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EFFICIENT SYSTEM DESIGN FOR NEXT GENERATION OF MEDICAL IMAGING FOR SKIN CANCER DETECTION

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ABSTRACT
Recent advances show the wide-ranging applications of machine learning for solving multi-disciplinary problems in cancer cell growth detection, modeling cancer growths and treatments, etc. There is growing interests among the faculty and students at Clayton State University to study the applications of machine learning for medical imaging and propose new algorithms based on a recently funded NSF grant proposal in medical imaging, skin cancer detection, and associated smartphone apps and a web-based user-friendly diagnosis interface. We tested many available open-source ML algorithm-based software sets in Python as applied to medical image data processing, and modeling used to predict cancer growths and treatments. We study the use of ML concepts that promote efficient, accurate, secure computation over medical images, identifying and classifying cancer cells, and modeling the cancer cell growths. In this collaborative project with another university, we follow a holistic approach to data analysis leading to more efficient cancer detection based upon both cell analysis and image recognition. Here, we compare ML based software methods and analyze their detection accuracy. In addition, we acquire publicly available data of cancer cell image files and analyze using deep learning algorithms to detect benign and suspicious image samples. We apply the current pattern matching algorithms and study the available data with possible diagnosis of cancer types.

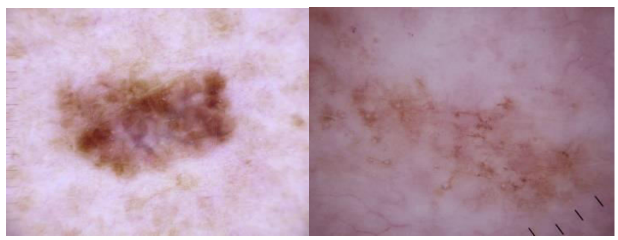
Index Terms – Apps for skin cancer detection. convolutional neural network, Melanoma detection, Skin cancer detection,

INTRODUCTION
The number of skin cancer patients is increasing significantly due to the changing lifestyle resulting in the increased exposure to harmful UV radiation from sun. It is estimated that more than 50,000 men and 40,000 women developed Melanoma of skin just in 2022, which is likely to be increasing with time. Determining the correct type of skin cancer is very important because it helps identify the suitable treatment. As camera and imaging technology is getting better every day, the usage of image processing and computer vision in the field of health care and medical applications has increased tremendously. In this paper, we examine several medical imaging technologies based upon convolution neural network (CNN) to detect and classify the skin cancer types.

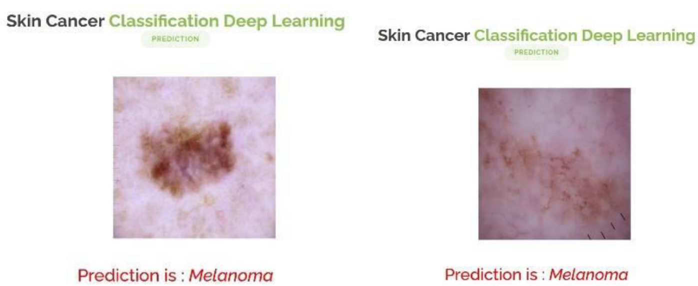
Skin cancer is the one of ten most common cancer types in the world. The abnormal growth of skin cells most often develops on the skin exposed to the sun. Skin cancer occurs when errors occur in the DNA of skin cells, it begins at the top of the skin. There are three most common types of skin cancer; 1. Melanoma 2. Basal cell Carcinoma 3. Squamous cell skin cancer. The mutation causes the cells to grow out of control and form a mass of cancer cells. Melanoma is the most dangerous skin form of skin cancer when compared to the other types. The main symptom of skin cancer is a visible mole or other growth on the skin. Skin cancer visual symptoms include darker looking skin yellowish and eyes reddened skin, itching and excessive hair growth. Detection of skin cancer at an earlier stage can increase the survival rate.

CNN APPROACH
Convolution neural networks (CNN) are used very effectively by data scientists to detect and classify historical cancer data of clinical images. In [1], using RESNET-50, the deep learning aspect of the project was implemented successfully categorizing skin lesions into seven distinct classes of most popular skin cancer types, including the most common and deadly Melanoma category.

