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A Mobile Application for Early Skin Cancer Screening and Skin Health Awareness: A Case Study of Muara Angke

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ABSTRACT

This study aimed to develop a mobile application for early skin cancer screening while simultaneously enhancing public awareness of skin health, with a case study conducted in the coastal area of Muara Angke, North Jakarta. The research was motivated by high levels of ultraviolet radiation exposure and limited access to healthcare services, which often lead to delayed skin cancer detection. An empirical quantitative approach was employed by utilizing a Convolutional Neural Network (CNN) based on the ResNet50 architecture, deployed through a cloud based infrastructure and integrated into a Flutter based mobile application. The system was designed using an edge cloud computing approach to address the computational limitations of mobile devices. The results indicated that the application effectively performed preliminary skin lesion screening, provided classification outcomes with confidence scores, and delivered accessible skin health education content. Although the application was not intended to serve as a medical diagnostic tool, it demonstrated significant potential to support early detection efforts and improve community level awareness of skin health. This study contributes to the advancement of mobile health (m-health) by emphasizing the practical implementation of AI based applications tailored to community needs.

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1. Introduction

Skin cancer is still a prevalent and fast growing type of cancer across the globe, mainly resulting from too much exposure to ultraviolet (UV) rays and not enough understanding among people about keeping their skin healthy [1]. The World Health Organization (WHO) states that finding skin cancer early greatly increases the chances of survival, but many developing nations, like Indonesia, still have trouble providing enough skin check-ups. People in coastal areas like Muara Angke often encounter more difficulties because they don't have good healthcare facilities and many can't use digital devices well, which means they are diagnosed and treated later.

The growth of mobile phones and technology has created fresh possibilities for taking care of health before problems start, specifically using health apps on phones (m-health). These apps can provide medical help that is easy to get to and doesn't cost a lot [2]. Using these kinds of apps has become more and more common to help spot diseases early and keep an eye on your own health [3]. In the field of skin care, tools that use artificial intelligence (AI) have proven to be very good at helping find different kinds of skin problems by looking at images [4].

Convolutional Neural Networks (CNNs) have greatly improved the correctness of categorizing medical images because they are good at pulling out key visual details [5]. Architectures built on CNNs, like ResNet50, are well-known for their powerful skill in both pulling out key details and using knowledge gained from other areas, making them a good fit for sorting medical images [6]. Getting data ready and making it better are essential for making the model work well in different situations and reducing the chance of it focusing too much on the training data [7]. Newer research has also looked at up to date structures like EfficientNet and ResNet, indicating that ResNet provides a more consistent way to pull out key details even when the images change, which is helpful for using them on cloud services and mobile devices [8].

However, putting deep learning models straight onto mobile devices is still hard because they need a lot of computing power and storage space [9]. Therefore, using both cloud computing and simple CNN structures has become a good way to help AI powered diagnoses on mobile devices [10]. Combining CNN-based models with mobile tools like Flutter lets developers create diagnostic apps that are quick to respond and work on different types of devices [11]. Also, methods for making AI clear (XAI) have become a key step in helping people trust and understand AI systems in medicine [12]. Human AI systems working together can now find skin cancer in real time using smartphone apps, connecting high level accuracy with easy access for the public [13].

This research seeks to create a mobile app designed for preliminary skin cancer detection and promoting understanding of healthy skin, focusing on the inhabitants of the Muara Angke area. The application combines a CNN model, which has been refined from the ResNet50 framework, alongside a Flutter-built mobile user interface and a Google Cloud infrastructure. Aside from the automated detection feature, the application offers instructional sections to increase users' knowledge regarding skin health practices.

The goals of this investigation are divided into three parts:

1. To create and enhance a CNN based system that precisely categorizes different types of skin lesions.
2. The plan is to incorporate the finalized model into a mobile application linked to the cloud, utilizing Flutter.
3. The aim is to determine how user friendly the developed application is, how accurate it is, and how well it performs in everyday scenarios.

The innovative aspect of this study is the combination of sophisticated learning techniques, mobile devices, and instruction on public health all within a single, useful platform. It makes a contribution in two ways: first, technologically, through the use of a CNN system hosted in the cloud; and second, socially, by encouraging prompt identification and understanding of digital health issues in populations that are often overlooked.

