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Designing UI/UX *Smart Mobile Healthcare* with The Integration of *Convolutional Neural Network* Model

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ABSTRACT

The rising number of skin cancer cases in recent decades and the limitations of early detection methods, such as costly and less accessible biopsies, highlight the need for an affordable, accessible solution. This study aims to design a smart mobile healthcare application integrating a *Convolutional Neural Network* (CNN) to detect skin cancer early through digital imaging. Using a dataset of 5,100 images categorized into *melanoma*, *non-melanoma*, and *normal skin*, the CNN model based on *VGG16* architecture was trained and evaluated using *accuracy*, *precision*, *recall*, and *F1-score*. The model achieved 93.14% *testing accuracy*, 86.93% average *training accuracy*, and the F1-score 0.89. The UI/UX design follows the design thinking approach, emphasizing a user-friendly, fast, and interactive interface. Core features include user login, skin image scanning, classification results, and AI-based consultation. The application is intended to serve as an effective, accessible tool for early skin cancer detection, supporting timely clinical diagnosis for all users.

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1. INTRODUCTION

Skin cancer is one of the most commonly diagnosed cancers worldwide, especially in white populations, incidence and mortality have continued to increase substantially over the past decade [20]. Statistical data from the *Global Cancer Observatory* (Globocan) 2020 reported from the *World Health Organization* that the total deaths due to cancer in the world reached 9.9 million people. This figure shows that cancer is one of the leading causes of death in the world. Globocan 2020 also noted that there have been 18,000 cases of skin cancer in Indonesia with a death rate of around 3,000 cases.

There are various factors that cause skin cancer, including skin type, genetic factors, *Human papillomavirus* (HPV) infection, organ transplantation, unhealthy lifestyle and the main driving factor in the pathogenesis of skin cancer is increased ultraviolet radiation [17]. It is widely recognized that exposure to *Ultraviolet radiation* (UVR) is carcinogenic and is considered a major cause of skin cancer due to its ability to act as a mutagen, triggering and initiating tumor growth without induction by other agents [19][30]. The *World Health Organization* and the *International Labour Organization* said that the increase in skin cancer cases in the world is directly proportional to the increase in geothermal heat and the frequency of sunlight intensity [18].

Based on these causal factors, hazards, and facts, early detection is one of the best ways to overcome and get treatment as early as possible. However, various journals report that according to dermatologists there are complex challenges in distinguishing between burns and moles. The visual similarity of the two can lead to misidentification, especially in certain cases with atypical early symptoms. This further complicates the process of early detection of skin cancer. Dermatologists can diagnose skin cancer with various tests, one of which is through the process of a puncture *biopsy*. However, there are disadvantages of *biopsy*, including that it can cause bleeding, infection, skin traction that causes the wound to heal for a long time, can cause allergic reactions, can spread malignant tumor cells, and is quite expensive. Because the process requires advanced technology, it will be difficult to do in areas that do not have sanitary facilities [1].

Nowadays the *Deep Learning* method has become one of the hot topics in the world of *Machine Learning* due to its significant capabilities in modeling various complex data such as images and sounds. The *Deep Learning* method

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that has the most significant and accurate results is the *Convolutional Neural Network* (CNN) which can perform image recognition with an accuracy that rival humans on a given dataset. This is because CNN is trying to imitate the image recognition system in human visuals [17].

This problem has led to the encouragement and interest to create a *smart mobile healthcare application* to classify, detect skin cancer images early, and facilitate clinically accessible diagnostics that can be accessed by all groups of people to improve early detection of skin cancer and get better treatment.

UI/UX design makes it easy for developers to create a product or application. In UI/UX development, the methods used include *design thinking*, a thought pattern from the designer's perspective in solving problems through a human-oriented approach [2]. The main goal of *user experience design* (UXD) in the industry is to increase customer satisfaction and loyalty through utility, ease of use, and convenience when interacting with certain products/services or services [3].

2. RESEARCH METHOD

This study uses a *quantitative method*, this method produces numerical data, such as *accuracy*, *precision*, *recall*, and *F1-score*, through a model with different datasets that can be compared to evaluate the success of early detection of skin cancer [17]. In addition, this study uses a *Design Thinking* approach in the process of designing UI/UX to ensure that the application design is in accordance with the needs of users.

