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Creating a Haptic 4D Model Along With Machine Learning Analysis by Developing a Non-Invasive Pressure Mapping Method to Screen Genital Skin Cancer

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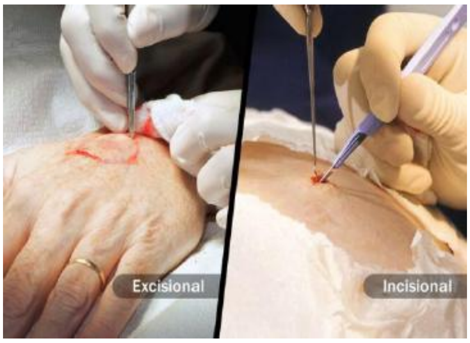
Abstract: Cancer is Curable, But only when it is detected in its early stages. When focusing on genital skin cancer matters become worse since factors like privacy, comforts, social hurdles and restrictions play a key role in postponing cancer detection in genital regions. Biopsy is an invasive method to accurately screen cancer, but when conducted in genital region causes pain, infection, numbness etc. Hence, our engineering goal is to screen suspicious skin lesions non invasively providing detailed analysis to doctors virtually, reducing the number of times patients experience an invasion of their privacy, giving them control of the screening process, respecting their privacy and promoting early detection.

We developed a machine learning model, executed and deployed as a mobile app. The image of the lesion is processed and fed into our Deep Convolutional Neural Network (DCNN) - trained and tested with 5000 images - yielding a percentage probability report of the lesion being classified as Malignant, benign or premalignant. If malignant, further classifying them within the 5 main skin cancers (Aktinik Keratosis, Squamous Cell Carcinoma, Melanoma,, Basal Cell Carcinoma and Intraepidermal Carcinoma) with an accuracy of 83% on confusion matrix.

For further analysis, the patient uses a pressure mapping kit and applies it on the lesion, which delocalizes a Non-Newtonian Fluid. Using gradient localization methods we map gel density against pressure to create a 3D support's file which is convoluted with the 3D STL file generated by the lesion's top image to produce a single 3D flexible printing file, when printed by the doctor gives a flexible haptic model which provides accurate tactile feedback.

I. Introduction

In our research we found that doctors use biopsy, the conventional method to identify the nature of any skin lesion.



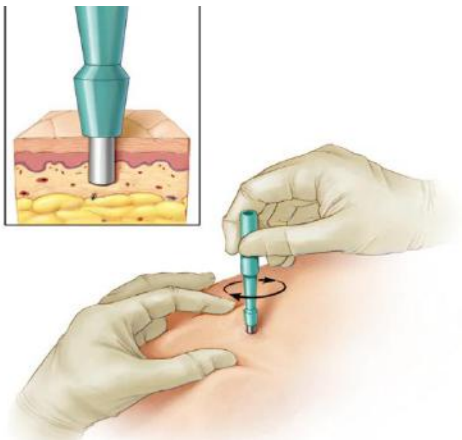
Fig[A]: Invasive Biopsy

Biopsy involves extraction and analysis of a small section of the skin lesion which is extremely painful and may lead to severe pain, infection, numbness, stinging, bleeding, and blackness when done in the genital region.

Upon conducting a survey, we realised that more than 80% of people were not comfortable showing their genital regions to a doctor, due to privacy reasons and personal comforts when the lesion is as small as a black spot.. They would rather have a remote check-up and be diagnosed physically only once.

The main goal is to screen suspicious skin lesions using existing materials in a non-invasive method. This screening shall aid doctors in making a decision of conducting a biopsy or not, which will help reduce costs and save time and pain of the patients by conducting only necessary biopsies in the genital region.

