Skin Scan: Cutting-edge AI-Powered Skin Cancer Classification App for Early Diagnosis and Prevention

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Mobile health applications (mHealth) use machine learning (AI)-based algorithms to classify skin lesions; nevertheless, the influence on healthcare systems is unknown. In 2019, a large Dutch health insurance provider provided 2.2 million people with free mHealth software for skin cancer screening. To evaluate the effects on dermatological care consumption, the research conducted a practical transitional and population-based study. To evaluate dermatological needs between the two groups throughout the first year of free access, the research compared 18,960 mHealth users who completed at least one successful evaluation with the app to 56,880 controls who did not use the app. The odds ratios (OR) were then computed. A cost-effectiveness analysis was conducted in the near term to find out the expense for each extra-diagnosed premalignancy. Here, results indicate that mHealth users had a three-fold greater incidence of requests for benign tumors on the skin and the nevi (5.9% vs 1.7%, OR 3.7 (95% CI 3.4–4.1)), and they had greater numbers of claims for (pre)malignant skin cancers as groups (6.0% vs 4.6%, OR 1.3 (95% CI 1.2– 1.4)). Compared to the existing standard of care, the expenses associated with using the app to detect one additional (pre) malignant skin lesion were €2567. These results suggest that AI in m Health may help identify more dermatological (pre)malignancies, but this could be weighed against the current greater rise in the need for care for benign tumors of the skin and nevi.

Keywords: Skin Cancer; AI-Powered; Skin Lesions; Skin Cancer Types (Basal Cell Carcinoma, Squamous Cell Carcinoma, Melanoma); Image Classification.

Introduction:

One of the most popular forms of cancer, skin cancer is becoming more common and more widespread, which puts considerable pressure on healthcare systems [1][2][3][4] Medical technology advancements like teledermatology and artificial intelligence (AI)-powered mobile health apps are being incorporated into medical treatments as a potential way to reduce this load. AI application could relieve stress on physicians and further minimize associated healthcare expenses by reducing the number of appointments for benign skin cancers and boosting the possibility of early identification of skin cancer [5].

The idea of using AI-based algorithms to identify skin cancer has a lot of assurance, but it has only been studied in controlled laboratory environments. Furthermore, even though AI is comparable to Dermatologists can identify cancers of the skin on dermoscopy-based images [6][7][8], but it's not yet clear how or for whom to use this technique in clinical care. The public can now use this method because AI-based algorithms for identifying skin cancer have been used in several mHealth apps in recent years [9]. The Netherlands is in a unique situation because of the quick advancement of AI-based mobile health apps in population-based settings. A mobile app for skin care is being paid for by multiple major health insurance carriers. Cancer detection for their consumers [10], allows consumers to assess whether to see a GP (general practitioner) for a potentially malignant skin lesion using an AI-based mHealth app. By evaluating how these real-world data affect doctors and their patients when they utilize such an app, we can gain a better understanding of the potential impact on healthcare consumption [11]. Thus, the purpose of this study is to assess how a mHealth app for questionable skin lesions affects the use of dermatological healthcare in a population-based scenario.

Related Work:

Skin cancer is a global issue affecting one in five people, with millions of new cases reported annually. It occurs when normal cells grow uncontrolled and disorderly, leading to contact inhibition of proliferation. There are two main categories of skin cancer: non-melanoma and melanoma. Melanoma skin cancer is further divided into two subtypes: squamous cell carcinoma (SCC) and basal cell carcinoma (BCC). Deep learning algorithms have become popular for early skin cancer detection. Tahir et al. introduce the DSCC_Net, a deep learning-based skin cancer classification network, aiming to identify different types of skin cancer. The model is tested on three standard datasets and provides a robust evaluation framework for six deep networks. DSCC_Net outperforms other models in skin cancer diagnosis, achieving a 99.43% AUC and outperforming baseline models in accuracy, recall, precision, and F1-score, making it a valuable tool for dermatologists and healthcare professionals. [12] Maad M. Mijwil's paper "Skin cancer disease images classification using deep learning solutions" focuses on image classification using deep learning models, which is a fundamental pillar of medical progress. The study uses a convolutional neural network (ConvNet) to detect skin cancer pictures, covering over 24,000 instances. Three architectures—InceptionV3, ResNet, and VGG19— are carefully used to identify the most effective architecture for the classification of benign and malignant cancer types with high accuracy. The research methodology focuses on artificial intelligence, specifically machine, and deep learning, with self-learning algorithms forming the foundation of artificial neural networks. TensorFlow, a flexible open-source library, is used for machine and deep learning tasks. The study uses a large dataset of high-pixel images from the ISIC collection from 2019-2020. The authors propose an enhanced framework for early skin cancer detection using the well-known CNN-based architecture, VGG-16. The model operates on the foundation of the VGG-16 network but introduces enhancements to improve accuracy. The International Skin Image Collaboration dataset is used for assessment. [13].