2. Research Method

2.1. Research Design

This investigation employs an AI based practical research framework that utilizes an experimental and straightforward quantitative method, centering on the creation and assessment of an advanced system designed for the timely identification of skin cancer.

The research makes use of an empirical data centric method, where AI algorithms are developed, refined, and confirmed using authentic dermatological visuals to replicate actual diagnostic scenarios.

The procedural approach conforms to the standard layout of AI empirical investigation, encompassing data collection, algorithm development, performance assessment, and system implementation. The utilitarian characteristic of this study is embodied in the conversion of abstract AI principles into an operational, tangible application that bolsters communal health examinations.

As highlighted by Lee and Park [14], AI empirical studies in the realm of medical imaging place importance on repetitive experimentation, constantly adjusting algorithmic parameters and evaluating algorithmic adaptability across varying conditions. Similarly, Elgendi et al. [15] underscore that the efficiency of AI healthcare studies hinges on quantifiable, reproducible experiments that involve both algorithmic and user-centered assessment criteria.

Consequently, this research strategy incorporates empirical AI algorithmic validation with applied mobile implementation, connecting the divide between AI advancement and ease of access to communal health resources. The integration of empirical exactness and real world implementation guarantees both technological and societal influence.

2.2. Research Time and Place

This research was conducted from November 2025 to December 2025. The case study took place in Muara Angke, North Jakarta, Indonesia, a coastal community characterized by high outdoor activity exposure. The location was selected to support the application's evaluation in a real world community setting and to assess its potential role in improving skin health awareness among the general public.

2.3. Application Workflow

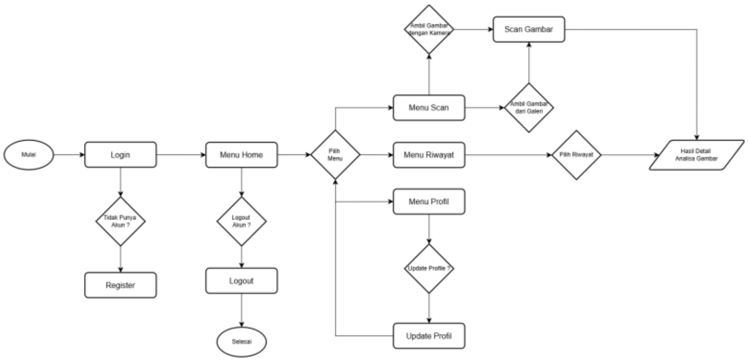

Figure.1 Application Flowchart Workflow

The proposed mobile application employs a user centered approach that prioritizes simplicity, usability, and clear interaction throughout the diagnostic process. The application workflow, illustrated in Figure 1, shows the sequence of steps users follow, beginning from authentication to receiving AI generated diagnostic results.

After signing in or creating an account, users access the main interface consisting of three key menus: the Scan Menu, the Result Menu, and the Profile Menu. In the Scan Menu, users upload or capture a skin image, which is then analyzed by a CNN model on a remote server to determine whether the detected lesion is benign or potentially malignant. Through the Result Menu, users can review previous scan outcomes along with timestamps and confidence scores. Meanwhile, the Profile Menu allows users to update personal information for a more personalized experience.

Users can also sign out to end their session. This streamlined workflow supports intuitive navigation, reduces cognitive load, and enhances user trust in AI based diagnostic outputs. As noted by Mehta et al. [16], user centered design strengthens clarity and trust, while Kim et al. [17] emphasize that improved usability contributes significantly to the acceptance and reliability of AI healthcare systems.

