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AI-Driven Mobile Application for Breast Cancer Detection Using CNN for MRI Images in Tanzania

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Abstract: Breast cancer remains a pressing health concern in Tanzania, characterized by rising incidence rates and consequential mortality. Traditional diagnostic methodologies, encompassing mammography, ultrasound, and biopsy, exhibit limitations concerning accuracy, subjectivity, and accessibility. In recent years, the advent of machine learning techniques, notably Convolutional Neural Networks (CNNs), has offered a promising avenue for breast cancer detection, addressing the deficiencies inherent in conventional approaches. This paper centers on the development of an AI-driven mobile application (Mobile App) integrated with breast cancer prediction model tailored for breast cancer identification in Tanzania, leveraging the capabilities of CNN models. The app will allow radiologists to capture breast MRI images through a mobile phone camera and receive predictions categorizing the captured images as Malignant or Benign, aiding in prompt diagnosis and improve the accuracy of the diagnosis. The developed model uses 30 MRI breast images from Muhimbili National Hospital (MNH). Subsequently, data augmentation techniques were implemented, bolstering the dataset to 1419 images, inclusive of 700 benign and 719 malignant cases. The resultant CNN model developed demonstrated an exceptional accuracy of 96.69%, underscoring its potential effectiveness in discerning breast cancer and its prospects for facilitating early detection within the Tanzanian context.

Keywords: Breast Cancer; Artificial Intelligence(AI); Convolutional Neural Networks (CNNs); Mobile App; Data Augmentation

1. INTRODUCTION

Breast cancer poses a significant and escalating health challenge in Tanzania, manifesting a surge in both the occurrence and fatality rates. It stands as the second most prevalent ailment among Tanzanian women, recording an estimated 3037 new cases and 1303 fatalities in 2018. Alarming projections anticipate an over 120 percent escalation in both incidence and fatality rates by 2040. The World Health Organization (WHO) reports that breast cancer contributes to 23% of cancer-related cases and 14% of cancer-related deaths in women (Breast Cancer Initiative, 2017; Zhao et al., 2018). Conventional diagnostic techniques, encompassing mammography, ultrasound, and biopsy, suffer from limitations in accuracy, subjectivity, and accessibility (Lu et al., 2019). However, the advent of machine learning, notably Convolutional Neural Networks (CNNs), has emerged as a potent alternative for breast cancer detection, transcending the deficiencies of traditional methods (Yue et al., 2018).

Artificial Intelligence (AI) is a branch of computer science that focuses on systems and devices capable of analyzing human intelligence in general It includes technologies that enable computers to simulate intelligent behavior, learn from data, recognize patterns and based on decision information A variety of techniques including machine learning, natural language processing, computer vision, and neural networks are used to simulate cognitive processes. These systems can analyze big data, gain insights, and automatically adapt to new data, enabling them to solve complex problems, predict, and act across industries, and change services ranging from healthcare finance to transportation and beyond.

Convolutional Neural Networks (CNNs) stand as specialized deep learning models tailored for scrutinizing visual data, presenting an ideal framework for tasks involving image classification. Diverging from traditional methodologies, CNNs alleviate the necessity for manual feature crafting by autonomously assimilating intricate patterns and configurations from unprocessed image data. Their efficacy in breast cancer detection surpasses that of traditional feature-centric approaches, showcasing substantial potential. CNNs excel in discriminating between benign and malignant lesions, identifying nuanced characteristics such as microcalcifications or masses, and gauging risk levels with commendable precision (Alanazi et al., 2021).

The structure of a Convolutional Neural Network (CNN) consists of three key components: convolutional layers for extracting features, pooling layers for reducing spatial dimensionality while retaining crucial details, and fully connected layers for classification. By using filters, convolutional layers identify important patterns in input images, while pooling layers preserve vital information. Fully connected layers learn to associate these features with intended output, enabling predictions. CNNs are trained using labeled data and iterative weight adjustments to minimize prediction differences. This training, called backpropagation, refines network parameters using optimization algorithms. Integrating CNNs has revolutionized breast cancer detection by automating feature extraction, enhancing accuracy and

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efficiency. Utilizing CNN capabilities in Tanzania shows promise for more accurate and accessible breast cancer diagnostic tools, enabling early detection and improved treatment outcomes, potentially reducing mortality rates (Buda et al., 2018; Masud, 2020; Lecun et al., 2015).