The paper "Detection and optimization of skin cancer using deep learning" by Balambigai, Elavarasi, Abarna, Abinaya, and Arun Vignesh focuses on improving Convolutional Neural Network (CNN) models for skin cancer classification. The authors used a dataset from

Kaggle and applied random search optimization for hyper-parameter selection, resulting in an improved accuracy of 77.17%. In the article "Classification of Skin Cancer Lesions Using Explainable Deep Learning," Muhammad Zia Ur Rehman introduced a unique technique by incorporating extra convolutional layers into pre-trained models. The modified DenseNet201 model showed a remarkable accuracy of 95.50%, demonstrating state-of-the-art performance compared to other approaches. The study highlights the importance of computer-aided diagnostic solutions in enhancing the detection process and supporting dermatologists in making informed decisions for early intervention and better patient outcomes.[14]

Types of Skin Cancer:

Skin cancer can be of three main forms. Melanoma, squamous cell carcinoma, and basal cell carcinoma are Thames of these varieties.

Basal Cell Carcinoma:

This is the type of skin cancer that occurs in the Basel cells. Basal cells are present in the lower part of the **outer layer** called the epidermis. On the skin, basal cell carcinoma appears as a tiny, usually shiny bump or scaly, flat patch that slowly expands which we can see in Figure 1.

Squamous Cell Carcinoma:

Squamous cell carcinoma (SCC), also known as cutaneous carcinoma of squamous cells (CSCC), is the second most common skin cancer which we can see in Figure 2, primarily affecting the **outermost layer** of the skin, often found in areas exposed to the sun.

Melanoma:

Melanoma, also known as "Black Tumor," is a dangerous skin cancer caused by melanocytes, which produce **melanin**, a black substance that gives skin shade. It spreads easily and expands quickly in Figure 1.

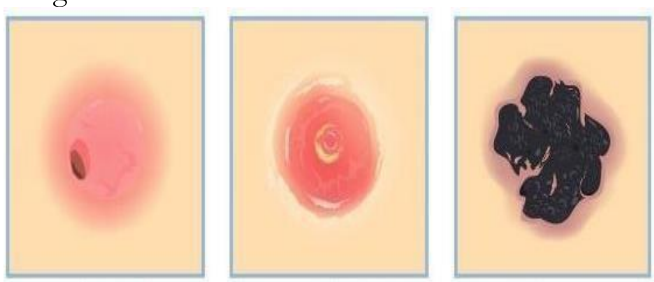

Figure 1: Main Types of Skin Cancer (Basel Cell Carcinoma, Squamous Cell Carcinoma, Melanoma)

AI algorithms are being developed to improve early skin cancer diagnosis and user experience. The **Skin Scan app** will be tested for accessibility, engagement, and impact on preventative healthcare measures. Ethical considerations like user consent and data privacy will be considered when releasing AI-powered health apps. The "Skin Scan" project combines advanced technology and user-centered design to improve skin cancer prevention and detection. It uses artificial intelligence algorithms, machine learning models, and ethical guidelines to ensure early diagnosis and tracking of health outcomes.

Methodology:

The proposed skin cancer detection system consists of the following features.