2.1. The Dataset

The data used was in the form of a skin cancer image dataset. The dataset was obtained by downloading the dataset from the *Kaggle* page and obtained from the *International Skin Imaging Collaboration* (ISIC) page. The data was divided into 3 classes, namely *normal skin*, *melanoma* and *non-melanoma*. The skin cancer image format is .jpeg taken from various types of cameras with a total of 1700 *normal skin* images, 1700 *melanoma* images and 1700 *non-melanoma* images.

2.2. Preprocessing Dataset

For the initial stage of this study, *preprocessing* is divided into 3 steps, namely *hyperparameter initialization*, *labeling*, and *normalization*. *Labeling* is the process of labeling datasets based on the type of skin lesions, namely *melanoma* and *non-melanoma*. At this stage, *initialization* and *hyperparameter* settings are carried out as shown in table 4.1.

Table 1. Initialization of *Hyperparameters Preprocessing*

Hyperparameter	**Value**
Epoch	100
Batch size	32
Learning rate	1e-4
Input shape	224x224x3

Then datasets with various sizes were normalized, namely resized with a uniform size of 224×224×3 pixels for the input of the architectural model used. After that, the image data is converted into an array and again normalized from the range of 0-225 to the range of 0-1. After *preprocessing*, the data will be divided into *training dataset* and *testing dataset* with a differential of 80% and 20%, respectively, with the number of images in the *training datase*t as many as 4080 and the *testing dataset* as many as 1020 images. Data splitting is done by coding algorithms in python.

Table 2. *Splitting* dataset result

Classification Class	***Training* (80%)**	***Testing* (20%)**
Normal skin	1360	340
Melanoma	1360	340
Non-melanoma	1360	340

2.3. Augmentation Dataset

Then the next process is *augmentation*, which is the process of processing, modifying image data in such a way as to increase the variety of datasets in the *training data*. *Augmentation* helps prevent *overfitting*, which is when the model only remembers small details in the *training data* and cannot generalize new data. So, this process can help the model be more resistant to data variations when tested.

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Table 3. Dataset *Augmentation* Parameters in *Python* Programming

Parameter	Value
rotation_range	25
width_shift_range	0.1
height_shift_range	0.1
shear_range	0.2
zoom_range	0.2
vertical_flip	*True*
horizontal_flip	*True*
fill_mode	*nearest*

2.4. Model Training

After the data has gone through the *preprocessing* stage, then it enters the CNN model training stage which consists of the *feature extraction* and *classification process*. This study uses a *Convolutional Neural Network* (CNN) algorithm with the *VGG16* architecture.

CNN is a type of *deep learning* model designed to mimic the functions of the *visual cortex*, and is primarily used in image recognition. One of the most important contributions of CNN's new era was its ability to solve the problem of digit classification. CNN can easily detect simple edges, lines, textures, and patterns in images. By grouping convolutional operations in *convolutional layers*, various specific features can be studied in a single layer [28].

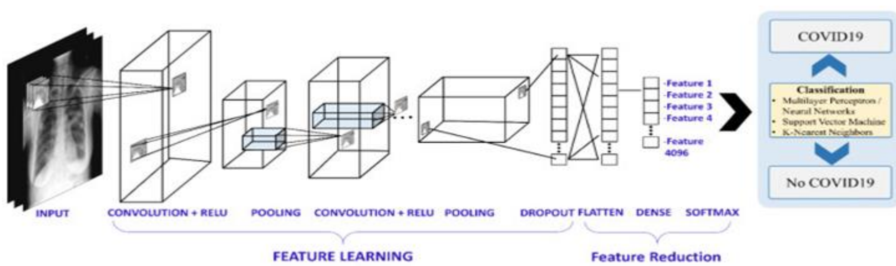

Figure 1. Architecture of *Convolutional Neural Network*

2.5. Model Evaluation

Researchers underwent an *epoch* of 100 periods to *train* and evaluate skin cancer dataset models. After that, the model evaluation was carried out together with a testing set to measure the model's performance in classifying skin cancer. The model evaluation will be carried out using the *Confusion Matrix* which is used to calculate accuracy, *precision* to show the accuracy of the model in predicting cancer, *recall* to measure how many cancer cases the model detects, and *F1-score* is an average score to assess the balance between *precision* and *recall* and give an idea of how well the model detects cancer.