This paper centers on the development of a mobile application that integrates a Convolutional Neural Network (CNN) breast cancer prediction model. The app's creation involves the utilization of Flask framework for API development and React Native for mobile application development. Specifically, Flask, a Python-based web framework, serves as the backend technology, enabling the construction of robust APIs. It facilitates the integration of the CNN breast cancer prediction model within the app's architecture, allowing seamless communication between the mobile interface and the predictive model. On the other hand, React Native is a JavaScript-based framework used for front-end mobile app development. It uses a single codebase for both iOS and Android platforms to facilitate the creation of responsive, user-friendly interfaces. It facilitates the creation of a responsive, user-friendly interface by leveraging a single codebase for both iOS and Android platforms. The app, thus, encompasses a harmonious synergy between Flask for backend API development and React Native for the mobile app's frontend, culminating in a comprehensive and efficient solution for breast cancer prediction accessible via mobile devices.

2. METHODOLOGY

The app development commences by employing Flask version 3.0.0 for API development, configuring endpoints, and integrating the pre-existing CNN breast cancer prediction model within the Flask framework. This process involves adapting the model to align with Flask's architecture and establishing seamless data exchange mechanisms between the mobile app and the predictive model. Concurrently, React Native version 0.72 is utilized for frontend mobile application development, focusing on crafting an intuitive user interface (UI) design ensuring consistent user experience (UX) across iOS and Android platforms. The methodology encompasses an iterative development approach, encompassing testing and refinement cycles to validate functionality, usability, and performance. Rigorous testing, evaluation, and optimization phases are undertaken to ensure the integrated mobile application's efficacy, accuracy, and reliability in facilitating breast cancer prediction via mobile devices.

3. MOBILE APP AND API INTEGRATION

3.1 Mobile App development

The mobile application (Mobile App) was developed using React Native version 0.72 within a development environment optimized on a powerful MacBook Pro using VS Code IDE version 1.84.

The development process utilized the React Native framework. Extensive testing procedures were carried out on an Android device operating on OS version 12 to guarantee smooth functionality across various Android platforms. For testing purposes, Expo Go was employed, known for its user-friendly interface and simplified setup, which streamlined the testing phase, hastened feature evaluations, and simplified quality assurance processes. This holistic approach aimed to create a top-tier, cross-platform mobile application with consistent and reliable performance across diverse Android devices.

Figure 1. A developed Mobile App user Interface

3.2 API Integration

The pre-trained model, saved as a BreastCancerPredictionModel.h5 file, underwent integration into an Application Programming Interface (API) leveraging the Flask framework version 3.0.0. This process was executed within the PyCharm development environment. Flask, a widely used Python web framework renowned for its simplicity and flexibility, served as the foundation for constructing the API. With Flask's capabilities, the pre-trained model was seamlessly incorporated to facilitate its accessibility and utilization for predictive tasks.

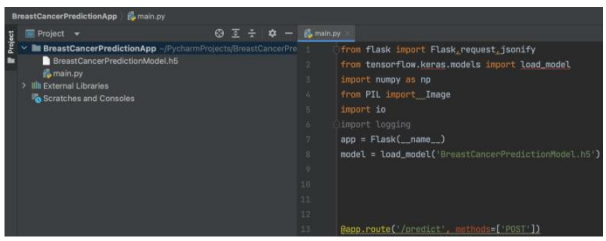

Figure 2. Code snippet and folder structures for the developed API

In the Figure 2 above, the developed model, referred to as "BreastCancerPredictionModel.h5," has been loaded and assigned as "model." The API utilizes this loaded model for conducting predictions.

