Keenskin: An end-to-end system for skin lesion detection

CS503 Term Project

Under the guidance of Dr. Shweta Jain and Dr. Shashi S. Jha

By Jadhav Abhilasha S and Protyay Dey

Why did we choose this problem?

When the skin turns malignant

On World Cancer Day, we take a look at few celebs who battled with the disease

SWATI SHARMA

DECCAN CHRONICLE

First Lady Jill Biden underwent a procedure to remove cancerous lesions called Basal Cell Carcinoma. According to the American Academy of Dermatology, it is the most common type of cancer in the world. According to the White House, the lesions were discovered during a routine skin cancer screening.

"Skin cancer is one of the most common cancers in the Western world, and its prevalence is rising in India as well. Skin cancers typically develop from various types of skin cells and are classified as Basal Cell Carcinoma, Squamous Cell Carcinoma, and Melanomas based on the cell type. These cancers are more common in those with prolonged UV light exposure, and in people with fair skin. Skin cancer incidence is typically lower in people with dark skin," says **Dr Vamshi Krishna** M, Director of Medical oncology AIG Hospitals, adding, "Other risk factors include chemical exposure and radiation exposure."

Dr. Kishore B. Reddy

TREATMENT

"It is slow growing, and if treated early, it is curable, and causes minimal damage," says **Dr. Madhu Devarasetty,** Sr. Consultant Surgical Oncologist & Minimal Invasive Surgeon, KIMS Hospitals, adding, "The delicate facial skin around the eyes is especially vulnerable to sun damage."

"Mohs Micrographic Surgery is a technique in which one layer of tissue at the site of visible leison is removed at a time and checked under a microscope for the presence of cancer. This process is repeated until all cancerous tissue has been removed. It is frequently used to remove skin cancer from the face, fingers, or genitals in order to minimise disfigurement and functional loss," adds Dr Madhu.

TYPES OF SKIN CANCERS

An ulcer, a new mole, or a dark-coloured lesion are common manifestations of skin cancer.

"The various types of skin cancer are named after the cells that cause them, as well as their clinical behaviour. Basal Cell carcinoma (BCC), Squamous Cell Carcinoma (SCC) (collectively known as nonmelanocytic skin cancers (NMSC)), and malignant melanoma (MM) are the most common types," says Dr Madhu.

"NMSC is the most common type of human cancer. Each year, 2-3 million new cases are reported worldwide. In people with fair skin, BCCs account for 75% to 80% of non-melanoma skin cancers, while SCCs account for up to 25% Melanoma is caused by the malignant transformation of melanocytes. Melanoma is the most lethal form of skin cancer, followed by BCC and SCC," adds Dr Madhu.

SQUAMOUS CELL CARCINOMA

The skin is made up of two layers, called the epidermis and dermis. The epidermis is the upper portion, which is very thin and has five layers. The most common type of skin cancer is squamous cell carcinoma. This cancer originates in the base layer. People with fair skin are more likely to develop SCC though it can develop in the dark-skinned too. SCC frequently appears as a red firm bump, scaly patch, or a sore that heals and then reopens. SCC forms on skin that is frequently exposed to sunlight, such as the rim of the ear, face, neck, arms, chest, and back. SCC can cause damage and disfigurement by growing deep into the skin. Early detection and treatment can prevent SCC from spreading to other parts of the body, says **Dr. Kishore B. Reddy,** HOD orthopaedics and orthopaedic Oncology, Amor Hospital.

AMERICAN REALITY TELEVISION STAR KHLOE KARDASHIAN WAS FORCED TO UNDERGO SURGERY AFTER DISCOVERING A CANCEROUS MOLE. SHE DISCUSSED THE INCIDENT IN A POST ON HER APP AND WEBSITE IN 2016. "I'M WRITING THIS POST IN THE HOPE THAT MY STORY WILL PERSUADE SOME OF YOU TO SEE YOUR DOCTOR IF YOU NOTICE SOMETHING WRONG WITH YOUR SKIN," SHE EXPLAINED.

CANCEROUS MOLES

American reality television star Khloe Kardashian was forced to undergo surgery after discovering a cancerous mole. She discussed the incident in a post on her app and website in 2016. "I'm writing this post in the hope that my story will persuade some of you to see your doctor if you notice something wrong with your skin," she explained. Eight inches of skin had to be removed at the time. "It was definitely painful because there was so much skin... but most of the time, the removals weren't that bad," she explained.

