Final Project Deep Learning:

Skin Cancer Detection Using Convolutional Neural Network.

IBM Machine Learning Professional Certificate

Course 05: Deep Learning & Reinforcement Learning| Brain Tumors Detection

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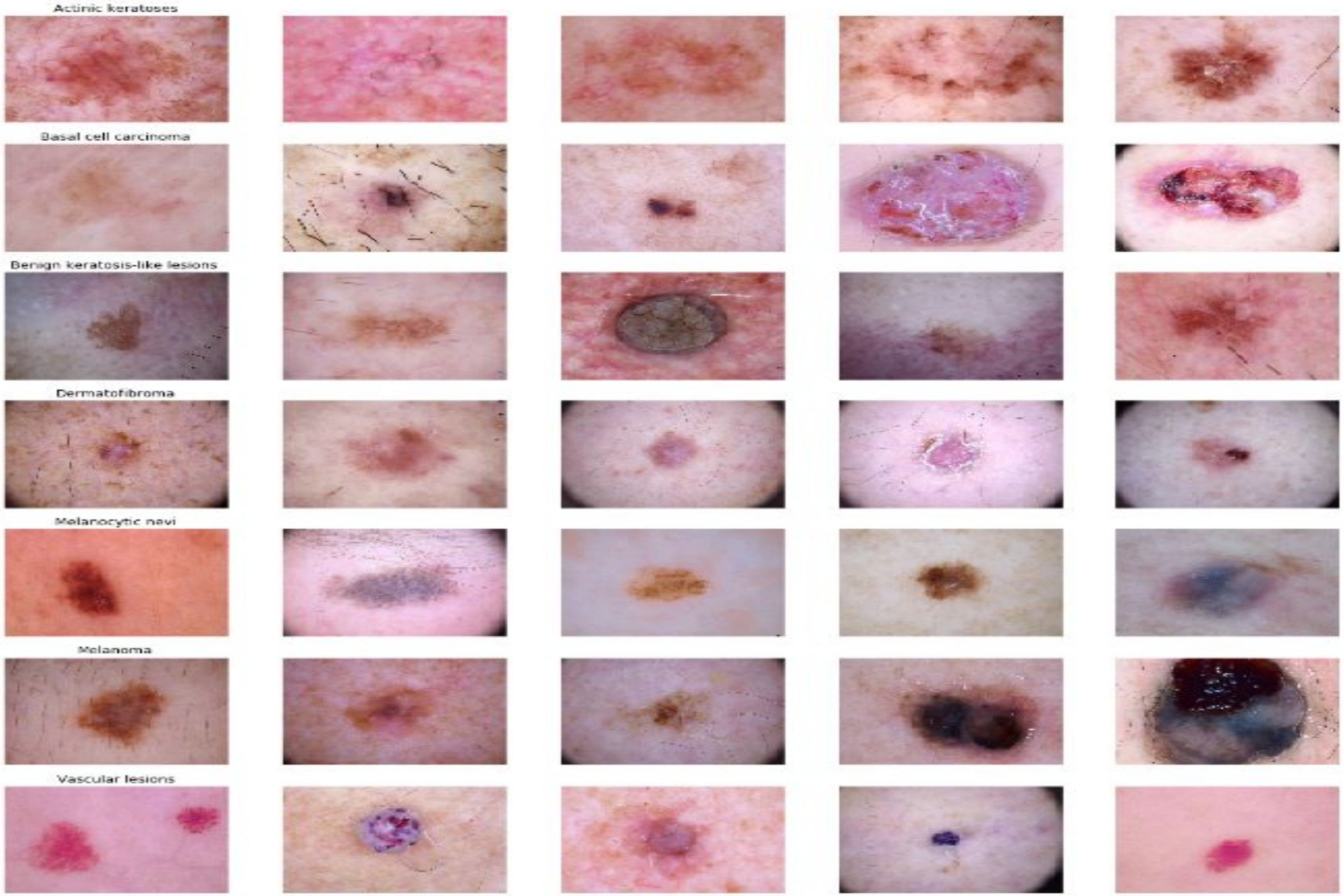
Data Description Section

Introduction

Skin cancer is the most common human malignancy, is primarily diagnosed visually, beginning with an initial clinical screening and followed potentially by dermoscopic analysis, a biopsy and histopathological examination. Automated classification of skin lesions using images is a challenging task owing to the fine-grained variability in the appearance of skin lesions.

This the HAM10000 ("Human Against Machine with 10000 training images") dataset.It consists of 10015 dermatoscopic images which are released as a training set for academic machine learning purposes and are publicly available through the ISIC archive. This benchmark dataset can be used for machine learning and for comparisons with human experts.

Dataset Description



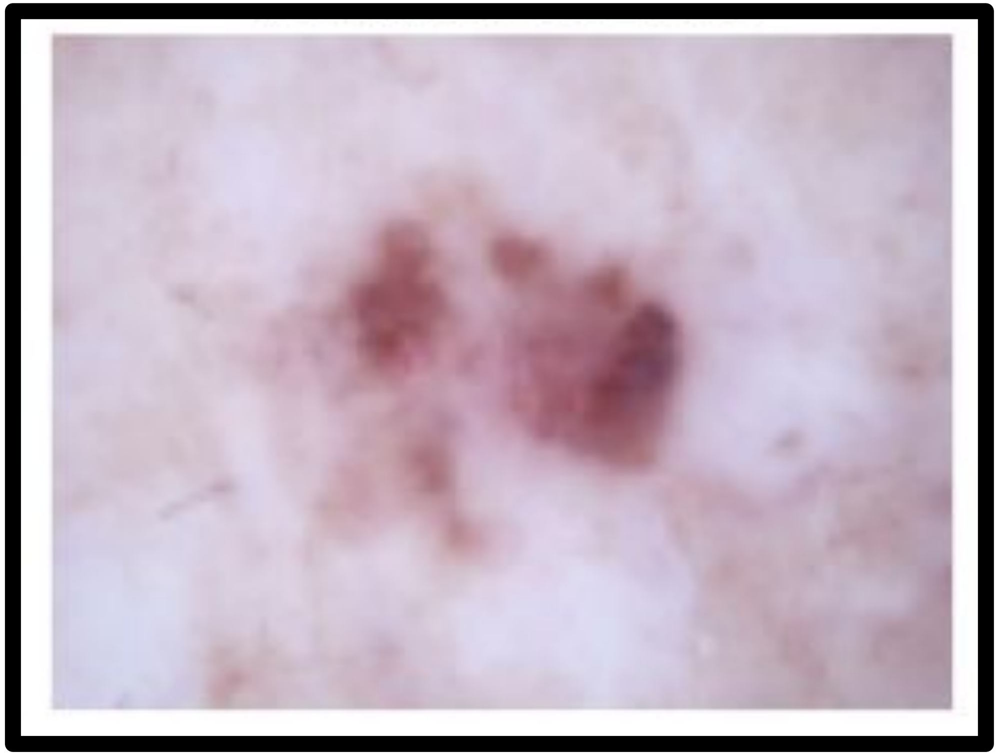
Main Objective of the analysis:

To demonstrate the effectiveness and potential of Convolutional Neural Networks (CNNs) in the early and accurate detection of skin cancer, showcasing their ability to analyze medical images with high precision and sensitivity, ultimately aiding dermatologists in providing timely and improved patient care.

