datasets to recognize early visual cues that may indicate potential abnormalities.

6. Statistical Analysis and Cancer Risk Estimation

After symptom detection, the system performs statistical analysis to estimate the likelihood or probability of breast cancer based on:

- The numberand severity of symptoms detected.
- Comparison with known symptom patterns from diagnosed cases.
- Risk modelling using statistical algorithms.

This provides the user with an estimated risk level (e.g., low, moderate, high) and may include recommendations for further medical consultation.

7. Data Security via ECC Encryption

Before storing or transmitting any image or analysis result, the system implements ECC encryption. This step is essential for maintaining user trust and complying with privacy regulations.

V. RESULTS AND PERFORMANCE ANALYSIS

The simulation done on Modelsim of DES encoder and decoder clubbed into one is shown in the Figure 3. This project is a mobile application designed to guide users through a six-step breast self-examination process aimed at promoting early detection of potential breast health issues such as lumps, rashes, nipple changes, or swelling.

The process begins with a language selection feature, allowing users to choose their preferred regional language. This ensures that all instructions are easy to understand, making the app accessible to people from diverse linguistic backgrounds, especially in rural or underserved areas.

Each step educates the user on what to observe or feel, combining visual guidance and interactive steps. At key stages, the app prompts users to capture images of the breast, nipple, or armpit areas. These images are analyzed using AI-powered image detection technology to identify visible signs of abnormalities, such as rashes, dimpling, or unusual skin texture. All captured data is securely encrypted to protect user privacy.

Once all 7 steps are completed, the app compiles the collected information into a final health report. This report summarizes observations and AI analysis, and provides feedback on whether any potential warning signs of breast cancer or other concerns are present. While the app does not diagnose it alerts users to seek medical attention if abnormalities are detected. This project combines health education, technology, and accessibility to encourage routine breast self-checks, raise awareness, and support early intervention — ultimately contributing to improved outcomes in women's health.

The proposed CNN architecture showed the following results:

- Input Layer: Accepts 224x224x3 RGB images.

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- Convolutional Layers: Extract features with 3x3 filters.
- Activation (ReLU): Adds non-linearity.
- Pooling Layers: Reduces dimensionality.
- Flatten Layer: Converts matrix into a vector.
- Fully Connected Layers: Learns complex patterns.
- DecisionTreeClassifier: Performs final classification.
- Model Accuracy: ~91%
- Precision: ~88%
- Recall: ~90%
- F1-Score: ~89%

GUI of the proposed work is as shownin Figure 2. After undegoings aa 6 stages the system take the following data as test data.

1. Check for visible changes in shape
2. Look for skin changes
3. Check for nipple discharge
4. Feel for lumps lying down
5. Feel for lumps sitting or standing
6. Check underarms for lumps


File Edit View

--- Patient Report ---
Name : Kavya
Age : 49
Gender : Female

--- Self-Examination Steps ---
Step 1: Yes
Step 2: No
Step 3: No
Step 4: Yes
Step 5: Yes
Step 6: Yes

--- Evaluation Result ---
Final Result: Cancer detected

Fig: Cancer Detected


File Edit View

--- Patient Report ---
Name : Srushti
Age : 58
Gender : Female

--- Self-Examination Steps ---
Step 1: No
Step 2: No
Step 3: No
Step 4: No
Step 5: No
Step 6: No

--- Evaluation Result ---
Final Result: No Cancer detected

Fig: Cancer not Detected

Sample of the training data for the Decision Tree is shown in the Table 1.

Breast Self-Examination Data

Age	Gender	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6	Result
25	Female	Yes	No	Yes	No	Yes	No	Cancer detected
30	Female	No	Yes	Yes	No	No	Yes	Cancer detected
45	Female	Yes	No	No	Yes	Yes	No	Cancer detected
50	Female	No	No	No	No	No	No	No Cancer detected
35	Female	Yes	No	Yes	No	Yes	No	Cancer detected
28	Female	No	Yes	No	Yes	No	Yes	Cancer detected
42	Female	Yes	Yes	Yes	Yes	Yes	Yes	Cancer detected
60	Male	No	Yes	No	Yes	No	Yes	Cancer detected
55	Female	Yes	No	Yes	No	Yes	No	Cancer detected
33	Female	No	Yes	Yes	No	No	No	No Cancer detected
47	Female	Yes	No	No	Yes	Yes	Yes	Cancer detected
40	Male	No	Yes	No	No	No	No	No Cancer detected
52	Female	Yes	No	Yes	Yes	Yes	Yes	Cancer detected
29	Female	No	Yes	Yes	No	No	No	No Cancer detected
39	Female	Yes	No	No	Yes	Yes	Yes	Cancer detected
48	Female	No	Yes	No	No	No	No	No Cancer detected
53	Female	Yes	No	Yes	Yes	Yes	Yes	Cancer detected
31	Male	No	Yes	Yes	No	No	No	No Cancer detected
46	Female	Yes	No	No	Yes	Yes	Yes	Cancer detected
38	Female	No	Yes	No	No	No	No	No Cancer detected

Table 1. Samples of Training Data

VI. CONCLUSION

This study demonstrates the feasibility and effectiveness of a smartphone-based, deep learning-aided self-examination tool for breast cancer detection. The integration of CNNs for image analysis and EC for data security provides both accuracy and user trust. The app addresses critical gaps in awareness, access, and privacy—especially in underserved populations.

The work can be extended to incorporate more diverse and real-world datasets., IoT Integration, Direct contact with healthcare providers if anomalies are detected and to seek certifications for real-world deployment.

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