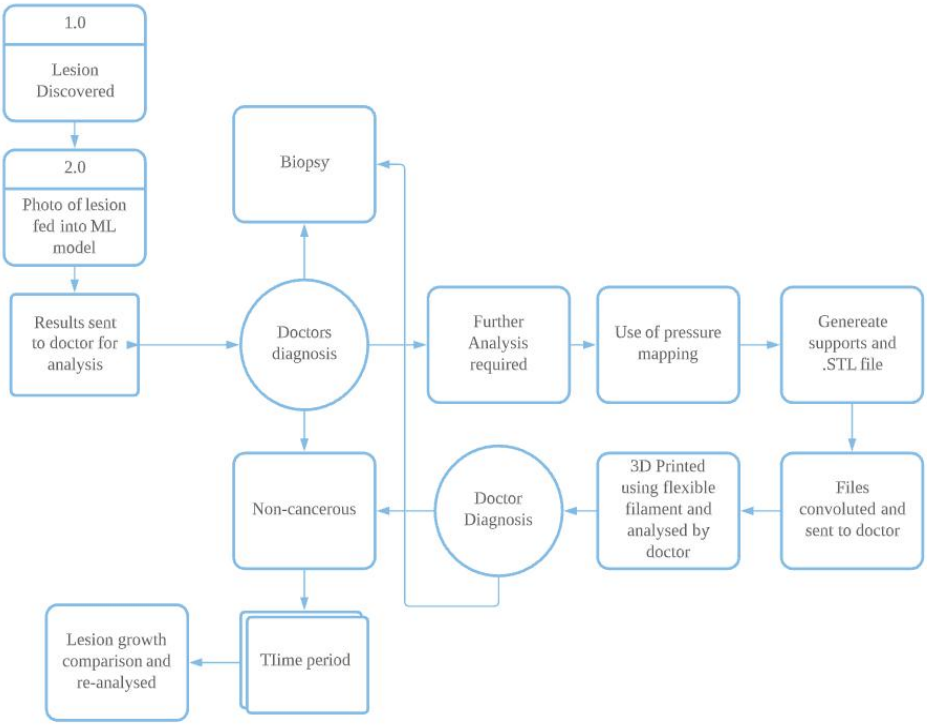
This will also reduce the number of times patients have to experience an invasion of their privacy, since we aim to give them control of the screening process.



Fig[B]: Concept of Invasive Biopsy

Patients being more comfortable and having control of the screening process will result in skin lesions being discovered and diagnosed early, preventing the cancer from spreading into more skin nodes.

II. Project Overview



Fig[C]: Architecture of workflow

Our novel solution includes a machine learning model executed as a screening app, that requires the user to take the image of the lesion in the genital area, which is then sent to secure servers for testing in the trained model, generating a detailed classification report, providing percentage probability values of the lesion being Cancerous, Non-cancerous; if its cancerous, the lesion is further classified as Actinic Keratosis (Pre-Malignant), Basal Cell Carcinoma, Intraepidermal Squamous Carcinoma, Melanoma, and Squamous Cell Carcinoma. This report is then sent to a professional Dermatologist for further actions and diagnosis. Along with the classification report we are also creating a heatmap of the lesion utilising a GradCam algorithm. This algorithm and the heatmap will help the doctor to visualise the different skin textures as colour and heat module mapping.

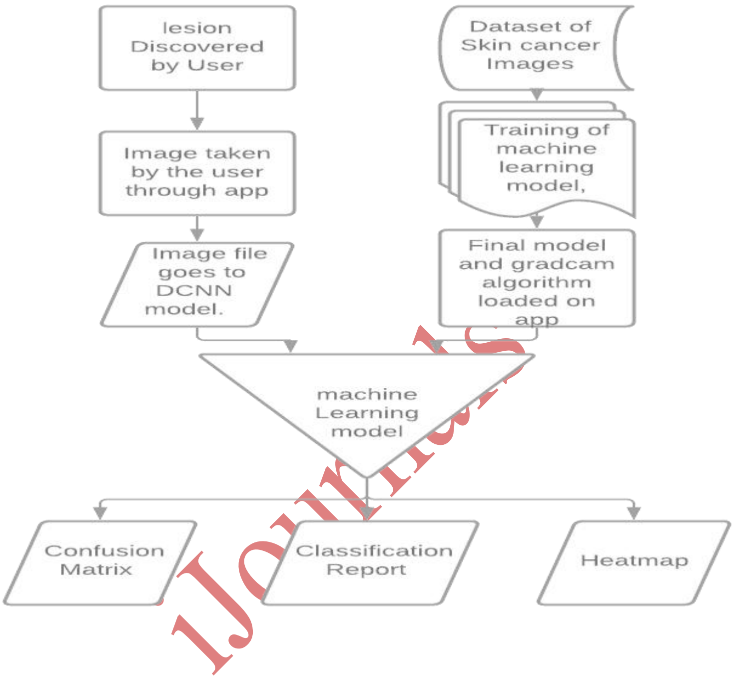
Once the Doctor has received the report and analysed it, they will give one of three diagnosis to the patient:

1) If the lesion is strongly Malignant - Biopsy is recommended
2) If the lesion is strongly Benign - Lesion is termed as safe and monitored for abnormal growth or disappearance over a period mentioned by the doctor
3) If the lesion's nature is suspicious (most frequent) - The doctor will request a further analysis from the patient using the pressure mapping kit

For further analysis, the patient uses a pressure mapping kit and applies it on the lesion, which delocalizes a Non-Newtonian Fluid. Using gradient localization methods we map gel density against pressure to create a 3D support's file which is convoluted with the 3D STL file generated by the lesion's top image to produce a single 3D flexible printing file, when printed by the doctor gives a flexible haptic model which provides accurate tactile feedback.