Jill Biden

Hugh Jackman

Actor Terry Bradshaw

MERKEL CELL CARCINOMA

Actor Terry Bradshaw, the Hall of Fame quarterback, revealed during a Fox NFL Sunday broadcast in the fall of 2022 that he had battled skin cancer. Bradshaw discovered a tumour on his neck that turned out to be Merkel Cell Carcinoma, a rare type of skin cancer. He told the audience that he was "cancer free and feeling great" after treatment.

Dr Vamsi Krishna

MELANOMA

When *'Dancing with the Stars'* actor Witney Carson was diagnosed with melanoma, she was only 22 years old. Carson, whose father died of melanoma, has been outspoken about the importance of regular skin exams and early detection. "Melanoma is the most dangerous type of skin cancer that frequently appears in moles. Moles are common skin lesions that affect many people as they age. If there is a sudden change in the size, colour, or consistency of a mole, this could indicate that the mole has transformed into a cancer. Melanomas necessitate surgery. Depending on the size and location of the melanoma, the surgery will need to be micrographic, with a good margin taken around the melanoma. Because the likelihood of recurrence is high. Melanomas have a strong proclivity to spread to nearby organs, including the lymph nodes," says Dr Vamshi.

"We also provide a one-year course of immunotherapy, which has been shown to reduce the risk of the disease returning if the melanoma is advanced and has spread to other organs. Other medications, such as chemotherapy, are used. However, the efficacy of chemotherapy is decreasing, and immunotherapy is now the standard care. If the cancer is localised, it is usually treated with surgery, followed by immunotherapy," adds Dr Vamshi.

BASAL CELL CARCINOMA

Perhaps best known for his role as Wolverine in the X-Men films, Australian actor Hugh Jackman openly discussed his skin cancer battle with fans. In recent years, Jackman has had several cancerous portions of skin removed, and he frequently uses social media to remind his fans of the importance of sun protection and regular skin exams.

"Basal Cell Cancers are commonly found on the face of the elderly, especially around the nose and under the eyelid. This type of cancer can only be treated surgically. If it is recurrent or in multiple locations, radiotherapy can be used after surgery in some cases. Chemotherapy is usually not required for such malignancies. Carcinomas are typically found in sun-exposed areas or in areas where the skin has been damaged," says Dr Vamshi.

PROTECTION FROM SUN

- Look for shade between 10 a.m. and 4 p.m.
- Avoid tanning and getting sunburned.
- Protect skin with clothing, a hat, UV-blocking sunglasses, and sunscreen.
- Use sunscreen lotions (SPF 15, 30).
- If in doubt, seek a doctor's examination of your skin from head to toe.

TREATMENT OPTIONS

- Surgical Excision
- Radiation Therapy

"MOHS MICROGRAPHIC SURGERY IS A TECHNIQUE IN WHICH ONE LAYER OF TISSUE AT THE SITE OF VISIBLE LEISON IS REMOVED AT A TIME AND CHECKED UNDER A MICROSCOPE FOR THE PRESENCE OF CANCER. THIS PROCESS IS REPEATED UNTIL ALL CANCEROUS TISSUE HAS BEEN REMOVED. IT IS FREQUENTLY USED TO REMOVE SKIN CANCER FROM THE FACE, FINGERS, OR GENITALS IN ORDER TO MINIMISE DISFIGUREMENT AND FUNCTIONAL LOSS"

— **DR. MADHU DEVARASETTY,** *Sr. Consultant Surgical Oncologist & Minimal Invasive Surgeon, KIMS Hospitals*

Hugh Jackman reveals new skin cancer scare as he makes public plea

- **1 in 5 Americans** will develop skin cancer by the age of 70.
- **More than 2 people** die of skin cancer in the U.S. every hour.
- Having **5 or more sunburns** doubles your risk for melanoma.
- When detected early, the **5-year survival rate for melanoma is 99 percent.**

Source: https://www.skincancer.org/skin-cancer-information/skin-cancer-facts/

Key Statistics for Melanoma Skin Cancer

Cancer of the skin is by far the most common of all cancers. Melanoma accounts for only about 1% of skin cancers but causes a large majority of skin cancer deaths.

How common is melanoma?

The American Cancer Society's estimates for melanoma in the United States for 2023 are:

- About 97,610 new melanomas will be diagnosed (about 58,120 in men and 39,490 in women).
- About 7,990 people are expected to die of melanoma (about 5,420 men and 2,570 women).