ResNet stands for Residual Network and is a specific type of CNN introduced in [2] that is widely used for computer vision applications. It can achieve state-of-the-art results in a wide range of image-related tasks such as object detection, image classification, and image segmentation. One of the main advantages is its ability to train very deep networks with hundreds of layers. Residual neural networks are a type of artificial neural network (ANN) that forms networks by stacking residual blocks. RESNET-50 is a 50-layer convolutional neural network (48 convolutional layers, one MaxPool layer, and one average pool layer). In traditional deep neural networks or plain deep neural networks, the vanishing gradient problem occurs, means that gradients become very small as they are propagated through many layers of a neural network. In simple words, as the number of layers increases training or test error gets worst. This can lead to slower learning and even a complete lack of learning in very deep architectures. RESNET solve this problem by introducing skip connections, also known as residual connections, which allow the gradient to bypass certain layers in the network.



(a) Reference 1 (b) Reference 2



(c): Prediction for reference 1 (d): Prediction for reference 2

Figure 1. Melanoma Detection

The classification model presented in [1], runs mostly accurately identifying and categorizing skin lesions based on the specified classes and their specifications were met as shown in Figure 1 for Melanoma detection.

From the analysis made in [1], it was noted that RESNET-50 performs the detection of skin cancer with an average testing accuracy of 82.87%. The paper concluded that if the model is modified further the accuracy and loss can be improved. Our own study using the model over skin data images collected from various hospitals/clinics, the diagnosis of various skin cancer types was possible as shown in Figure 2.

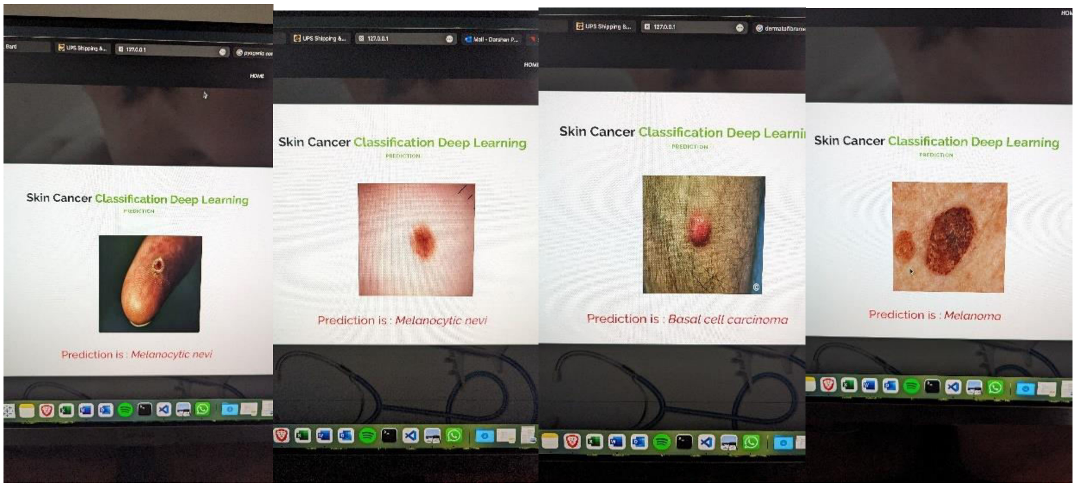


Figure 2. Skin Cancer Detection Using Ml Approach [1]

Despite the overall accuracy of approach used in [1], some limitations were identified during additional testing. When random images from online sources, only 1 out of 4 of them yielded correct predictions. This indicates a potential challenge in handling diverse image sources and variations. Furthermore, the size of the images proved to be a factor in the detection rate, with variations in dimensions affecting the model's accuracy. Additionally, the angle and distance from which images were captured also emerged as variables impacting the detection capabilities of the model. While the current implementation excels under specific conditions, addressing these limitations could enhance the model's effectiveness and broaden its applicability to a wider range of scenarios and image sources.