Working Principle

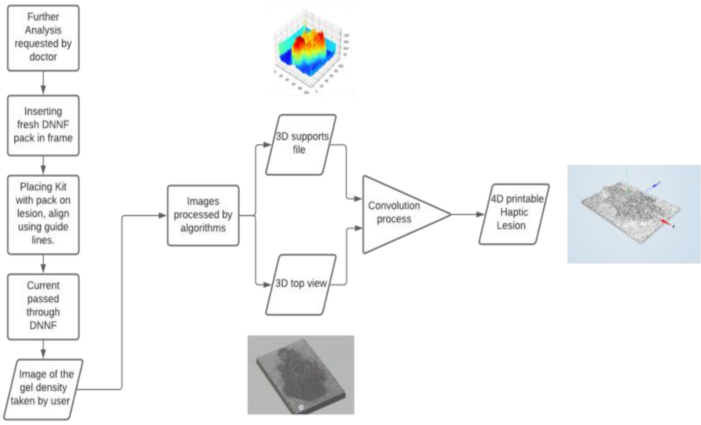
Process 1: Detection and Recognition of genital Skin Cancer using Deep Learning Model



Fig[D]: Working Principle of Machine Learning Model

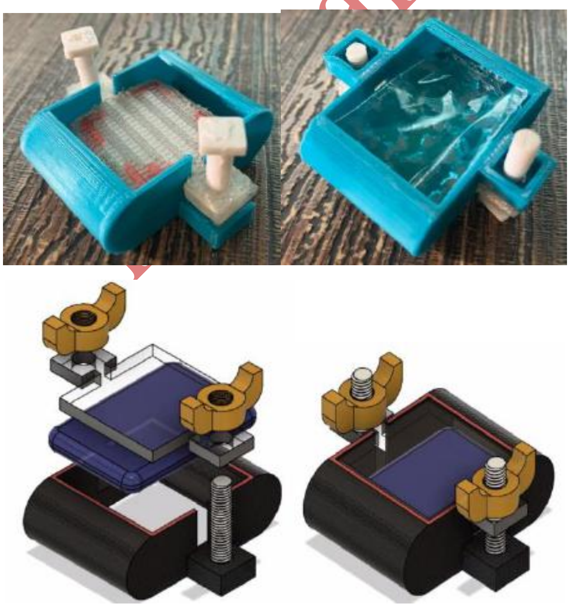
Upon discovering a suspicious spot or lesion, the patient takes an image of it through our application which will take the image and feed it into the machine learning/deep learning model. This model has been trained and tested with 5000 authentic images and an accuracy of 83%. Apart from this, there is a GradCam algorithm which converts the lesion into a heatmap to allow the doctor to visualise the textures of the skin. This algorithm and the deep learning model give 3 main outputs - Confusion Matrix, Classification Report and the Heatmap. The Classification report and the heatmap are sent to the doctor for analysis while the confusion matrix is for our analysis of the model, allowing us to monitor the False-Negatives and False Positives since higher values are dangerous for the patient and provide an area for improvement.

Process 2: Creating Haptic Flexible 3D Printable model of genital area.



Fig[E]: Working Principle of Creating Haptic 4D Flexible Model for genital area

The patient will have access to the pressure mapping kit either through stores or provided by the doctor. This kit will consist of a simple 30mm x 30mm device with replaceable gel packs at the bottom of the kit. These gel packs are made of Non-Newtonian Fluid which take the shape of the lesion when a small current is passed through it. The user takes the photo of the impression of the lesion on the gel pack through the transparent top of the 30mm x 30mm frame which has guidelines for more accurate photos.