The rates of melanoma have been rising rapidly over the past few decades, but this has varied by age. In adults ages 50 and older, rates continue to increase in women by about 1% per year from 2015 to 2019 but have stabilized in men.

Melanoma mortality rates declined rapidly over the past decade (2011 to 2020) because of advances in treatment, by about 5% per year in adults younger than age 50 and 3% per year in those 50 and older.

Source: https://www.cancer.org/cancer/melanoma-skin-cancer/about/key-statistics.html

Skin cancer sign: 21 year old's growing mole on collarbone turned out to be melanoma

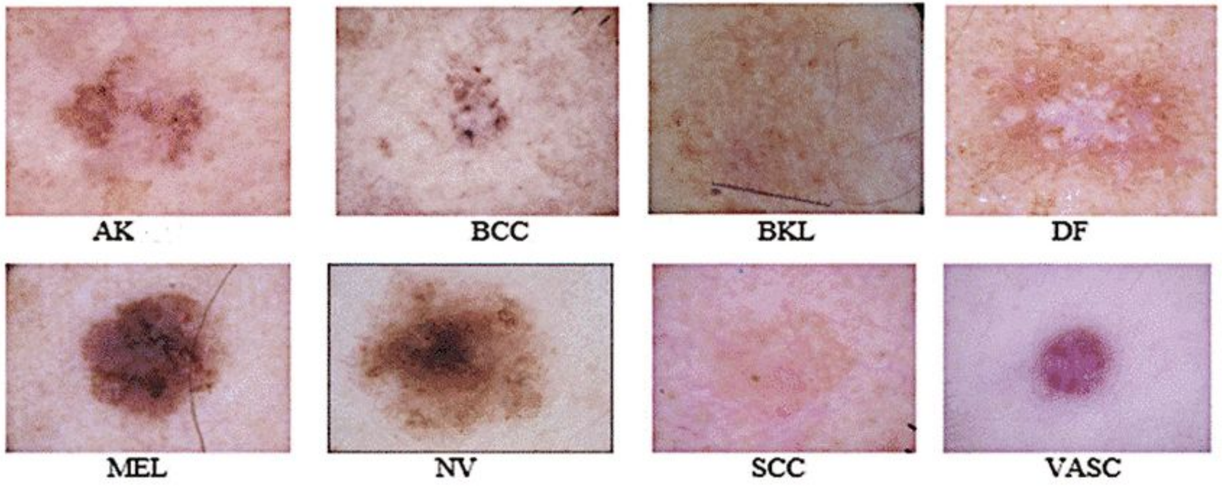
Images have been taken from google images