A recent survey reviewed the most recent research articles on skin cancer classification using deep learning methods [3]. The paper also provided an overview of the most common deep-learning models and datasets used for skin cancer classification. RESNET-50 has been shown to improve on other proposed and existing models, such as Alexnet [4], Visual Group Geometry (VGG) [5], Densenet [6] and Mobilenet [7]. Imagenet [9] was the widely used dataset for these models. A detailed comparative analysis of deep learning methods for skin cancer classification is presented in [3]. Some of the other commonly used datasets in these studies have been ISBI [9], ISIC [10], and HAM10000 [11].

We note an implementation of a skin cancer detection model using Tensorflow in [12]. A dataset that contains images for the two categories that are malignant or benign is used. The transfer learning technique to achieve better results with less amount of training is illustrated. Authors use EfficientNet architecture as the backbone of their model along with the pre-trained weights of the same obtained by training it on the image net dataset [13].

Skin Image Datasets

CNNs are particularly suited for image classification tasks due to their ability to automatically learn relevant features from the data. Leveraging the power of CNNs, our utilized model is trained on the HAM10000 ("Human Against Machine with 10000 training images") dataset, which consists of 10015 high-resolution dermatoscopic images sourced from diverse populations and acquired through various modalities. The achieved results demonstrate the efficacy of our proposed approach. The model achieved an impressive training accuracy of 96.00% and a validation accuracy of 97.00%. These high accuracy rates signify the potential of our deep learning-based skin cancer prediction system as a reliable tool for early diagnosis, thereby aiding healthcare professionals in making informed decisions and improving patient outcomes. By contributing to the field of dermatological research and machine learning, our project provides valuable insights into the application of deep learning techniques for skin cancer prediction. Furthermore, the publicly available HAM10000 dataset, enriched with a wide range of dermatoscopic images, can serve as a valuable resource for academic research and further advancements in the domain of medical image analysis and classification.

HAM10000 (“Human Against Machine with 10000 training images") is a dataset of 10000 training images for detecting pigmented skin lesions. The authors of this dataset collected dermatoscopic images from different populations, acquired and stored by different modalities [14]. The entire image set is shown in Figure 3. This benchmark dataset can be used for machine learning and for comparisons with human experts. Cases include a representative collection of all important diagnostic categories in the realm of pigmented lesions.

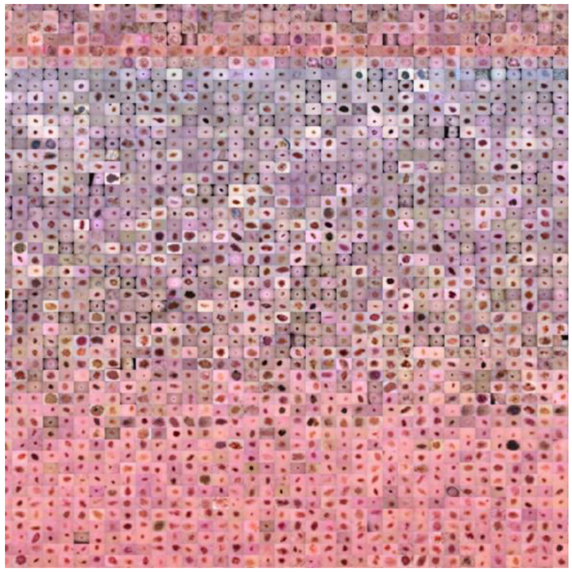


Figure 3. HAM1000 Dataset [3]

We illustrate the approach to use the HAM10000 as suggested in [15]. The first approach consists of loading the dataset into one data frame consisting of images, file paths and metadata. However, this approach requires more RAM to run. The second approach requiring lesser RAM consists of reorganizing the dataset into subfolders according to the categories which makes it easy for labelling while working with the data.

The first approach consists of loading the dataset is to load entire data into a python dataframe. The Metadata file is used as a reference to match every image to its correct entry in the csv file. The advantage of using this method is that it gives options for data analysis, forecasting and Prognosis. The major drawback of this method is that it can be used on high configured machines to develop the models. As it requires more memory to run and load. Figure 4 shows the associated Python code.