2.6. Designing UI/UX

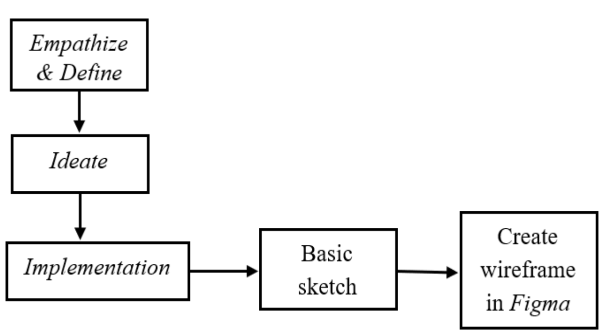

Figure 2. UI/UX Design

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3. RESULTS AND DISCUSSION

3.1. Epoch Result

Researchers underwent an *epoch* of 100 periods to *train* and evaluate skin cancer dataset models. So that an analysis of 4 evaluation curves was obtained, including *accuracy*, *loss*, *validation accuracy*, and *validation loss*.

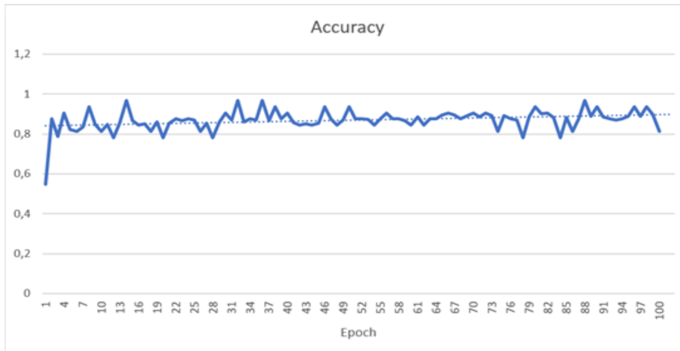

Figure 3. *Accuracy* Curve

Figure 3 shows the *accuracy curve* during the 100 epochs period process. As can be seen in Figure 4.7, there was a drastic improvement in the initial *epoch*, then the model obtained more stable *accuracy* results after several periods of epoch. Even if there are small fluctuations that are not significant. The evaluation of the *accuracy curve* showed that the model successfully studied and remembered the skin cancer imagery dataset well. *Accuracy* stability shows that the training model process takes place consistently without major interruptions such as too high learning rates or unbalanced data.

Figure 4. Loss Curve

Figure 4 shows the *Loss curve* during the training process in the training dataset. A very significant decline in the initial *epoch*, then the model managed to stabilize in the later *epoch*, indicating that the model could quickly learn and understand the representation of the data. The stability of the Loss value in the next *epoch* indicates that the model is not *underfitting* and is able to achieve an integrated learning process.

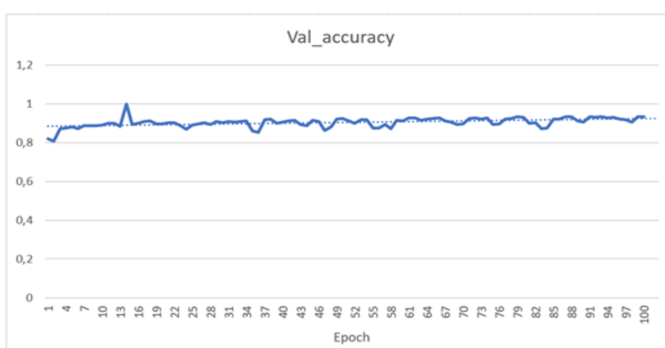

Figure 5. Validation Accuracy Curve

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Validation Accuracy is an evaluation parameter to analyze the success rate of the model in detecting and classifying validation data that was not properly trained beforehand. The curve shows a steady trend of increasing validation accuracy and has managed to reach an accuracy value with a fairly high range of 0.90 to 0.95, even in an epoch period, the accuracy reaches 1.00. The high *validation accuracy*, indicating that the model has an accurate ability to classify skin cancer datasets.