Exploratory Data Analysis (EDA) + Feature Engineering Section

Exploratory Data Analysis

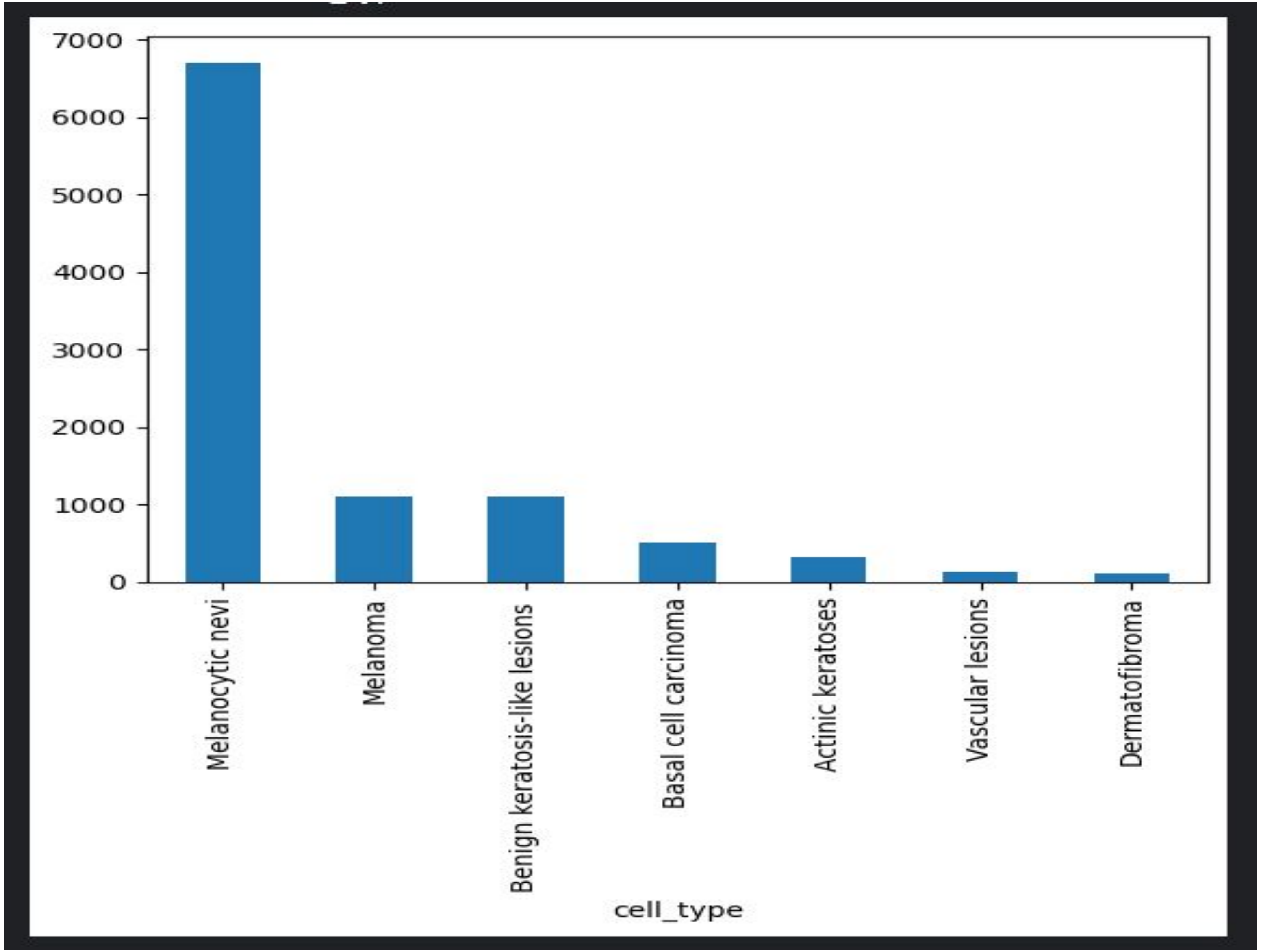
- **Images type : JPG**
- **Dimensions : (width, height, 3)**
- **Image sample: “ISIC_0031633.jpg”**
  - **(75,100,3)**