Motivation behind picking this project

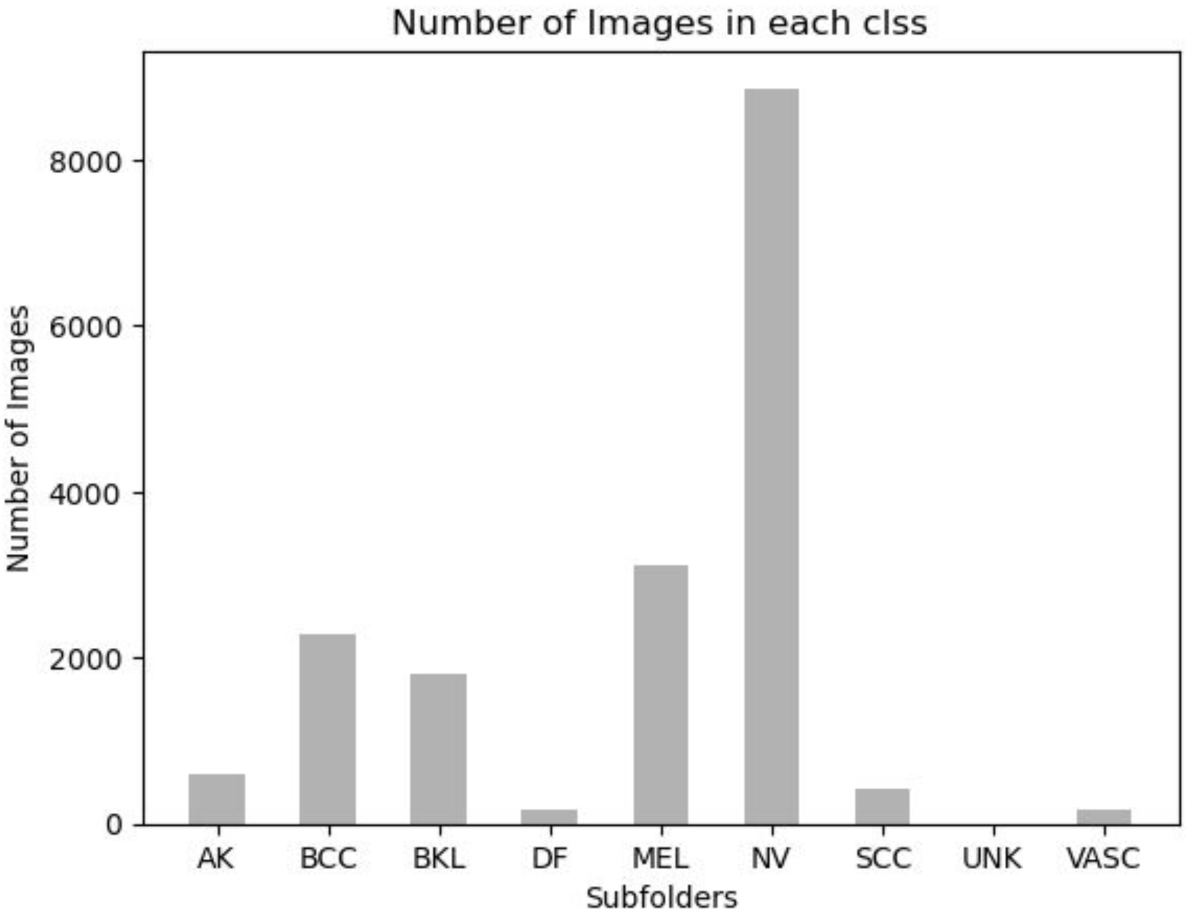
- Skin cancer is one of the most common types of cancer globally, with an estimated 2 to 3 million new cases being diagnosed each year. Early detection and diagnosis are crucial in treating skin cancer effectively and increasing the chances of survival.
- However, the traditional method of diagnosing skin cancer involves a visual examination by a dermatologist, which can be time-consuming and expensive. This is where an automated system like Keenskin can play a vital role in improving the detection and diagnosis of skin cancer.
- Keenskin can analyze images of skin lesions and accurately identify the presence of different types of skin cancer. This not only speeds up the diagnosis process but also makes it more accessible and affordable for patients. Additionally, an app like Keenskin has the potential to improve the accuracy of diagnoses, reducing the number of false positives and false negatives and improving patient outcomes.

Dataset

- ISIC 2019 : https://challenge.isic-archive.com/data/#2019
  - The dataset was compiled by the ISIC organization in collaboration with leading dermatologists and researchers from around the world. It includes images taken using a variety of imaging modalities, including clinical images, dermoscopy images, and images captured with smartphone cameras. The dataset also includes additional metadata such as patient demographics and lesion characteristics.



Dataset is highly imbalanced!



Rectification

We have use data augmentation which is provided by ImageDataGenerator library. It does image augmentation on the fly, so there is no need of storing the augmented images into the memory, providing us to actually augment huge image datasets and still train the model when the memory size is not that large. We have also used class weights so that the model is rewarded when it is correctly predicting the class which has less examples and penalized to moderate overfitting when it is correctly identifying those class examples which are more in number.

```
datagen = ImageDataGenerator(rescale=1./255)
```

```
train_generator = datagen.flow_from_directory(img_dir,
                                              target_size=(width, height),
                                              batch_size=batch_size,
                                              class_mode='categorical',
                                              shuffle=False)
```

```
Found 25345 images belonging to 9 classes.
```

```
class_weights = compute_class_weight('balanced',
                                      classes = np.unique(train_generator.classes),
                                      y = train_generator.classes)
```

```
class_dict = {}
for i, val in enumerate(class_weights):
    class_dict[i] = val
```

```
for key, value in class_dict.items():
    print("Class {}'s weight: {:.3f}".format(key, value))
```

```
Class 0's weight: 3.248
Class 1's weight: 0.847
Class 2's weight: 1.073
Class 3's weight: 11.783
Class 4's weight: 0.623
Class 5's weight: 0.219
Class 6's weight: 4.484
Class 7's weight: 201.151
Class 8's weight: 11.131
```

Data Split

Since the ground truth values of the test dataset was not provided, so we had to work only with 25331 images provided by ISIC 2019 challenge and 14 extra images were added into the model for the unknown or clean skin images. These 14 images were taken from shutterstock.