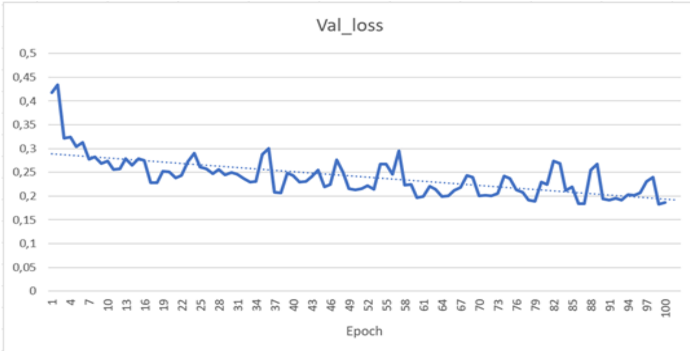

Figure 6. Validation Loss Curve

Validation loss was used to analyze how well the model performed in narrating skin cancer datasets against previously untrained data. The validation loss value in figure 4.10 shows a fairly stable trend with a consistent decline. However, there are slight fluctuations that are still within reasonable limits due to the complexity of the dataset. The decrease in validation loss indicates that the model is not significantly overfitting.

3.2. *Confusion Matrix*

Confusion Matrix is a type of model evaluation that functions to display the performance of the model by comparing the actual data and prediction data on the skin cancer dataset against 3 classifications of skin cancer classes, namely normal skin, melanoma, and non-melanoma. Figure 7 is a confusion matrix image of the VGG16 architecture which represents 3 classes of skin cancer model classifications. This confusion matrix provides information about the number of correct and false predictions from each class trained. From the results obtained in figure 4.11 it shows that the Normal skin class model managed to correctly classify 3 out of 4 images, while 1 other image was mistakenly classified as Melanoma. For the Melanoma and Non-Melanoma classes, overall the model managed to correctly classify the 2 images.

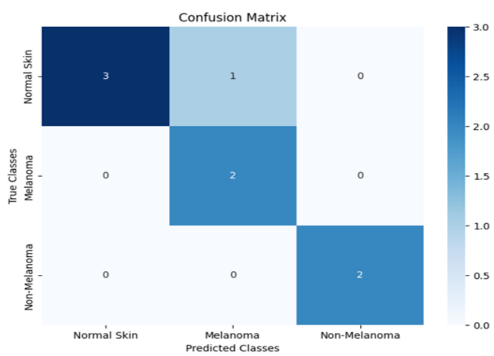

Figure 7. VGG16 Confusion Matrix

Table 4. Splitting Dataset Result

Classification	*Precision*	*Recall*	*F1-score*	*Support*
Normal skin	1.00	0.75	0.86	4
Melanoma	0.67	1.00	0.80	2
Non-melanoma	1.00	1.00	1.00	2

Table 4 is the performance evaluation parameters of the VGG16 model on skin cancer images. Precision is a measurement of a model's ability to predict all positive classifications of a truly positive model. For example, table 4 shows a non-Melanoma precision = 1.00, which means that the model can classify the non-Melanoma class very well, which is 100% predicted to be correct. Recall refers to the model's ability to detect the correct actual data as a positive class. A recall value of 0.75 indicates that the model can only detect 75% of all the actual data of the Normal skin image. While f1-score is a harmonious average between precision and recall. F1-score balances the importance between precision and recall values. An f1-score close to 1.00 indicates that the model performs well, as it is not only accurate in predicting, but also consistent in detecting actual data.

3.3. UI/UX Designing

a. Navigation Flow

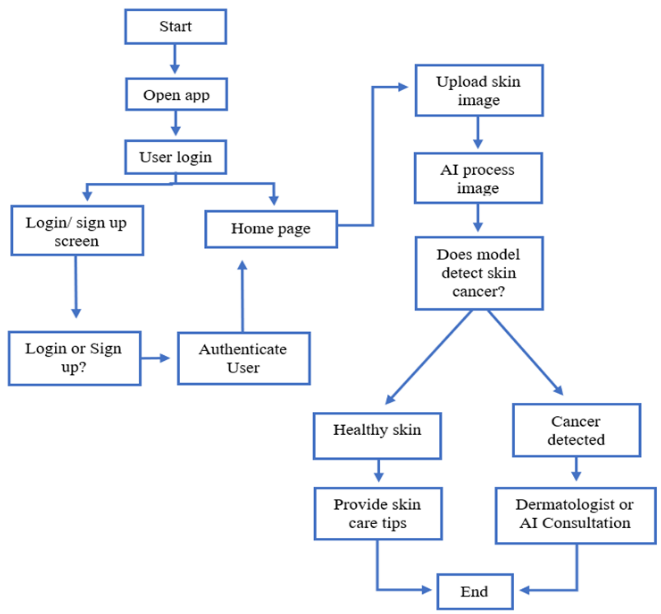

Figure 8. Navigation Flow of Oncare Application.