Exploratory Data Analysis

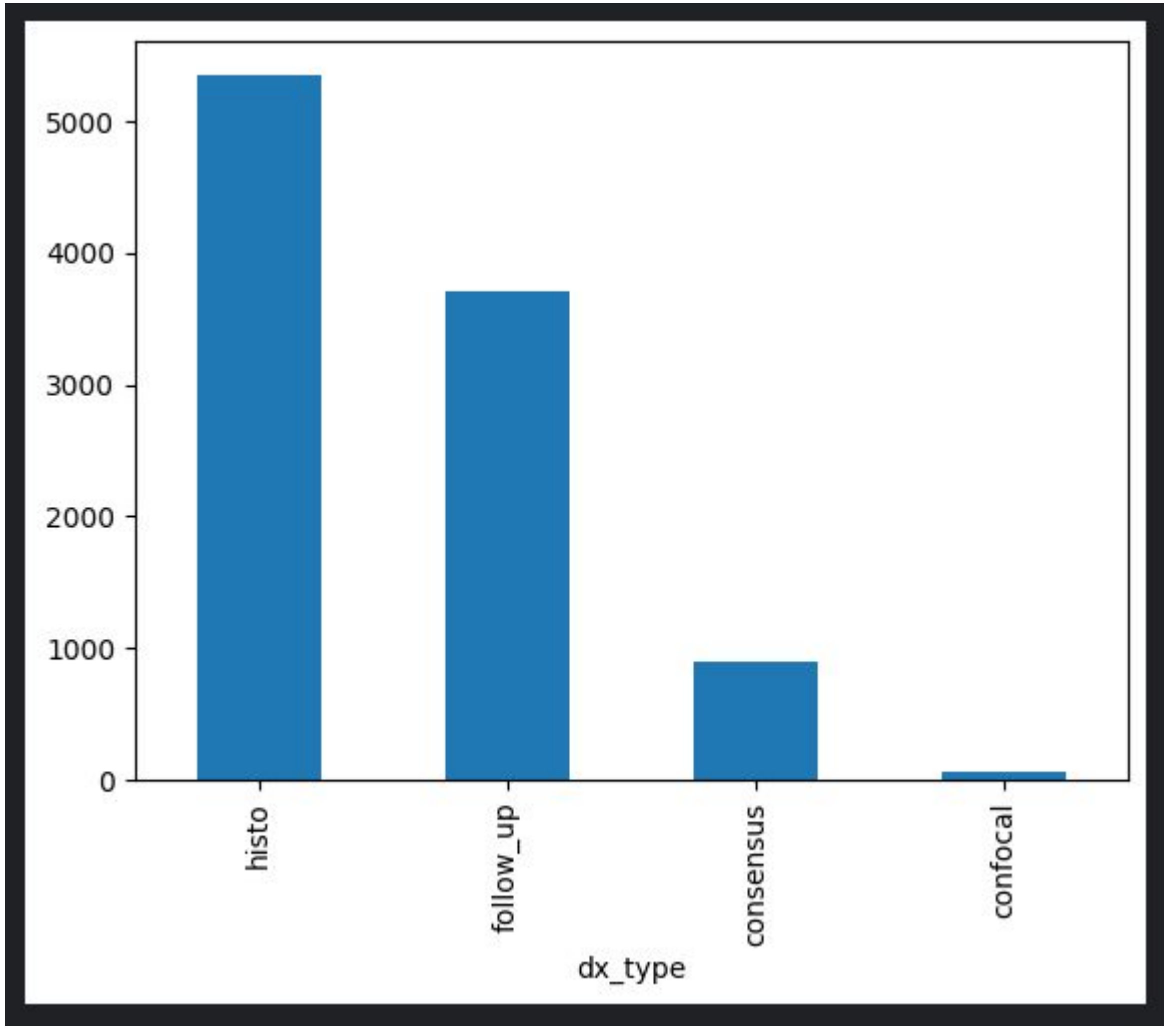
- **Melanocytic nevi:** Commonly known as moles, these are benign tumors or growths composed of melanocytes, the cells that produce pigment in the skin.
- **Melanoma:** A type of skin cancer that develops from melanocytes. It is the most serious form of skin cancer and can spread to other parts of the body if not detected and treated early.
- **Benign keratosis-like lesions:** These are non-cancerous skin growths that often appear as rough, scaly patches on the skin. They are typically harmless but can sometimes be confused with more serious conditions.
- **Basal cell carcinoma:** The most common form of skin cancer, basal cell carcinoma affects the basal cells, which are found in the outer layer of the skin. It is usually slow-growing and rarely spreads to other parts of the body.
- **Actinic keratoses:** Also known as solar keratoses, these are pre-cancerous growths that develop on sun-exposed areas of the skin. They can progress to squamous cell carcinoma if left untreated.
- **Vascular lesions:** These are abnormalities of the blood vessels in the skin, which can manifest as birthmarks, hemangiomas, or other vascular tumors. Most vascular lesions are benign but may require treatment if they cause symptoms or cosmetic concerns.
- **Dermatofibroma:** A benign skin growth that often appears as a small, firm bump on the skin. Dermatofibromas are usually harmless but can sometimes be confused with other skin conditions.