User Login/Register:

Doctors and patients can start by creating an account and entering basic information like their username and password. Users returning can safely log in. The system confirms user identity with a strong authentication procedure, ensuring allowed access to Skin Scan features.

Skin Scan Interface:

Skin Scan interface offers skin cancer screening services, including scanning body areas, viewing results, learning about forms, taking pictures, uploading, and providing details on different types of skin cancer.

Selecting Body Part:

Users select a body area for skin cancer analysis using their device's camera. They can capture or upload images, which are preprocessed for analysis. These images are then imported into the Skin Scan program for further examination.

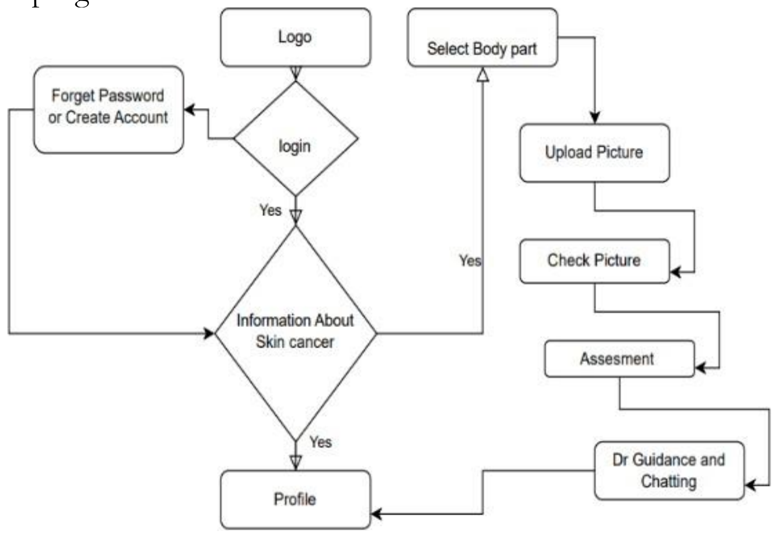

Figure 2: Skin Scan Flow Diagram

View Result:

Users obtain the results of a skin scan, which may include details regarding anomalies found, potential forms of cancer of the skin, and suggested courses of action. To help users comprehend scan results, the system may indicate areas of concern on uploaded photos using remarks or visualizations and the flow diagram can be seen in Figure 2. This figure explains the functionality of the overall proposed system for skin cancer.

Connecting Patients and Doctors:

The application's chat feature facilitates easy communication between doctors and patients, promoting a patient-centered approach to healthcare delivery, enhancing access, and empowering patients. Patients can easily communicate with the doctor for further guidance.

Model Architecture:

In our investigation, we utilized an enhanced version of the Swin Transformer architecture. The process of fine-tuning involves retraining a pre-existing model on a specific dataset or task, thereby enhancing its effectiveness for that particular objective. The model classifies various dermatological conditions, including actinic keratoses, basal cell carcinoma, benign keratosis-like lesions, dermatofibroma, melanocytic nevi, melanoma, and vascular lesions which we can also see in Figure 4, aiding early diagnosis and treatment planning.

Architecture of Swin Transformers:

With a linear computing complexity resulting from self-attention processing within each local window, the Swin Transformer is a Vision Transformer that may be used for image identification and classification tasks. It builds hierarchical feature maps by combining picture areas in layers whose classification can be seen in Figure 3.

Data Set:

The HAM10000 ("Human Against Machine with 10000 training images") dataset, consisting of 10,015 images, aims to address the scarcity of dermatoscopic images for the automated diagnosis of pigmented skin lesions. It covers diagnostic categories like Actinic keratoses, Basal cell carcinoma, benign keratosis-like lesions, dermatofibroma, melanoma, and vascular lesions which can be seen in figure 4 with all types of skin cancer.