While splitting the images into train, test and validation, we chose 72.25:12.75:15 split ratio and stratified splitting was implemented so that each class has sufficient representatives in each split of the data.

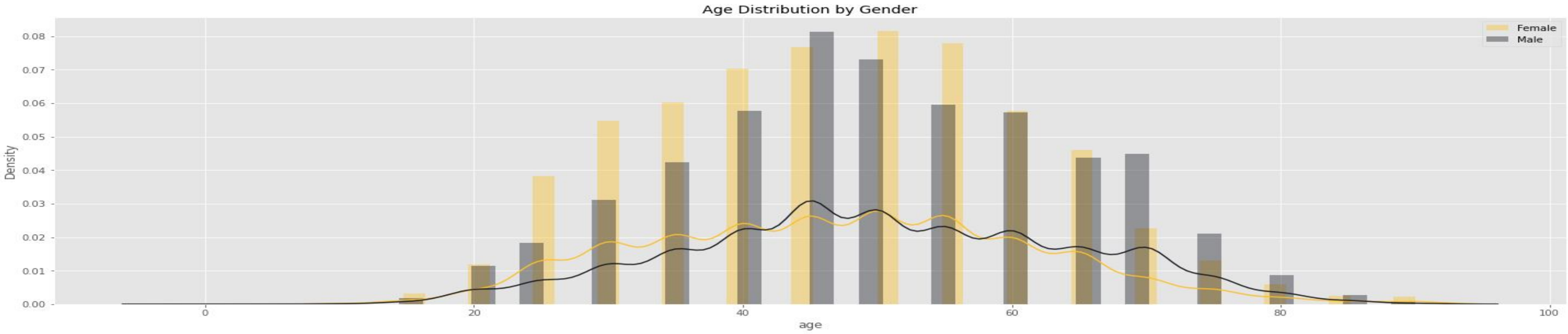
Data augmentation was also applied to both training and validation sets.

```
X_trainval, X_test, y_trainval, y_test = train_test_split(train_generator.filenames,
                                                          train_generator.classes,
                                                          test_size=0.15,
                                                          stratify=train_generator.classes,
                                                          random_state = 9)

X_train, X_val, y_train, y_val = train_test_split(X_trainval,
                                                  y_trainval,
                                                  test_size=0.15,
                                                  stratify=y_trainval,
                                                  random_state = 9)
```

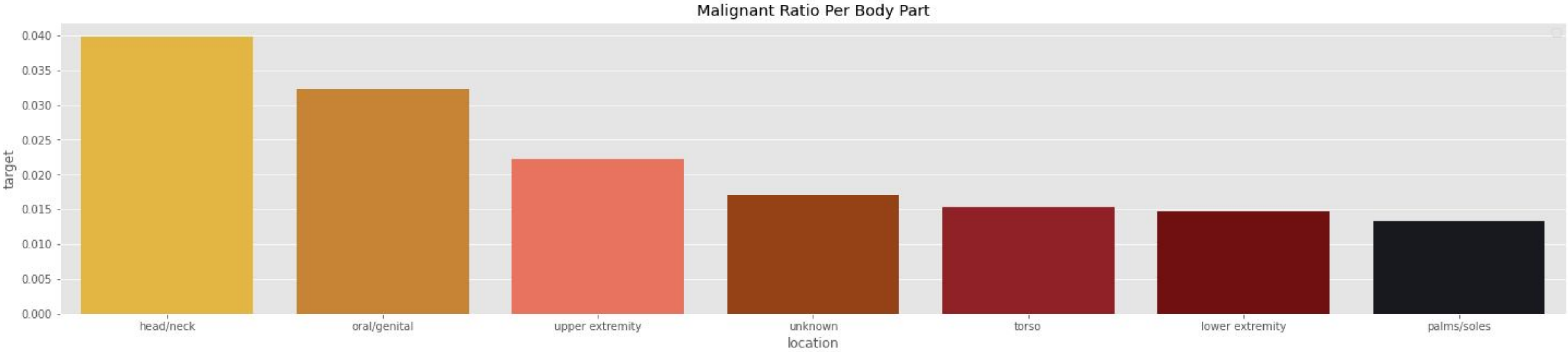
```
train_datagen = ImageDataGenerator(rescale=1./255,
                                   vertical_flip=True,
                                   horizontal_flip= True,
                                   rotation_range=180,
                                   width_shift_range=0.1,
                                   height_shift_range=0.1)
val_datagen = ImageDataGenerator(rescale=1./255,
                                 vertical_flip=True,
                                 horizontal_flip= True,
                                 rotation_range=180,
                                 width_shift_range=0.1,
                                 height_shift_range=0.1)
test_datagen = ImageDataGenerator(rescale=1./255)
```