Exploratory Data Analysis

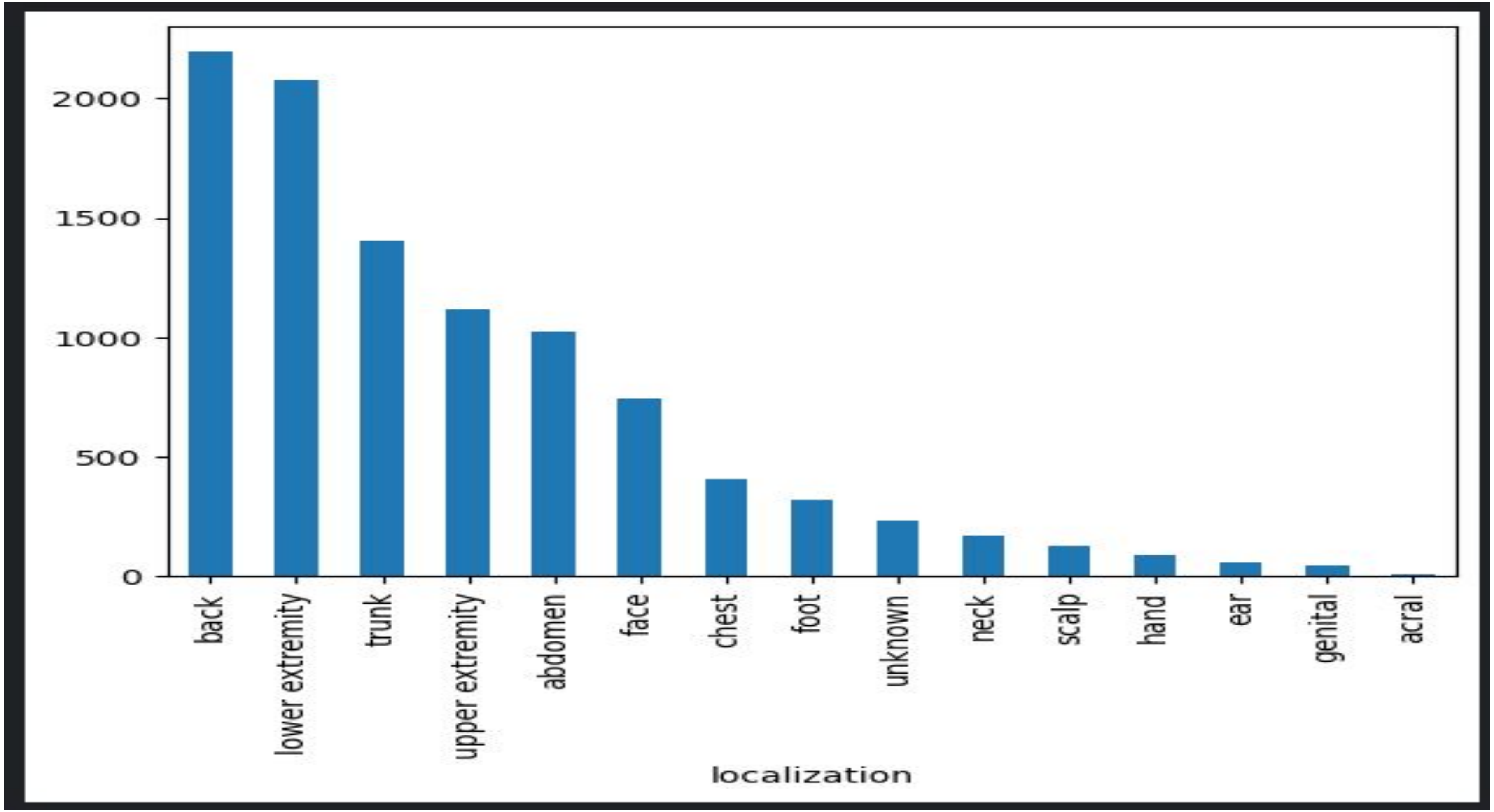


Exploratory Data Analysis

- **Histopathology(Histo):** Histopathologic diagnoses of excised lesions have been performed by specialized dermatopathologists.
- **Confocal:** Reflectance confocal microscopy is an in-vivo imaging technique with a resolution at near-cellular level , and some facial benign with a grey-world assumption of all training-set images in Lab-color space before and after manual histogram changes.
- **Follow-up:** If nevi monitored by digital dermoscopy did not show any changes during 3 follow-up visits or 1.5 years biologists accepted this as evidence of biologic benignity. Only nevi, but no other benign diagnoses were labeled with this type of ground-truth because dermatologists usually do not monitor dermatofibromas, seborrheic keratoses, or vascular lesions.
- **Consensus:** For typical benign cases without histopathology or followup biologists provide an expert-consensus rating of authors PT and HK. They applied the consensus label only if both authors independently gave the same unequivocal benign diagnosis. Lesions with this type of ground truth were usually photographed for educational reasons and did not need further follow-up or biopsy for confirmation.