2.4. System Architecture

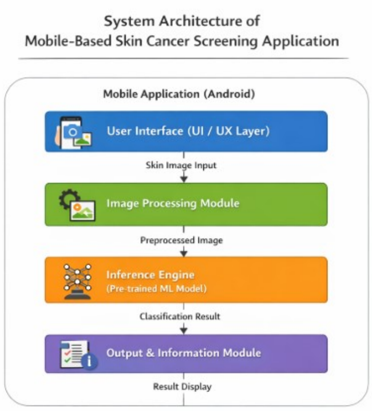

Figure.2 System Architecture

The proposed system employs a distributed artificial intelligence architecture that integrates mobile-edge processing with cloud-based inference to enable real time skin cancer detection. As illustrated in *Figure 2*, the system comprises four main components: a user interface (UI/UX layer) for image input and user interaction, an image processing module for normalization and resizing, an inference engine utilizing a fine-tuned *ResNet50* CNN model deployed via *Google Cloud Run*, and an output module that visualizes classification results, confidence levels, and health related information. This multi layered architecture ensures efficient image flow and responsive communication between the mobile application and the cloud server [18].

The overall framework adopts the edge cloud collaboration principle, which enhances computational efficiency, scalability, and system flexibility [19]. This approach is widely applied in healthcare oriented AI systems, allowing the mobile client to handle lightweight operations while delegating heavy computation to the cloud infrastructure [20]. Consequently, the system achieves low latency, high accuracy, and sustainable performance, aligning with current standards for mobile based medical diagnostic applications.

2.5. UML-Based Application Design

2.5.1. Use Case Diagram

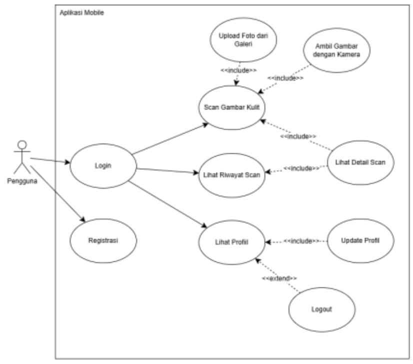

Figure.3 Use Case Diagram Application

The application was modeled using the Unified Modeling Language (UML) to represent user interaction and system functionality. As shown in Figure 3, the Use Case Diagram illustrates the main system functions, including Login, Registration, Scan Image, View Scan Result, Update Profile, and Logout. Each use case defines a functional requirement that supports the application's user centered design. The UML approach provides a clear visualization of user system interactions, ensuring design consistency during implementation. This modeling method aligns with current practices in mobile health and AI enabled applications, as discussed by Martins et al. [21] and Nguyen and Patel [22], who emphasize UML's role in improving maintainability and traceability in intelligent software systems.

2.5.2. Activity Diagram

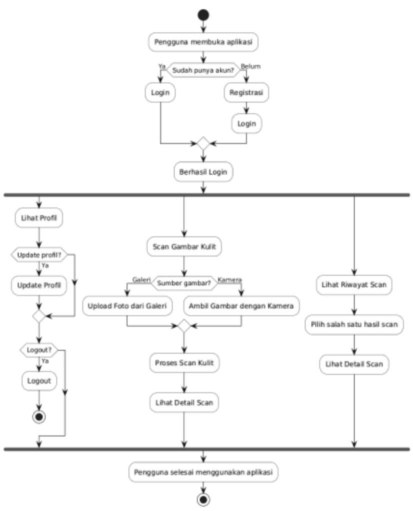

Figure.4 Activity Diagram

The Activity Diagram describes the sequential flow of processes and interactions within the mobile-based skin cancer screening application. As shown in Figure 4, the diagram illustrates user activities such as login, image upload, data validation, AI based image analysis, and result display. Each process flows through a series of decision points that represent conditional logic handled by the system. This modeling approach enables developers to visualize how user actions trigger background AI operations, ensuring smooth synchronization between the mobile interface and the cloud based inference module. The use of UML activity diagrams is widely applied in AI enabled healthcare systems for workflow optimization and process clarity, as emphasized by Kumar et al. [23] and Lopez and Fernandes [24].