The loaded CNN model, was developed using Keras in Python, underwent training and testing using 1419 MRI images sourced from MNH. It comprises several layers:

i. An initial 2D convolutional layer with 16 filters (3x3 size, stride 1), employing the ReLU activation function. This layer transforms inputs of shape (256, 256, 3) to an output tensor of shape (254, 254, 16), featuring 448 parameters.
ii. Subsequent max pooling layers that down sample data.
iii. Following the initial layer, additional 2D convolutional layers (with 32 and 16 filters respectively, also 3x3 size, stride 1) were incorporated, each employing ReLU activation. These layers alter the tensor shapes and contain 4,640 and 4,624 parameters respectively.
iv. Fully connected layers, including one with 256 neurons and ReLU activation (with L2 regularization), amounting to 3,686,656 trainable parameters.
v. Dropout layers to prevent overfitting during training.
vi. Finally, a fully connected layer with 1 neuron using the sigmoid activation function, featuring 257 parameters.

The integration process involved configuring routes and endpoints within Flask to establish a structured interface for interacting with the pre-trained model. PyCharm, an integrated development environment (IDE) known for its robust features and support for Python, provided a conducive environment for coding, testing, and deploying the Flask-based API. This combination of Flask and PyCharm offered a conducive ecosystem for handling the integration intricacies, enabling efficient development and management of the API.

The Flask framework, being Python-based, ensured compatibility and ease of integration with the pre-trained model, streamlining the API development process. Leveraging Flask's capabilities within PyCharm, developers were empowered to create a functional and accessible API, encapsulating the pre-trained model's functionalities for consumption by various applications and systems. This approach aimed to provide a scalable, efficient, and user-friendly interface to access the predictive capabilities encapsulated within the pre-trained model.

3.3 Testing a Model API using Insomnia

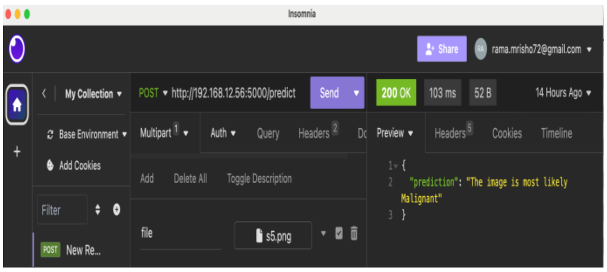

Figure 3 shows a result of an API end point after submit an MRI image file.

3.4 AI – Mobile App after integration

The integration process involved the development of a Flask API hosting a pre-trained breast cancer prediction model. Within the Flask framework, endpoints were set up to handle requests from a React Native Mobile App, acting as a bridge for data flow between the app and the predictive model. The React Native app was tailored to capture breast MRI images via the phone's camera and initiate HTTP requests to the Flask API for prediction processing. Upon receiving image data, the Flask API processed it through the pre-trained model and relayed the prediction results (benign or malignant) back to the React Native app. This integration aimed for a seamless connection between the frontend React Native Mobile App and the backend Flask API, ensuring accurate predictions for breast cancer using captured MRI images.

Following the integration, rigorous testing verified the functionalities, including image capturing, data transmission, model prediction accuracy, and user interface responsiveness. The React Native app's user-friendly design facilitated image capture and displayed prediction outcomes while maintaining a smooth user experience. With optimizations made to enhance performance and stability, the complete Mobile App for breast cancer predictions, combining the React Native frontend and Flask backend, was readied for deployment. This integration offered a reliable solution for users, enabling them to obtain accurate breast cancer predictions conveniently through their mobile devices, ensuring accessibility and efficacy in breast cancer diagnosis.

4. MOBILE APP PREDICTIONS

Once the application is initiated, radiologists can capture an MRI image by tapping the "Capture MRI Image" button. This action triggers the mobile camera, enabling users to take an MRI image. Refer to the figure below for visual guidance.

Figure 4 . A user interface for capturing an image

Next, the app will display the captured image, offering users(radiologists) the option to submit it for predictions. See Figure 5 below for a visual representation.