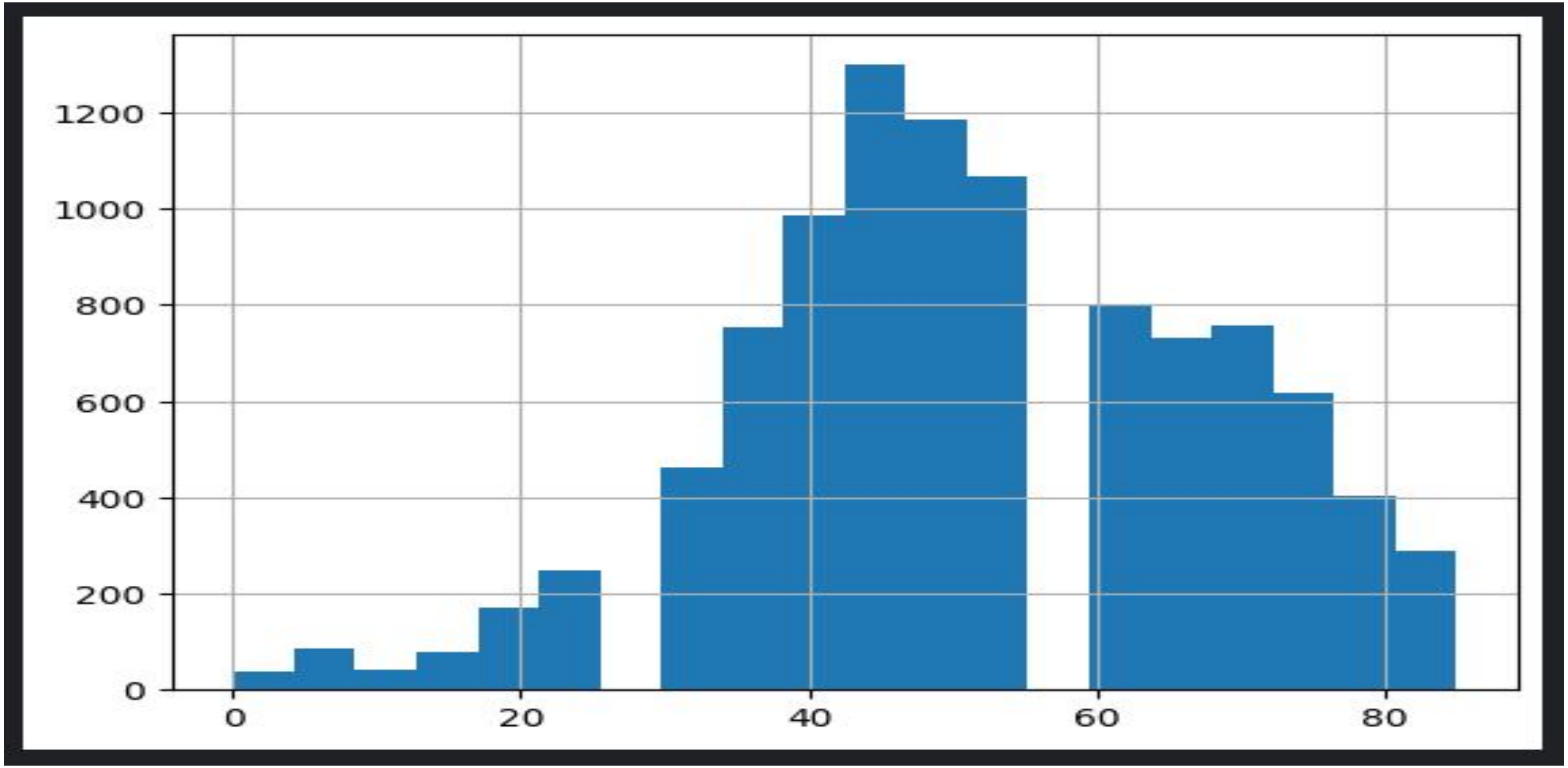


Exploratory Data Analysis



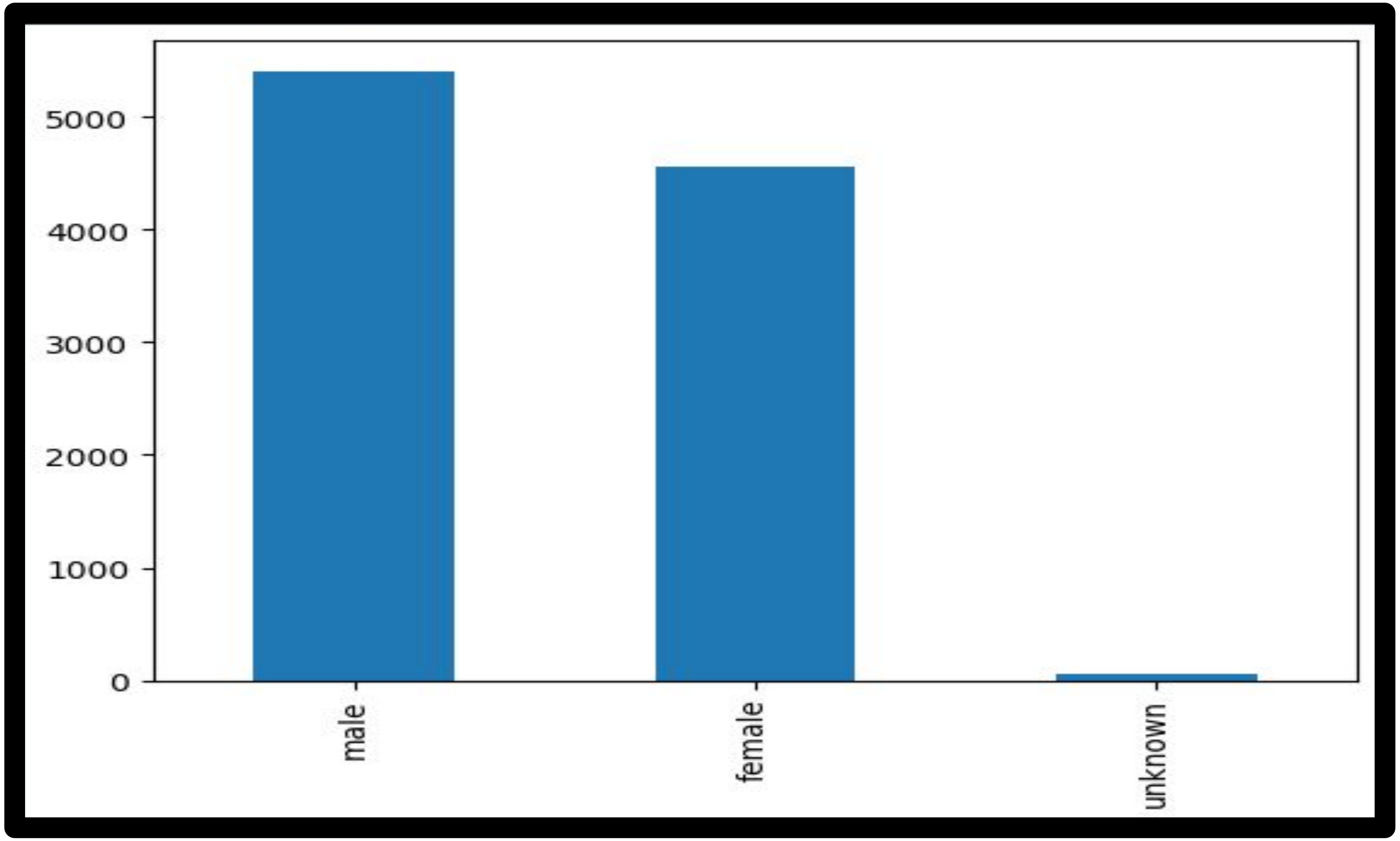
Localization

Exploratory Data Analysis



Age

Exploratory Data Analysis



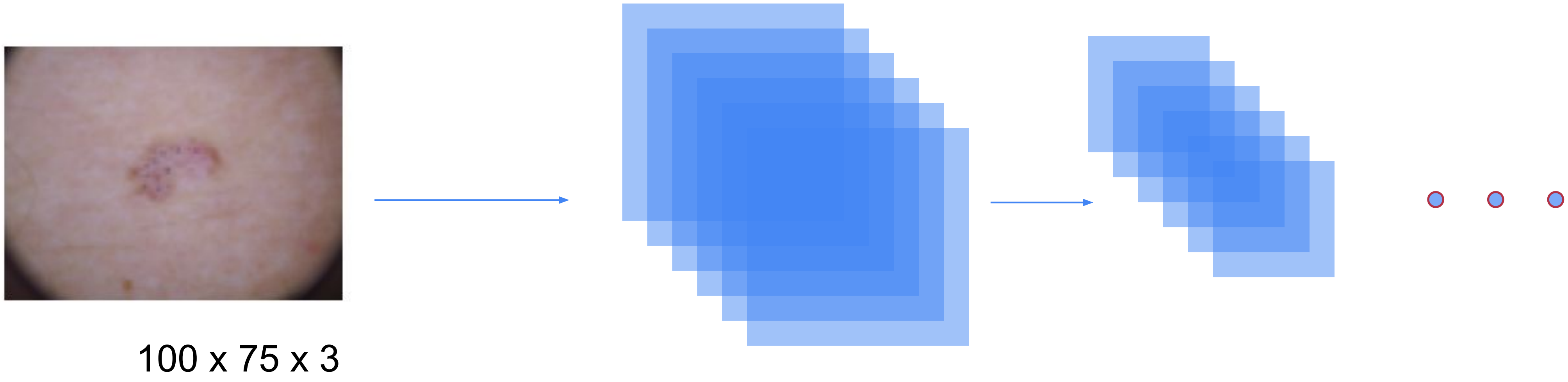
Sex

Feature Engineering

Images Resizing

Since we have images with different dimensions, we must uniform all the dimensions due to the architecture of deep learning models :

- Input shape = 64 pixels
- After reshaping every image, we store them in a NumPy array

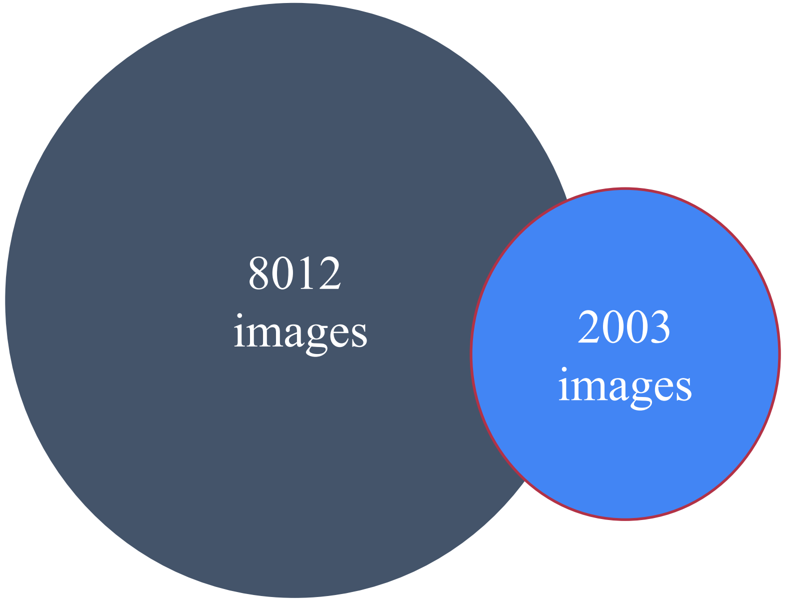


Feature Engineering

Dataset Splitting

As we mentioned before in this presentation, we have in total 3000 images from this point we are going to split these images into two sets 80% for training set and 20% testing set