2.5.3. Class Diagram

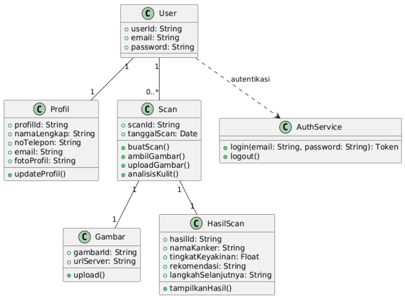

Figure.5 Class Diagram

The Class Diagram presented in Figure 5 illustrates the object oriented structure of the mobile based skin cancer screening system, defining the relationships between classes and their attributes, methods, and interactions. The system is composed of six primary classes: User, Profil, Scan, Gambar, HasilScan, and AuthService. The User class is responsible for user authentication and session management, while Profil stores personal information such as name, contact number, and photo. The Scan class acts as the controller for the scanning process, invoking methods like ambilGambar(), uploadGambar(), and analisisKulit() that connect with the Gambar class for image management and the HasilScan class for diagnostic result handling.

Meanwhile, the AuthService class provides secure authentication functions including login() and logout(), ensuring that system access complies with privacy and security protocols. This class based architecture enhances modularity, code reusability, and system scalability, which are crucial for intelligent mobile health applications. Such design practices follow the principles of modular AI driven architecture discussed by Fernandez et al. [25] and Rahman and Choudhury [26], who emphasize the importance of UML class modeling for maintaining system integrity and simplifying integration between AI inference modules and mobile user interfaces.

3. Result and Discussion

3.1. Mobile Application User Interface Design Implementation

This section describes the mobile application user interface (UI) design in a structured and analytical manner. The discussion focuses on interface design principles, user interaction flow, and the main application screens. The UI is designed to support usability, efficiency, and clarity, ensuring that users can interact with the application effectively and intuitively.

3.1.1. User Authentication Screens

a. Login Screen

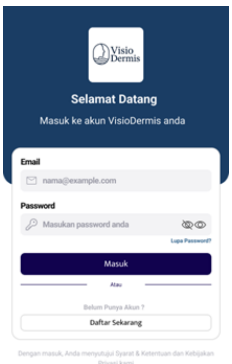

Figure.6 Login Screen

The login screen, as illustrated in Figure 6, serves as the initial access point for authenticated users. This screen contains input fields for user credentials, such as email or username and password, along with a clearly visible login button.

Supporting interface elements, including error notifications, loading indicators, and password visibility options, provide immediate system feedback. A navigation link directing users to the registration screen is also available, ensuring smooth onboarding for first-time users. The design emphasizes simplicity, security, and accessibility.

b. Register Screen

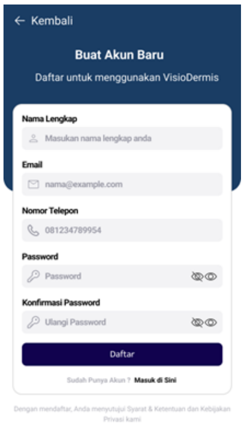

Figure.7 Register Screen

The registration screen shown in Figure 7 enables new users to create an account. It includes structured form fields for essential user information and applies validation mechanisms to ensure data accuracy before submission.

Clear instructional text and confirmation feedback guide users throughout the registration process. Upon successful registration, users are redirected to the login screen or automatically signed in, depending on system configuration. The layout minimizes user effort while maintaining clarity and data integrity.

3.1.2. Main Application Screens

a. Home Screen

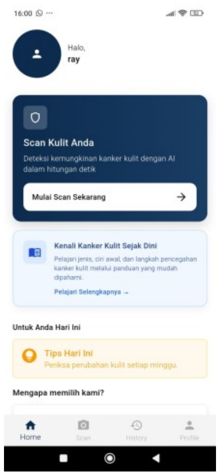

Figure.8 Home Screen

The home screen, shown in Figure 8, functions as the main entry point of the application, providing a personalized greeting and direct access to the core feature. The primary "Scan Your Skin" card is prominently displayed, guiding users to start an AI based skin analysis quickly and intuitively.

Additional sections offer brief educational content and daily skin health tips to support user awareness. A bottom navigation bar enables easy access to the main features: Home, Scan, History, and Profile, ensuring a simple and efficient user experience.

b. Scan Screen

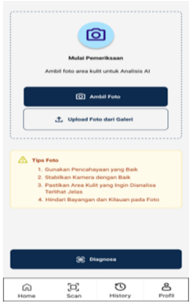

Figure.9 Login Screen

The scan screen depicted in Figure 9 allows users to capture a new image using the device camera or select an existing image from the gallery. A preview area is provided to confirm the selected image before processing.