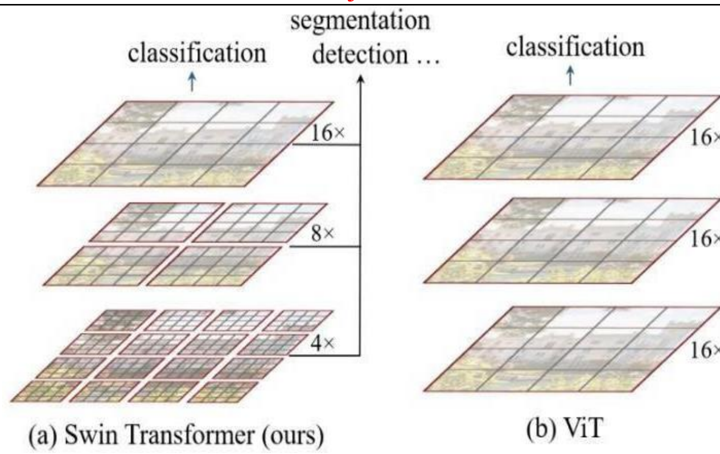

Figure3: Swin Transformer

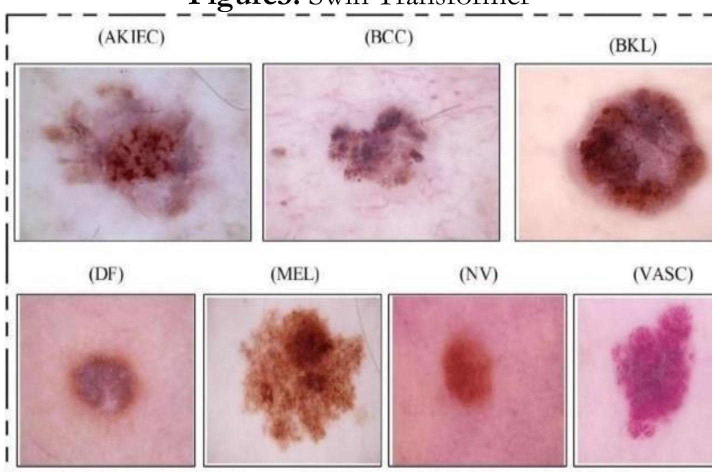

Figure 4: Types of Skin Cancer

Training Procedure:

We carefully chose and adjusted several hyperparameters during the training process to maximize the effectiveness of our skin cancer classification model

Training Hyperparameters:

Learning Rate:

The number of steps taken during optimization to update the model's parameters is determined by the learning rate which is 5e-05 in this case.

$$\text{New Weight} = \text{Old Weight} - \text{Learning Rate} \times \text{Gradient} \qquad (1)$$

Train Batch Size:

The number of training examples used in each training cycle is determined by the batch size. The train batch size of this model is **32**.

Eval Batch Size:

It determines the number of examples utilized for evaluation in each iteration, much as the train batch size. The Eval batch size of this model is 32.

Seed:

For reproducibility, the random number generator is initialized with a seed in Figure 4, which is a random number. The seed in this model is **42**.

Gradient Accumulation Steps:

In advance of changing the model's parameters, gradient accumulation permits gradients to build across several batches. The value is 4.

Total Train Batch Size:

The product of train batch size and gradient accumulation steps yields the effective batch size that is used for parameter updates. The total train batch size is 128.

$$\text{Train Batch Size} \times \text{Gradient Accumulation Steps} = \text{Total Train Batch Size} \quad (2)$$

Table 1: Training Results & Accuracy of Swin Transformer model

Training Result & Accuracy of Model	
Training Loss	0.3261
Epoch	1.0
Step	3.30
Validation Loss	0.2744
Accuracy	0.8984
Precision	0.9030
F1	0.8985
AUC-Roc Curve	0.9935

Optimizer:

The Adam optimizer, with betas = (0.9, 0.999) and epsilon=1e-08, uses adaptive methods to adjust learning rates and momentum, ensuring stability during parameter updates.

Learning Rate Scheduler:

Type: A linear learning rate scheduler adjusts the learning rate linearly during training epochs.

Learning Rate Scheduler Warmup Ratio:

The value of 0.1 indicates that **10%** of the epochs are allocated for the learning rate warmup.