General trends of the dataset

Age around 50 for males and age around 50-55 are the prime regions for cancer development. Also around the age of 70, male to female cancer ratio is quite high



General trends of the dataset



The head/neck region seems to be most common area for development of skin lesions

Evaluation Metrics used

Accuracy, Precision and Recall / Sensitivity

	Predicted Positive	Predicted Negative	
Actual Positive	TP *True Positive*	FN *False Negative*	Sensitivity $\frac{TP}{(TP+FN)}$
Actual Negative	FP *False Positive*	TN *True Negative*	Specificity $\frac{TN}{(TN+FP)}$
	Precision $\frac{TP}{(TP+FP)}$	Negative Predictive Value $\frac{TN}{(TN+FN)}$	Accuracy $\frac{TP+TN}{(TP+TN+FP+FN)}$

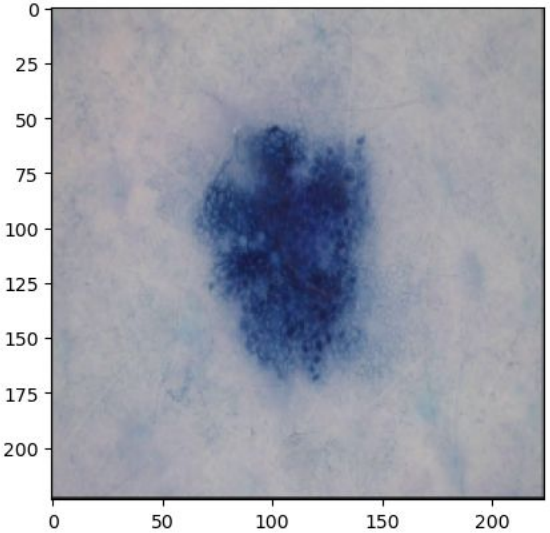
Source: https://medium.com/@danyal.wainstein1/understanding-the-confusion-matrix-b9bc45ba2679

F1-score

$$F1\ score = 2 * \frac{Precision\ * Recall}{Precision + Recall}$$

Source: https://towardsdatascience.com/the-f1-score-bec2bbc38aa6

Input



```
img = np.expand_dims(img, axis = 0)
test_datagen = ImageDataGenerator(rescale=1./255)
img = test_datagen.flow(img, shuffle=False).next()
```

Output

```
pred = model.predict(img, verbose = 0)
res = np.argmax(pred, axis = 1)
class_labels[res[0]]
✓ 0.2s

'NV'
```

KeenSkin Application

Steps followed in our approach

- Tried various image processing techniques to take out the features from the images.
- One such technique: Color Constancy
- Augmented Data on the fly to make the model more robust.
- Training over ~18000 images and validating over ~3200 images
- Tested the model over ~3800 images from 9 different classes.

Approaches tried

- First approach we tried was to use morphological operations on the images and to extract only the lesion part from the image using binary masking. (Made a UNet model to extract the mask).
- Made a XGBoost classifier to perform classification over 9 classes. (Dropped the idea since accuracy and AUC were ~85%)
- Made a novel architecture but due to computation limitations, could not fine tune and generalize it better for test images.

Model used

We used the power of transfer learning (VGG16 architecture) to perform the classification task.