Fig[F]: Method for generation of pressure map

The photo is passed through our algorithms and the gel density across the fluid is mapped with the gradient scale. This provides a 3D top view of the lesion and a 3D supports file. When the 3D top view and the 3D supports file are convoluted, a 3D Printable Flexible file is generated. When this file is printed either by the doctor or by an industrial printing service and then sent to the doctor, the final product is a 4D replica of the lesion since it matches a scaled version of the lesion while providing haptic feedback due to the supports and pressure mapping. This means, the doctor is able to analyse the nature of the lesion through tactile analysis which is very useful in cases where the lesions have clots or lumps underneath them, which are replicated in the 4D model of the lesion.

III. Machine Learning Algorithm

The DCNN needs many images for training and testing to accomplish high classification accuracy. This is a great hurdle especially with five types of skin cancer datasets where the number of available labelled images for training and testing is very limited specially because we need images in the genital region.

In this study we have created our own Keras Sequential model from the Tensorflow model. With Keras we have used numpy, cv2 and matplotlib libraries for data augmentation and representation in the model. The Convolutional neural network is trained with 3 main layers with 32, 64, 64 neurons per layer respectively. Note that the input and output layer are not being counted as Hidden layers. Due to the presence of so many layers the CNN has now become a Deep CNN. Throughout the layers activation function relu has been used and since the output classifies the images into 5 classes we have used activation function "softmax" and One-Hot Encoding for the output layer. While compiling the model the optimizer in this case is "rmsprop" since it fitted our use for image classification the best.

Using these parameters we are able to yield an accuracy of 83%. One of the other main factors leading to this accuracy is the use of 5000 authentic images, with 1000 images per class divided into a 4:1 train to test ratio. Along with this tuning hyperparameters to optimum levels such as higher epochs and lower batch rate reduced training time and loss for the sequential model.

IV. Haptic Model

4D Haptic model design consists of the following 3 processes.

1. *Scanning for to top layer of skin lesion*

We have used python 3.6.5_rc version along with numpy and img2stl along with opencv libraries to create the top layer of skin lesion, we have used matplotlib and PIL library to process and show output to users in the pictorial format. Firstly we took an image of the skin lesion. It will be converted into grayscale and cropped using the reference marker points. Based on grayscale we got the intercity of the specific pixel. When we reverse the intensity values (255 becomes 0 and 0 becomes 255) with that we can get data for top layer creation using intensity manipulation method.using the same process we can create a stl file for top layer of skin lesion.

2. *Scanning for Pressure points on skin lesion*

In this case, the image taken by the user of the gel density is fed into the same code for the top layer of the skin. However, instead of taking the intensity of the lesion, we are taking the intensity of the gel. Due to this, we are also not reversing the intensity values since a gel density of white shows the pressure is greater. We have used the same method to convert the raw data into STL files. With this method, our output data is the coordinate of the pixel and the estimated height of the pixel.

3. *Combining of 2 3D stl files*

Using Convolution we are combining 2 stl files of different sizes but of same dimensionality using image processing where operators are implemented and the output values of their pixels which are simple linear combinations of input pixel values are merged through array augmentation techniques. The main challenge was to map the supports with the 3D top view without overfitting the data or missing out support data. This was achieved by normalising both the data and comparing the values with each other for increased validation.

Mathematically we can write the convolution as:

$$O(i,j) = \sum_{k=1}^{m} \sum_{l=1}^{n} I(i+k-1, j+l-1)K(k,l)$$

where i runs from 1 to M - m + 1 and j runs from 1 to N - n + 1.

V. Advantages

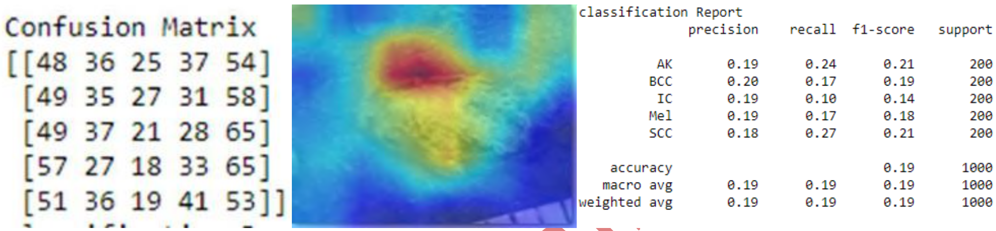
- 83% accurate report along with precise tactile feedback supports the hypothesis of aiding doctors in the decision of need of biopsy.
- The DCCN model can be trained with a dataset of other skin disorders such as dermatitis, skin warts, inflammatory skin disorders etc. and be used to produce a similar report for them.
- In cases such as breast cancer, the liquid glass putty pack and 3D printing techniques can be used by the patient to remotely assess their conditions without revealing their private parts and allowing for early detection and action.
- This method can be widely used to visually assess various skin disorders even in rare situations such as pandemics.