- Training set: 8012 images
- Testing set: 2003 images



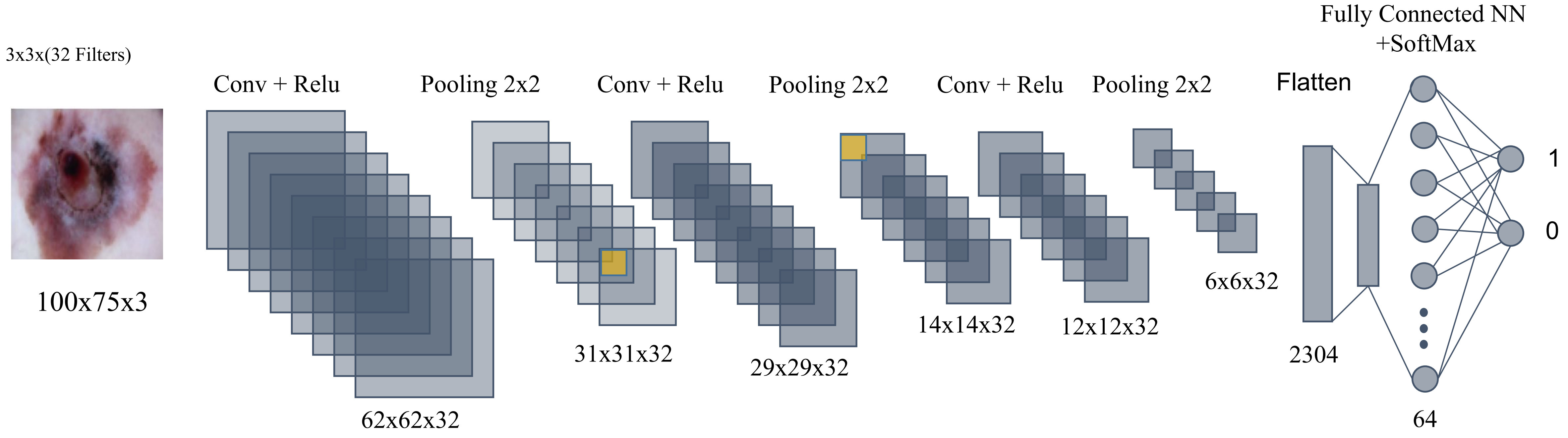
Machine Learning Analysis & Findings

Machine Learning Analysis & Findings

In the following slides we will compare between 2 different convolutional neural networks (CNN) one is based on Categorical Cross Entropy and SoftMax function for the final prediction layer.

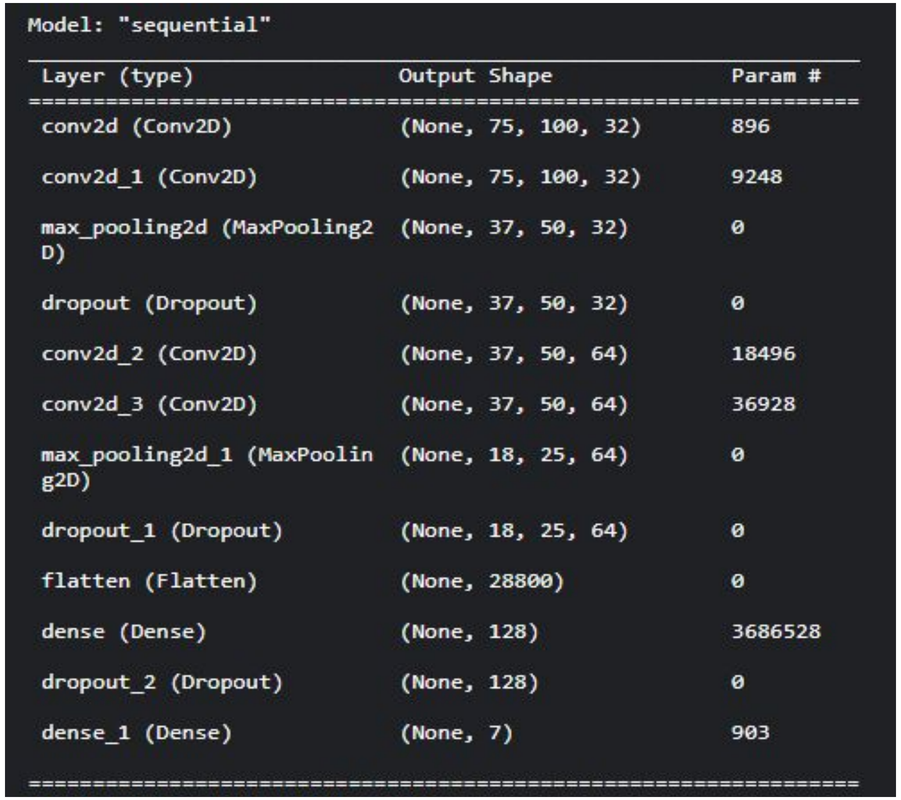
These two models aim to classify dermatoscopic images to distinguish between the images that contain cancerous lesion and those that don’t , for the sake of helping doctors in the diagnostic processes in the healthcare sector.

Machine Learning Analysis



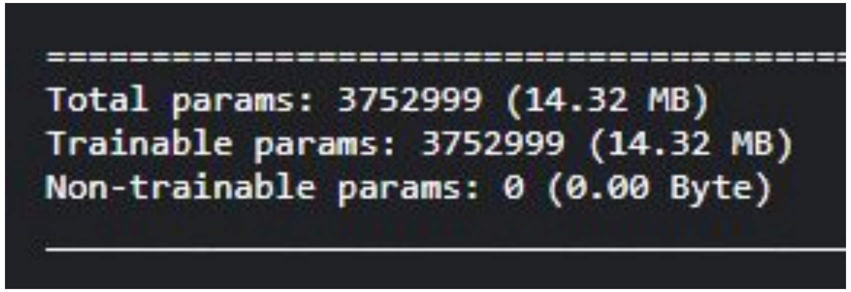
Machine Learning Analysis

Model: CNN Binary Cross Entropy Based & SoftMax Function.