Optimizer used: Adam(learning_rate=0.00004, beta_1=0.9, beta_2=0.999)

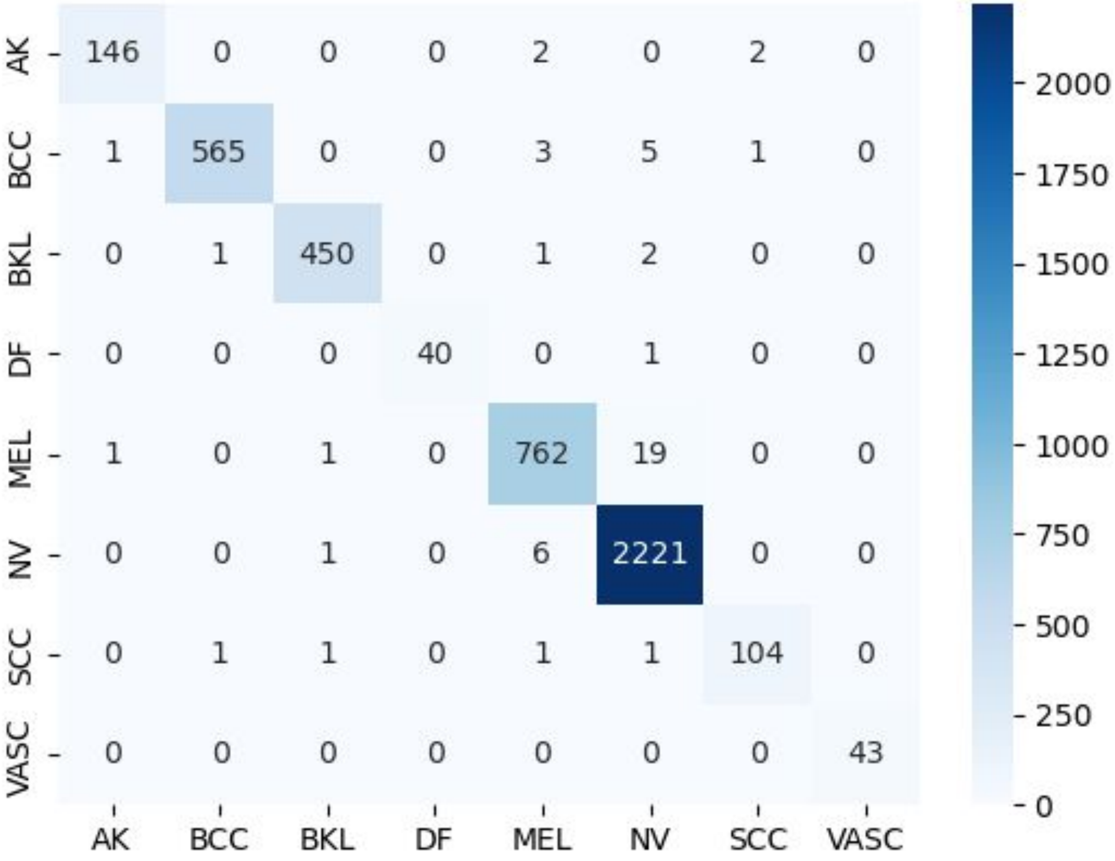
All the parameters were trained from scratch, only the architecture of VGG16 was used by dropping the last layer and we added a 9 output dense layer.

```
Model: model
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 image_input (InputLayer)    [(None, 224, 224, 3)]     0

 vgg16 (Functional)          (None, None, None, 512)   14714688

 flatten (Flatten)           (None, 25088)             0

 dense (Dense)               (None, 128)               3211392

 dense_1 (Dense)             (None, 9)                 1161

=================================================================
Total params: 17,927,241
Trainable params: 17,927,241
Non-trainable params: 0
_________________________________________________________________
```