EARLIER SETBACKS	OUR PROJECTS FEATURES TO OVERCOME THEM
Biopsy was taken immediately after discovery of lesion	Helps doctors to decide the necessity of a biopsy
Biopsy is invasive, costly, time consuming, and can lead to infections	Non-invasive, cost-efficient, can be done from home, no danger at all
More than 80% people feel uncomfortable to show their genital areas to doctors	Screening process in control of user, doctor gets tactile feedback of genital region consisting of lesion only
Due to late reveal of lesions, cancer spread past treating stage	Patients can screen lesions immediately after discovering them, early detection

VI. Results and Conclusion

Overall, we achieved an accuracy of 83% for the Keras Sequential model. Class-wise Accuracy is as follows:

- Accuracy of Actinic Keratosis (AK): 75 %
- Accuracy of Basal Cell Carcinoma (BCC): 80 %
- Accuracy of Intraepidermal Squamous Carcinoma (ISC): 66 %
- Accuracy of Melanoma: 86 %
- Accuracy of Squamous cell carcinoma (SCC): 65 %
- Further to scrutinize the model accuracy, we can test metric values as follows:
- ❖ Sensitivity (TPR) = Tp/(Tp+Fn)
- ❖ Specificity (TNR)= Tn/(Fn+Tn)
- ❖ Precision (PPV) = Tp/(Tp+Fp)



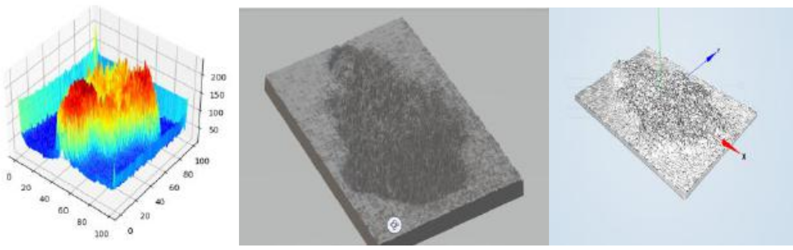
```
Confusion Matrix
[[48 36 25 37 54]
 [49 35 27 31 58]
 [49 37 21 28 65]
 [57 27 18 33 65]
 [51 36 19 41 53]]
```

classification Report

	precision	recall	f1-score	support
AK	0.19	0.24	0.21	200
BCC	0.20	0.17	0.19	200
IC	0.19	0.10	0.14	200
Mel	0.19	0.17	0.18	200
SCC	0.18	0.27	0.21	200
accuracy			0.19	1000
macro avg	0.19	0.19	0.19	1000
weighted avg	0.19	0.19	0.19	1000

Fig[G]: Results of Confusion Matrix, Heatmap and Classification Report

These values, along with the heat maps generated by Grad-CAM are used to give the final diagnosis about the skin lesions. While the Classification report and Heatmap are sent to the doctor for analysis the confusion matrix is analysed by us to monitor the false negatives and false positives. The False negatives in this case are the number of times the model predicts a Cancerous lesion as a non-cancerous lesion, which is extremely dangerous and puts the user's life in danger. Hence, we monitor this value per scan to analyse the threat to the patient and make the doctor aware of the chances of the prediction being wrong.



Fig[H]: Results of Support File, Top view, Final 3D print File

To conclude, we can safely say with an accuracy of 83% that the solution is very widely needed as it promotes early detection of genital skin cancer by eliminating the largest hurdle of privacy. By adapting to this solution users are not only able to be remotely diagnosed accurately, but it also increases awareness about genital skin cancer urging people to conduct self checks in those regions. Lastly, this also addresses one very important factor from the doctors

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perspective since they are now able to track the growth of the lesion both visually and through tactile measures through the haptic model since they can store models of the same lesion at different age to compare growth side by side, which was impossible to do earlier.

Acknowledgment

Dr. Palak Sheth, Dermatologist, London, helped us understand the characteristics and nature of genital skin cancer, as she is a pioneer in her field. We had several online meetings discussing progress of the solution and its effective impact on the dermatology field.

Dr. Neha Dalal, Dermatologist, India, helped us drive the need for a remote analysis and the importance of tactile feedback in the diagnosis of skin cancer.

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