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Figure 5 . Shows the captured MRI image through the camera

Then, in order for an App to predict , radiologist must click the button Submit Image, then the results will be displayed on the screen as either the captured image is Malignant or Benign. See Figure 6 below.

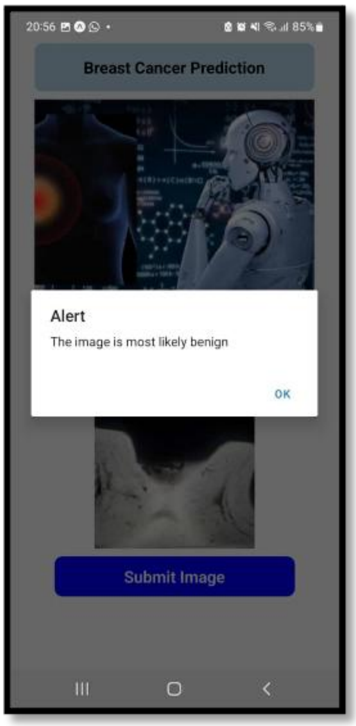

Figure 6. Shows a result of the captured image

Figure 6 depicted above displays the prediction output of the captured image as "Benign," as determined by the model's predictions.

Additionally, the model is also capable of predicting whether the captured image is Malignant. Refer to the figure 7 below for more details.

Figure 7. Another captured image for prediction

Also again, upon clicking the "**Submit Image**" button, the model will process the image and generate the output results. This process is demonstrated below.

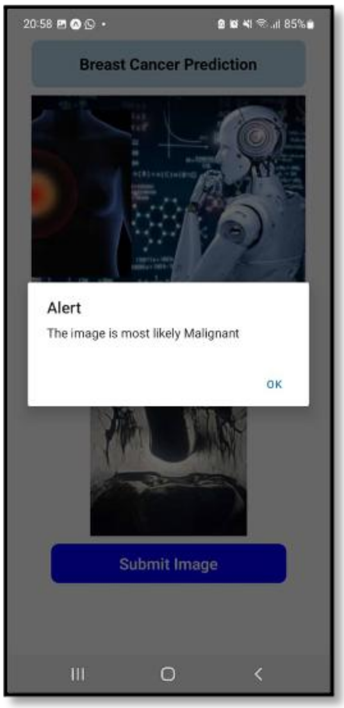

Figure 8. Results of a captured image

The figure depicted above displays the prediction output of the captured image as "Malignant" as determined by the model's predictions.

5. CONCLUSION AND FUTURE WORKS

The study focuses on the integration of a Flask API model with a mobile app, establishing an AI-driven platform for predicting MRI images in breast cancer detection. Using Python, the research aimed to craft a CNN breast cancer prediction model capable of categorizing MRI images as either benign or malignant. Employing 30 MRI images sourced from Muhimbili National Hospital and expanding the dataset to 1419 images through data augmentation, the developed CNN model comprised multiple layers and exhibited remarkable evaluation metrics, affirming its efficacy in accurately discerning breast cancer cases. This underscores the potential of CNNs and data augmentation in bolstering breast cancer detection, underscoring the necessity for expanded research with more comprehensive and diverse datasets.

The application of deep learning, particularly CNNs, holds significant promise in enhancing breast cancer detection in Tanzania as it will helps radiologist to improve the accuracy of diagnosis, offering a potential solution to the limitations of traditional detection methods. The paper explores the application of deep learning techniques, delves into the effectiveness of data augmentation, addresses the constraints of conventional methodologies, and proposes a neural network model aimed at augmenting breast cancer detection rates in Tanzania. Future research avenues include broadening the dataset to encompass images from diverse demographics, thereby enhancing the model's adaptability across various patient cohorts. Moreover, integrating the model into clinical settings and assessing its real-world advantages and constraints would provide invaluable insights. This study contributes to the breast cancer detection domain by presenting an efficient CNN-based approach and sets the stage for further advancements in precision and dependability.

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