Results for 8 class classification model on test data

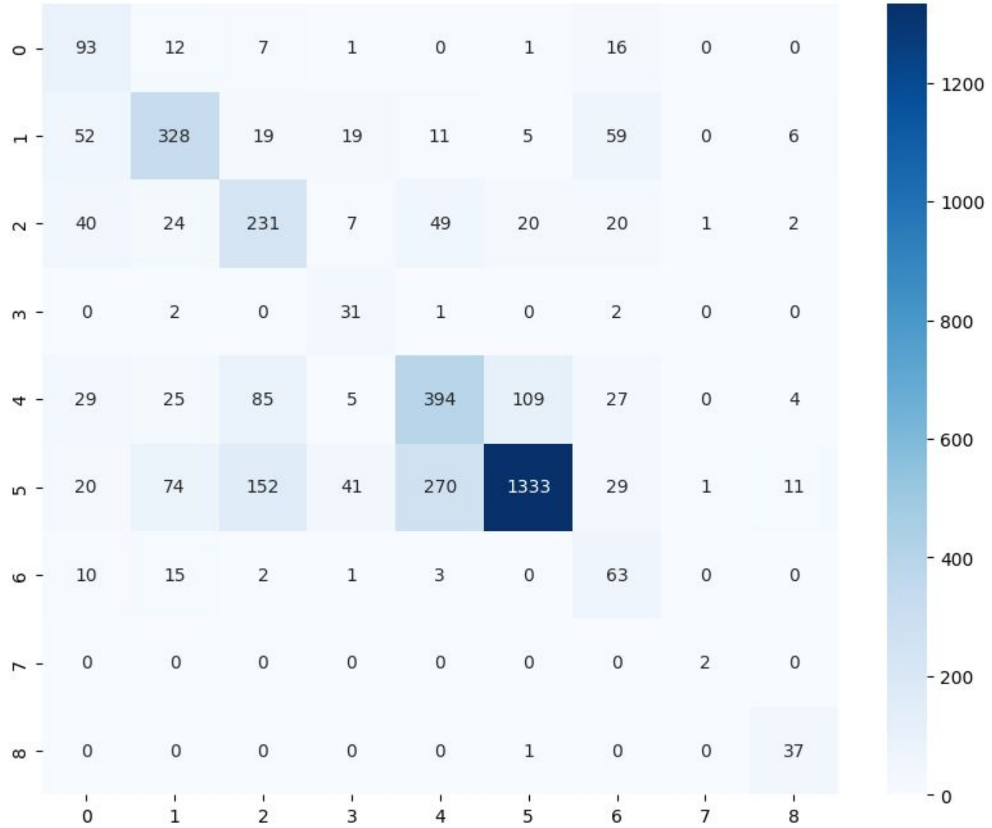
```
Accuracy  : 0.9883614787768142
Precision : 0.988370002364923
f1Score : 0.9883401000188734
```

```
% Correct Predictions by Class:
AK: 97.33%
BCC: 98.26%
BKL: 99.12%
DF: 97.56%
MEL: 97.32%
NV: 99.69%
SCC: 96.30%
VASC: 100.00%
```



Results for 9 class classification model on test data

Accuracy: 0.6607
Precision: 0.7248
Recall: 0.6607
F1-score: 0.6790
Weighted sensitivity: 0.6607
Weighted specificity: 0.9272
Balanced multiclass accuracy: 0.7484



Comparative Results

Literature	Algorithm Used	Balanced Multiclass Accuracy	F1-score	Recall	Precision (Average)	Weighted Specificity
Gessert et. al [8] - ISIC 2019 Winner	Ensemble of Multi-Res EfficientNets with Meta FC-NN	0.634	0.495	0.453	0.570	**0.983**
To Tat Dat et. al [19]	Voting several models	0.597	0.540	0.601	0.543	0.949
Pacheco A. et. al [6]	Best 3 models + hierarchical approach to select outliers + meta-data	0.56	0.492	0.511	0.54	0.961
Zhang P. et. al [15]	MelaNet: A Deep Dense Attention Network for Melanoma Detection in Dermoscopy Images and metadata	0.534	0.494	**0.708**	0.537	0.869
Seffi Cohen - ISIC Leaderboard rank 4	AAAR Appoach with meta data	0.541	0.503	0.464	0.552	0.964
Ours	VGG16 Architecture	**0.748**	**0.679**	0.660	**0.725**	0.927

Comparative Results

In the previous slide, all the results are obtained from the ISIC 2019 leaderboard. Every team has used some kind of ensemble to get the best model. Also the models they have used are very heavy and not suitable for mobile/web applications. Mostly they have used DenseNet or Efficient Nets or ResNeXt models which have more than 40 million parameters whereas VGG16 has only 17 million parameters and is not that heavy on GPU as compared to the above models.

Majority of them have created some form of ensemble model to get the best possible performance whereas we have only created a single model which gives the above mentioned results. If provided with further GPU and external data resources, we would also have created ensemble models to get even better performance.

Even with such a small model, the results are comparable to the winning solutions accepted at ISIC 2019 challenge.

Learnings :

1. Data preprocessing
2. Choosing the right architecture
3. Training and fine-tuning the model
4. Integration with a user interface
5. Application Development

source:https://www.dreamstime.com/stock-photo-ideas-thoughts-knowledge-intelligence-learning-meeting-concept-image47450085

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Thank You!