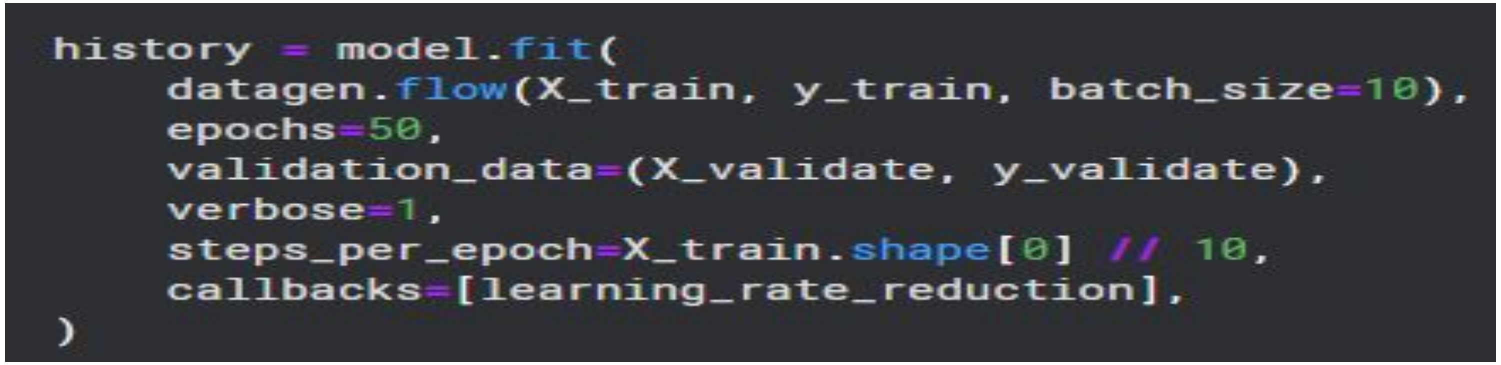
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 75, 100, 32)       896

 conv2d_1 (Conv2D)           (None, 75, 100, 32)       9248

 max_pooling2d (MaxPooling2  (None, 37, 50, 32)        0
 D)

 dropout (Dropout)           (None, 37, 50, 32)        0

 conv2d_2 (Conv2D)           (None, 37, 50, 64)        18496

 conv2d_3 (Conv2D)           (None, 37, 50, 64)        36928

 max_pooling2d_1 (MaxPoolin  (None, 18, 25, 64)        0
 g2D)

 dropout_1 (Dropout)         (None, 18, 25, 64)        0

 flatten (Flatten)           (None, 28800)             0

 dense (Dense)               (None, 128)               3686528

 dropout_2 (Dropout)         (None, 128)               0

 dense_1 (Dense)             (None, 7)                 903

=================================================================
```

Model architecture & total number of parameters

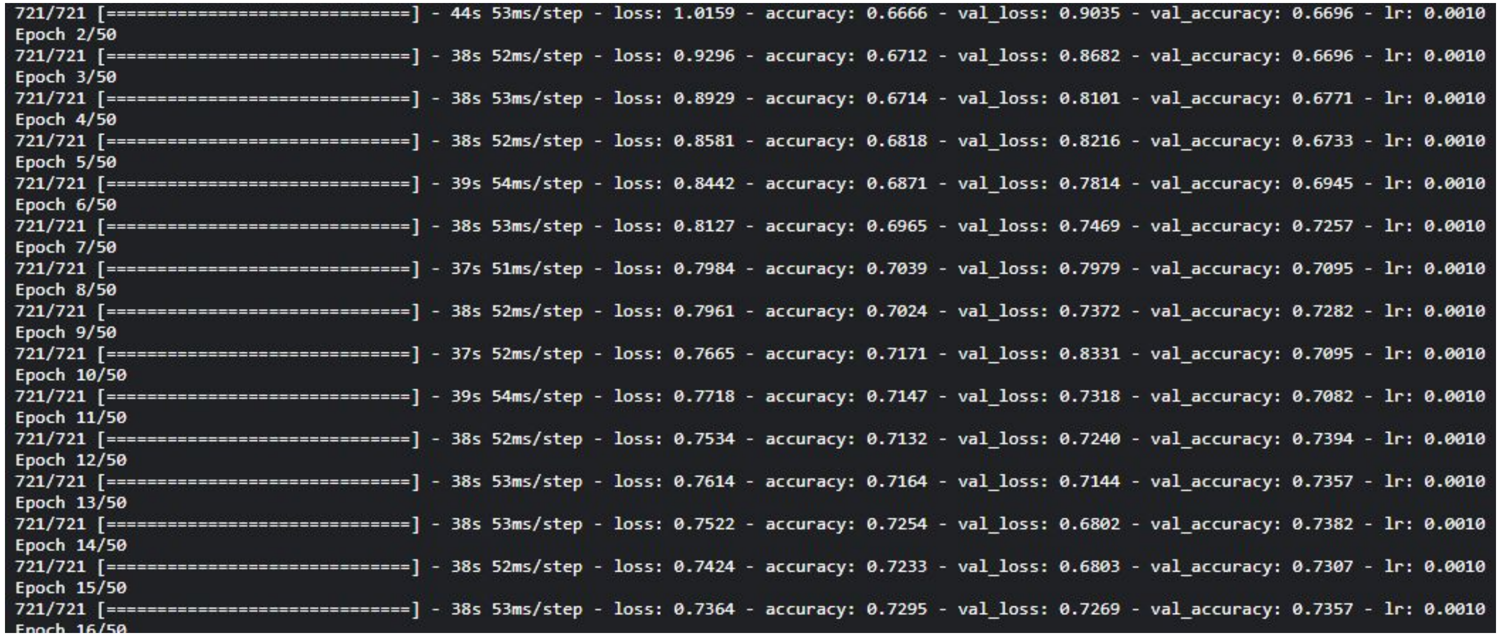