Action buttons are positioned ergonomically to support comfortable interaction, while visual feedback confirms successful image selection. This design ensures efficiency and reduces the likelihood of user error.

c. *Result Detail Screen*

Figure.10 Result Detail Screen

The result screen, as shown in Figure 10, presents the output generated from the inference process. The analysis results are displayed in a structured and readable format, using textual explanations and visual indicators where appropriate.

Navigation options allow users to return to the home screen or initiate a new analysis. The layout prioritizes clarity and interpretability, enabling users to quickly understand the system output.

d. *History Screen*

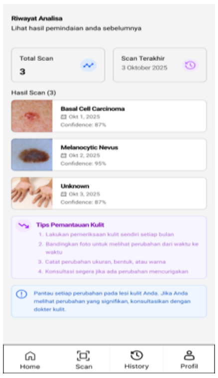

Figure.11 Result Detail Screen

As presented in Figure 11, the history screen provides a chronological record of user activities, such as previously uploaded photos and analysis results. Each history item may include a timestamp, thumbnail image, and a brief summary of the output.

The interface enables users to review past results efficiently and may support actions such as viewing detailed results. This screen enhances usability by supporting traceability, transparency, and repeated analysis.

e. Profile Screen

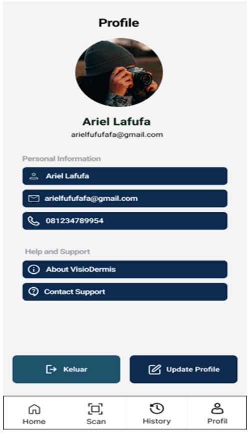

Figure.12 Profile Screen

The profile screen illustrated in Figure 12 allows users to view and manage their personal account information. This screen typically displays user details such as name, email address, and profile image.

Additional features may include options to edit profile information, change passwords, and log out of the application. The design emphasizes data clarity and secure access while maintaining a clean and organized layout.

3.2. Limitation

Despite its potential as an early screening tool, the proposed mobile application has several limitations. First, the application is intended solely for preliminary screening and does not provide a medical diagnosis. Therefore, the screening results must be interpreted as supportive information and require further confirmation by healthcare professionals.

Second, the system performance is influenced by the quality of the input images, including lighting conditions, camera resolution, and image capture distance. Variations in user generated images may affect the reliability of the screening results.

Third, the use of publicly available datasets may limit the representation of local skin characteristics, potentially affecting the generalizability of the results when applied to broader community settings. In addition, the application relies on an internet connection for server based inference, which may impact usability in areas with unstable network access.

3.3. Practical Implication

Despite these limitations, the application offers meaningful practical benefits for public use. It enables independent early screening of skin cancer, promoting greater awareness of skin health among the general population. By providing accessible and easy to use screening functionality, the application can help reduce barriers to early detection and encourage timely medical consultation.

Furthermore, the application serves as a health education tool by delivering clear and non technical information alongside screening results. This approach supports preventive health behavior and demonstrates the potential of mobile health applications in community based skin health awareness initiatives.

4. Conclusion

This study presented a mobile application designed for early skin cancer screening and skin health awareness, implemented as a client–server system using a pre-trained inference model. The application enables users to upload skin images via a mobile interface and receive screening results directly on their devices, providing an accessible and user-friendly approach for preliminary skin health assessment.

The results demonstrate that the application functions effectively as an early screening and awareness tool, supporting independent use by the general public without requiring immediate involvement of medical professionals. The system architecture and application workflow successfully facilitate image submission, server based inference, and result visualization, highlighting the feasibility of mobile health solutions for community based preventive care.

This research contributes to the field of mobile health (m-health) by emphasizing application-level implementation rather than model development, and by demonstrating the practical use of mobile technology to improve skin health awareness in a community setting. Although the application is not intended to replace clinical diagnosis, it can serve as a supportive tool that encourages early attention to skin conditions and timely consultation with healthcare providers.

Future work may focus on expanding application features, integrating localized datasets, improving network efficiency, and conducting broader user based evaluations to further enhance the effectiveness and adoption of the application in real world settings.

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