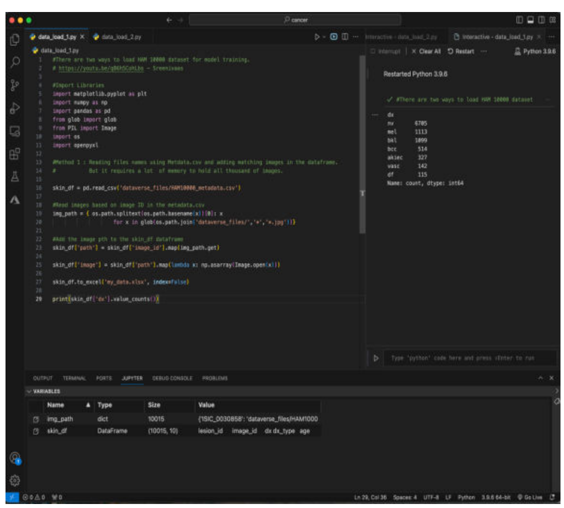


Figure 4. Python Dataframe to Load HAM10000

Resampling of the dataset is required for the quantitative analysis of HAM10000. For instance, it is noted that seven categories of the dataset are heavily imbalanced with Melanocytic Nevi having 6705 images and Dermatofibroma having only 115 images which would result in a biased result from the model that would be trained. So, we would have to resample it.

Following techniques are used for resampling:

- Use a combination of techniques: Try both under sampling and oversampling approaches (SMOTE) to compare their impact on model performance.
- Start with smaller oversampling or under sampling ratios: Begin with moderate changes, like oversampling minority classes to half the size of the majority class or under sampling the majority class to twice the size of the smallest minority class.
- Evaluate impact on key metrics: Monitor how resampling affects the desired performance metrics, such as accuracy, precision, and recall for each class.
- Iterate and adjust: Based on the evaluation, refine the resampling strategy with different ratios or techniques until a satisfactory balance between performance and class representation is achieved.

Image processing tasks:

- High-resolution images: If images contain many fine details crucial for task success, using the full 600x450 resolution might be necessary. For example, medical images for disease diagnosis often require high resolution to capture important subtle features.
- Basic classification tasks: For simpler tasks like classifying objects with clear and distinguishing characteristics, even downscaled images (e.g., 224x224) can often work well, potentially offering computational efficiency benefits.

Model complexity and learning capacity:

- Complex models: Larger models like VGG16 or ResNet can handle high-resolution inputs better and might benefit from richer information in 600x450 images. Smaller models, like Mobile Net, might not fully utilize the information and could be more efficient with smaller inputs.
- Limited learning capacity: If model's capacity (number of parameters) is limited, it might struggle to learn effective representations from high-resolution images, potentially leading to worse performance or overfitting.

Computational resources:

- Powerful hardware: If a GPU or powerful workstation is available, processing larger images might be feasible and not significantly impact training time.
- Limited resources: On laptops or less powerful GPUs, training with 600x450 images might be slower or impractical due to increased memory and computational demands.
- General trends:
- Modern trend: There's a general trend towards using smaller image sizes (e.g., 224x224 or even lower) due to computational efficiency, especially for pretraining models and transfer learning.
- Downscaling options: If unsure, start with downscaled versions (e.g., 300x225, 224x224) and compare performance and training time. You can always experiment with the original size later if needed.

Image size	Efficiency	Performance
600x450	Less efficient	Potentially higher if details are important

Downscaled	More efficient	May be similar or lower, depends on task and model

Apps for Skin Cancer Detection

Many people have started to use a skin cancer app to increase their chances of identifying skin cancer as early as possible. It is becoming increasingly important due to widespread skin cancer cases. According to the American Academy of Dermatology, skin cancer is the most common type of cancer in the United States. In fact, approximately 9,500 people receive a diagnosis every day. Early detection makes skin cancer more treatable and, for some people, completely reversible. Identifying and managing skin cancer before it spreads is the best way to achieve a good outcome. Doctors recommend carrying out regular skin checks at home, usually once per month.

It is noted that over 50% of moles or marks that turn out to be cancerous are initially identified by the patient themselves. As a result, the number of self-examinations has increased. Development of apps has further increased self-examinations. In the last few years doctors and organizations have also started recommending consumers to use photography as an aid to skin self-examinations. Now, there are dedicated skin monitoring apps you can use for photos to keep track of changes to your skin. You can either photograph individual moles and marks you want to keep a closer eye on, or you can photograph wider areas of your skin – The latter could help you identify new moles or marks on your skin. A mole tracking app can help you photograph individual moles and capture wider photos of large areas of your skin.