```
=========================================
Total params: 3752999 (14.32 MB)
Trainable params: 3752999 (14.32 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________
```

Machine Learning Findings

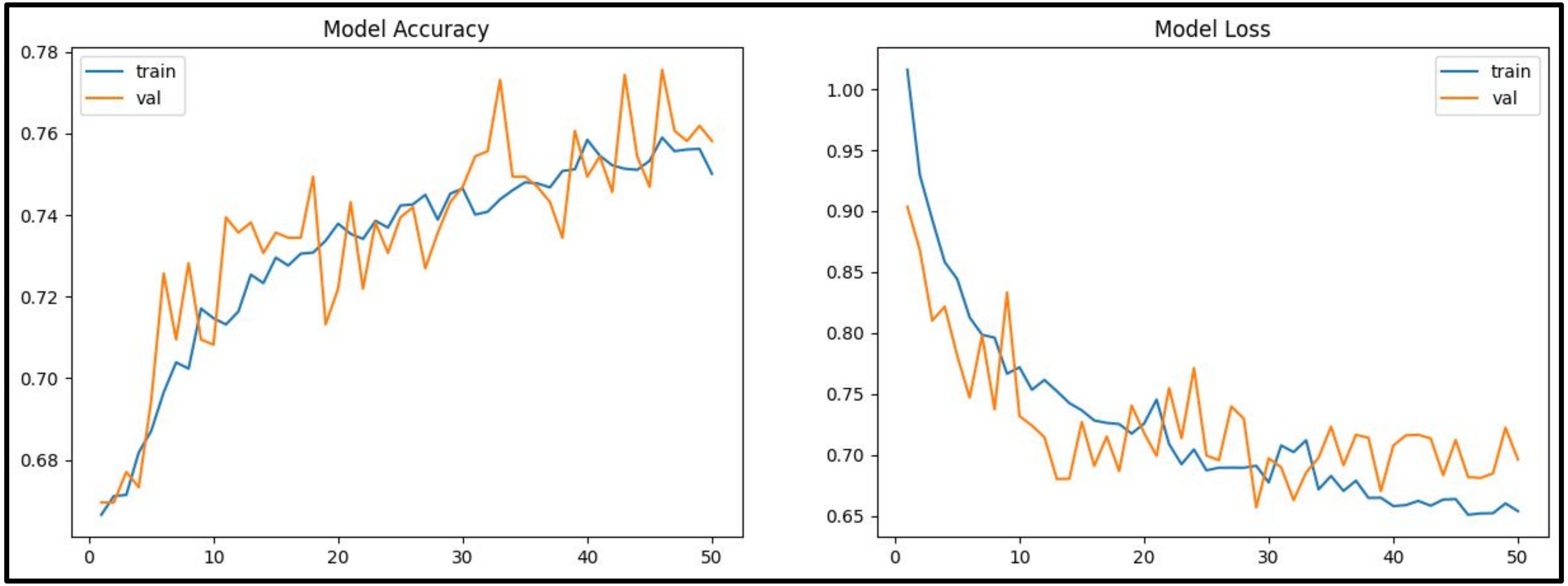


```
history = model.fit(
    datagen.flow(X_train, y_train, batch_size=10),
    epochs=50,
    validation_data=(X_validate, y_validate),
    verbose=1,
    steps_per_epoch=X_train.shape[0] // 10,
    callbacks=[learning_rate_reduction],
)
```



```
721/721 [==============================] - 44s 53ms/step - loss: 1.0159 - accuracy: 0.6666 - val_loss: 0.9035 - val_accuracy: 0.6696 - lr: 0.0010
Epoch 2/50
721/721 [==============================] - 38s 52ms/step - loss: 0.9296 - accuracy: 0.6712 - val_loss: 0.8682 - val_accuracy: 0.6696 - lr: 0.0010
Epoch 3/50
721/721 [==============================] - 38s 53ms/step - loss: 0.8929 - accuracy: 0.6714 - val_loss: 0.8101 - val_accuracy: 0.6771 - lr: 0.0010
Epoch 4/50
721/721 [==============================] - 38s 52ms/step - loss: 0.8581 - accuracy: 0.6818 - val_loss: 0.8216 - val_accuracy: 0.6733 - lr: 0.0010
Epoch 5/50
721/721 [==============================] - 39s 54ms/step - loss: 0.8442 - accuracy: 0.6871 - val_loss: 0.7814 - val_accuracy: 0.6945 - lr: 0.0010
Epoch 6/50
721/721 [==============================] - 38s 53ms/step - loss: 0.8127 - accuracy: 0.6965 - val_loss: 0.7469 - val_accuracy: 0.7257 - lr: 0.0010
Epoch 7/50
721/721 [==============================] - 37s 51ms/step - loss: 0.7984 - accuracy: 0.7039 - val_loss: 0.7979 - val_accuracy: 0.7095 - lr: 0.0010
Epoch 8/50
721/721 [==============================] - 38s 52ms/step - loss: 0.7961 - accuracy: 0.7024 - val_loss: 0.7372 - val_accuracy: 0.7282 - lr: 0.0010
Epoch 9/50
721/721 [==============================] - 37s 52ms/step - loss: 0.7665 - accuracy: 0.7171 - val_loss: 0.8331 - val_accuracy: 0.7095 - lr: 0.0010
Epoch 10/50
721/721 [==============================] - 39s 54ms/step - loss: 0.7718 - accuracy: 0.7147 - val_loss: 0.7318 - val_accuracy: 0.7082 - lr: 0.0010
Epoch 11/50
721/721 [==============================] - 38s 52ms/step - loss: 0.7534 - accuracy: 0.7132 - val_loss: 0.7240 - val_accuracy: 0.7394 - lr: 0.0010
Epoch 12/50
721/721 [==============================] - 38s 53ms/step - loss: 0.7614 - accuracy: 0.7164 - val_loss: 0.7144 - val_accuracy: 0.7357 - lr: 0.0010
Epoch 13/50
721/721 [==============================] - 38s 53ms/step - loss: 0.7522 - accuracy: 0.7254 - val_loss: 0.6802 - val_accuracy: 0.7382 - lr: 0.0010
Epoch 14/50
721/721 [==============================] - 38s 52ms/step - loss: 0.7424 - accuracy: 0.7233 - val_loss: 0.6803 - val_accuracy: 0.7307 - lr: 0.0010
Epoch 15/50
721/721 [==============================] - 38s 53ms/step - loss: 0.7364 - accuracy: 0.7295 - val_loss: 0.7269 - val_accuracy: 0.7357 - lr: 0.0010
Epoch 16/50
```

Machine Learning Findings



Set	Accuracy	Losses
Training	75.01 %	0.6537
Validation	75.81 %	0.6962

Models flaws and strengths and advanced steps

Models' strengths

Models Strengths:

The model which is based on Categorical Cross Entropy as loss function and SoftMax for final prediction layer was not that accurate where it is achieved 75.01% on the training set and 75.81% on the validation set. We can also further tune our model to easily achieve the accuracy above 80% and I think still this model is efficient in comparison to detection with human eyes having 77.0344% accuracy.

Thank you

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Deep Learning and Reinforcement Learning

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