3.4. Application Features

The login page in figure 8, serves as an initial authentication system for users to be able to access applications securely. Users can log in using email and password, or through third-party accounts such as Google, Facebook, and Apple. The goal is to protect users' personal health data as well as simplify the registration process.

The home page in figure 9 is the main page that presents personalized and educational information based on location and user status. Environmental information such as UV index and temperature is useful for the prevention of skin cancer. Users are also directed to increase awareness of risks and preventive measures through education and professional recommendations in the form of articles about skin cancer, a list of nearby hospitals, and recommended doctors. And there's also quick navigation to the Skinning and Aicare features. This feature is designed to increase user awareness of environmental risk factors and encourage preventive actions.

Skinning in figure 10, the main feature of the Oncare application is the ability to detect skin cancer using a mobile phone camera or upload images from the gallery. With the help of trained Convolutional Neural Network (CNN) models, the system can identify possible melanoma, non-melanoma, or normal skin. Users are directed to ensure ideal shooting conditions with checklists, such as good lighting, optimal distance, and the right skin position. The goal is to ensure accurate and reliable detection results.

The result page in figure 11 is the result of skin cancer risk analysis which is displayed visually and percentages in the form of melanoma, non-melanoma, and signs of healthy skin, which can make it easier for users to understand their health status. The system also provides evidence-based medical recommendations and directs users for follow-up such as direct examinations or specialist doctor consultations.

AIcare in figure 12 is an AI-based chatbot feature that function as a virtual health assistant. Users can submit complaints or concerns about their skin conditions, either in the form of text or images. Aicare will provide an initial

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response based on the symptoms presented and suggest next steps, such as follow-up examinations or in-person consultations. This feature supports the initial screening process and improves the efficiency of medical consultations.

3.5. User Interface

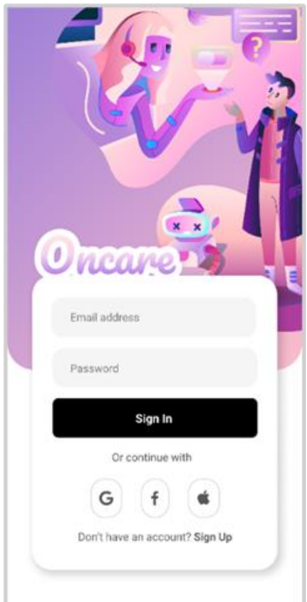

Figure 8. Login page

Figure 9. Home Page

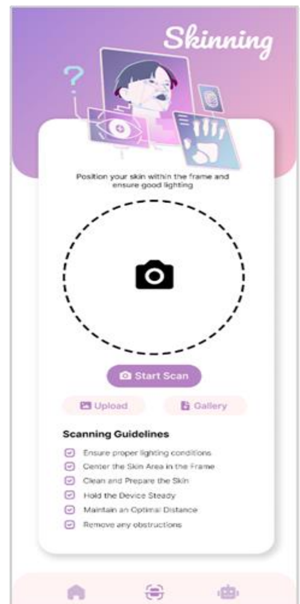

Figure 10. Screening Page

Figure 11. Result Page

Figure 12. AIcare Consultation

4. CONCLUSION

Based on the results of the research obtained, basically this research is going well. However, it is not a mistake if researchers want to put forward some suggestions that can be useful for the progress of researchers in general. The suggestions submitted by the researcher include the following: Developing a CNN model that can not only detect skin cancer, but also play a role in detecting all skin diseases; Improving the accuracy of the model in the classification and identification of dataset imagery, in the next study it is suggested to try to use various other architectural models such as *Inception-v4*, *ResNet-50*, *Inception ResNet-v2*, and *DenseNet121*; Developing the "Oncare" UI/UX into an

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interactive smart mobile healthcare that can be used to detect various diseases, quick AI-based consultations, prevention efforts, recommendations from doctors and nearby hospitals, and online drug purchases using doctor's prescriptions.

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