Some studies suggest that the accuracy of Primary Care physicians to detect skin cancer is relatively low due to lack of specific training to detect skin cancer. It was estimated to be below 60% in British and Dutch studies [16, 17]. One US study found that only 35% of patients had a correct diagnosis [18]. These studies suggest that human errors may result in a delay in diagnosis or missing the cancer in its earlier stages when patient survival is more favorable, and treatment is less costly.

Image analysis using advanced camera technology on mobile phones provides the power of AI and advanced medical imaging in the palm of everyday user. Recent advances in skin cancer detection have been made by Google using AI [19, 20]. This tool is not approved by the FDA and is not perfect but is considered very helpful in early detection of cancer based upon dermatological conditions. As the camera technology for mobile phones keeps advancing, it is expected that 3D images of the skin will be very helpful for matching with the known stored images of skins affected by cancer.

We studied two apps and compared their results. The apps are Scanoma [21] and Skinive [22]. Images were sampled from the cancer image folder located in the public NSF drive file. Sample cancer images were selected from the designated folder in the NSF drive. These images were chosen to represent Benign and Malignant. Two images (image number 45 and 98) were picked from the Benign folder and two (image number 317 and 257) from the malignant folder. The selected images were uploaded and analyzed using Skinive. The app's algorithms were utilized to detect and identify any abnormalities indicative of cancerous growths. The Skinive app demonstrated the ability to analyze cancer images effectively. Navigation within the app was straight forward and user-friendly, making it accessible to individuals with varying levels of technical expertise. However, it was noted that Skinive operated on a subscription-based model, requiring payment for full access to its features. An image sourced from the Norris Dermatology [23] was successfully analyzed using the Skinive app. Results indicated potential abnormalities, aligning with the intended purpose of the analysis as shown in Figure 5.

There are few review papers comparing the performance of several apps. Among them [24] and [25] are notable. Apps developed between 2011 and 2019 were reviewed in [24]. Some of the older apps store images and track changes rather than offering diagnostics. SkinVision is one of the popular 2019 apps with about 80% accuracy. Comparison results of the skin cancer detection apps according to the histogram-based local descriptors using the LAB color space [26] on Dataset 1 of Kaggle are presented in [25]. The study determined the most successful skin cancer detection methods by comparing the outcomes and effectiveness of the various apps that categorize benign and malignant forms of skin cancer.

Some of the popular current apps are as follows:

A. UMSkinCheck:

The University of Michigan launched a free app that guides users through a full home skin check exam. This app also offers the opportunity to create a mole library. This enables people to compare and track any skin changes over time. This app also provides helpful advice on how to perform a skin exam. The app stores the baseline photos for comparison. It also furnishes prompts to remind users to check their skin regularly.

B. MoleMapper

The Oregon Health & Science University developed this app. It allows users to take photos and gather measurements of any moles on their body. Like UMSkinCheck, the app allows users to

take regular photos of their moles to facilitate change tracking over time. It is the result of a cancer biologist's efforts to help his wife. OHSU collaborated with Apple and Sage Bionetworks to develop this app. It's available at no cost. OHSU guides physicians to help monitor suspicious lesions without monthly in-person visits.

C. Miiskin

This app uses high resolution photography to take photos of large parts of the body to track their moles over time. This may help them identify new