Number of Epochs:

The model is trained for one epoch, completing one pass through the entire training dataset. In our proposed system the training loss after one epoch is 0.3261, while the validation loss is 0.2744 as shown in table 1. The training method achieved an accuracy of 89.84%, precision of 90.30%, F1 score of 89.85%, and Area Under the Curve (AUC ROC) of 99.35%. Additionally, it implies that the value at the given stage is 3.30 as given in Table 1. These indicators collectively reflect the model's performance and efficacy after the stipulated training period, providing information about its capacity to make accurate predictions and manage the given data.

Working:

The application features a logo screen, a login screen, and password reset options. It raises consumer awareness about skin cancer and provides access to important information. Users can create accounts, customize profiles, and upload pictures for skin assessment. They can preview submitted photos before starting the assessment via the Check Picture screen in Figure 2. The Skin Scan program offers a user-friendly interface with distinct functions, allowing users to create accounts, access instructional materials, upload photos, and receive detailed skin scan findings after processing supplied photographs.

Results:

Presenting Skin Scan, a cutting-edge AI-powered software for prevention and early detection of skin cancer. We have reached significant goals through thorough research and testing, proving the app's performance in precisely detecting possible skin problems. The artificial intelligence model utilized in Skin Scan has exhibited remarkable efficiency, attaining elevated levels of precision in identifying skin cancer in various datasets. The measures for accuracy, recall, and F1-score consistently show how reliable our model is in differentiating between various kinds of skin lesions. Early feedback from users and engagement data demonstrate how well-liked Skin Scan's functionality and user experience is. Users value the app's ability to raise awareness and its simplicity of use, as well as its clear and instructional content regarding skin cancer. One of the main concerns with Skin Scan has been its picture processing pipeline efficiency which can be seen in Figures 5 and 6, we have provided it with images, and it has shown us the results. Our findings demonstrate that the program offers quick analysis, guaranteeing a smooth user experience. The app's usefulness for daily use is enhanced by its real-time processing capabilities. The image was classified using a model, predicting it to be a Melanoma or Melanocytic-nevi, with lower confidence values for other classifications, aiding in skin lesion diagnosis in Figures 5 and 6, based on the precision and accuracy results we conclude that this is the desired type of cancer.

Figure 5: Skin Cancer Classification Output

Discussion:

There was a 32% rise in reports for (pre)malignant lesions of the skin among users of the app in comparison to a comparable number of those who avoided using the mHealth app. However, a three- to four-fold increased likelihood of claims for benign skin cancers and nevi among mHealth users also offset this effect. Based on the previously published diagnostic precision of the analyzed app [15][16], these results were anticipated. Additionally, they align with other highly recognized population-based cancer screening programs that strike a balance between accurately diagnosing malignancies and producing false positive results [17], as well as contemporary clinical dermatological practice, which excises about 8 nevi for every melanoma [18].

Figure 6: Classification Results for Skin Cancer

Using a mHealth app could be an option even though traditional skin cancer screening according to a full body check by a qualified healthcare provider is not advised [19]. a stage in between to think about focused screening for high-risk lesions. According to this study, using the app was associated with a rise in (pre)malignancy claims; as a result, it may be a useful first step in enhancing skin cancer detection. But as it stands, the app can now detect any cutaneous (pre)malignancies, including actinic keratosis, keratinocyte carcinomas, and melanomas. The morbidities and fatalities of these (pre)malignancies vary greatly [20][21][22][23], and early diagnosis of cutaneous pre-malignancies such as actinic keratosis is medically less significant. The incorrect diagnosis and hence inefficient use of limited healthcare resources could be a major drawback of implementing these kinds of apps across the population [24].

Conclusion:

The SkinScan app, using the Swin Transformer model, is a groundbreaking solution for early skin cancer detection and prevention. With an accuracy rate of 0.89, it facilitates user-friendly skin examinations, enabling timely medical interventions and potentially life-saving treatments. SkinScan also raises awareness and promotes proactive health behaviors, potentially improving patient outcomes and reshaping skin cancer management.

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