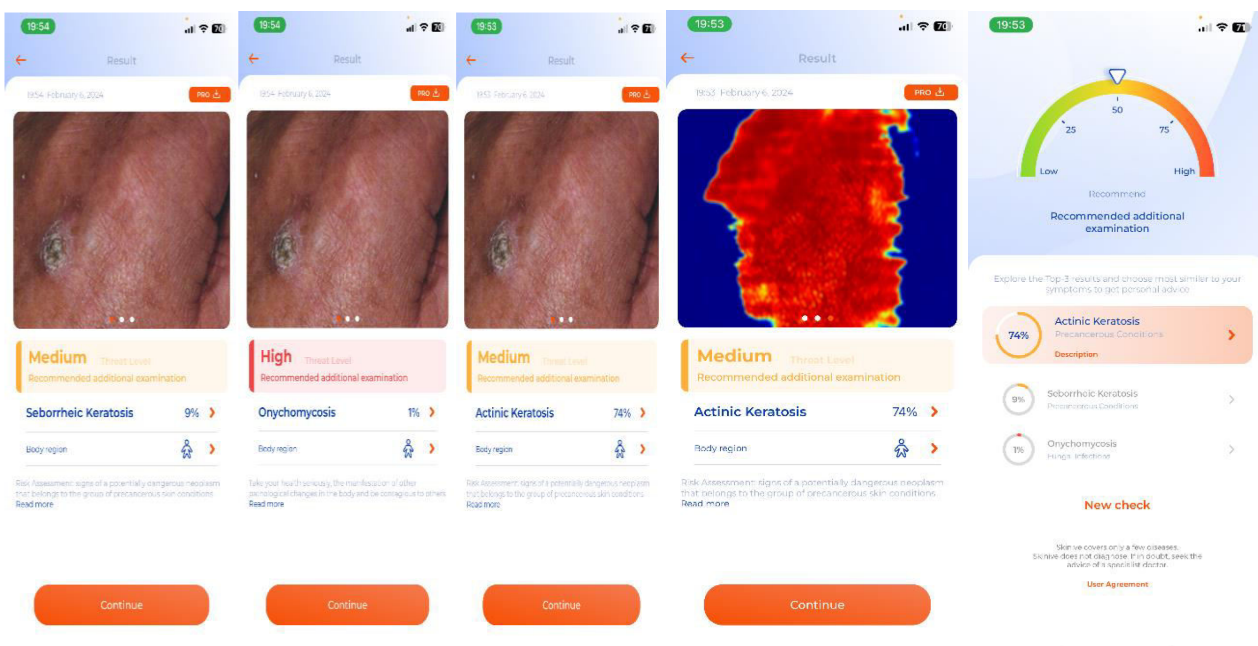


Figure 5. App Results Showing Various Threat Levels, Diagnosis Probabilities, and Recommendations.

Marks and Moles They Might not Otherwise Have Seen. the App Allows the User to Compare Individual Moles Over Time to Detect Changes.

D. MoleScope

This is a high resolution camera compatible with many different smartphones. This camera uses high magnification and special lighting to take more detailed and better-quality photos than other skin cancer apps. It also contains many features that other apps do, such as skin mapping, image management, and regular reminders. Users must purchase a device that attaches to their smartphone. Photos taken with the attachment are sent to a dermatologist for an online opinion.

E. SkinVision

This app helps users identify high risk moles that require further testing. A board of dermatologists developed this paid app. The app uses a deep learning algorithm to analyze mole photos and assess whether it is high-risk within a minute.

Many studies and dermatologists point to the dangers of relying too much on AI-based tools that are not yet ready for prime time. One dermatologist said, "We were concerned that these apps would label everything as melanoma, leading to a lot of worry and unnecessary biopsies." Another one says, "These apps may be creating a false sense of security by failing to identify melanoma as the real thing." Another important problem to address is the fact these apps may not work nearly as well on people of color, some researchers acknowledge. "Skin cancer is one area where we really need more data before encouraging patients to rely on an app completely."

We plan to acquire two high image quality smartphones using the current project funding and compare their 3D imaging capabilities including depth analysis, image reproduction capabilities using the 3D printers, and 3D skin imaging for melanoma and other skin cancer detection. We propose to compare the features of real-time 3D skin images with stored images using AI techniques. This task would first be applied to known images in 2D for pattern matching and recognition using reverse image searches like online image searches used by search engines. We propose to compare samples of suspicious skin cancer samples with the available image database on skin cancer. This will be a challenging task because of the limited availability of collection of datasets that are publicly available.

WEB ACCESS FOR DATA ANALYSIS

Considering a vast resource of data that could be used for various types of skin cancer research, we propose a web interface that would allow a central repository of data collected via apps that would be used for further analysis. The CNN and deep learning models can be utilized more effectively once a central repository of data is available. The proposed web-based dashboard would have the capability of organizing the data under various categories based upon the detected cancer types, the threat level of detected cancer, probability range of detected cancer types, and suggested action.

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