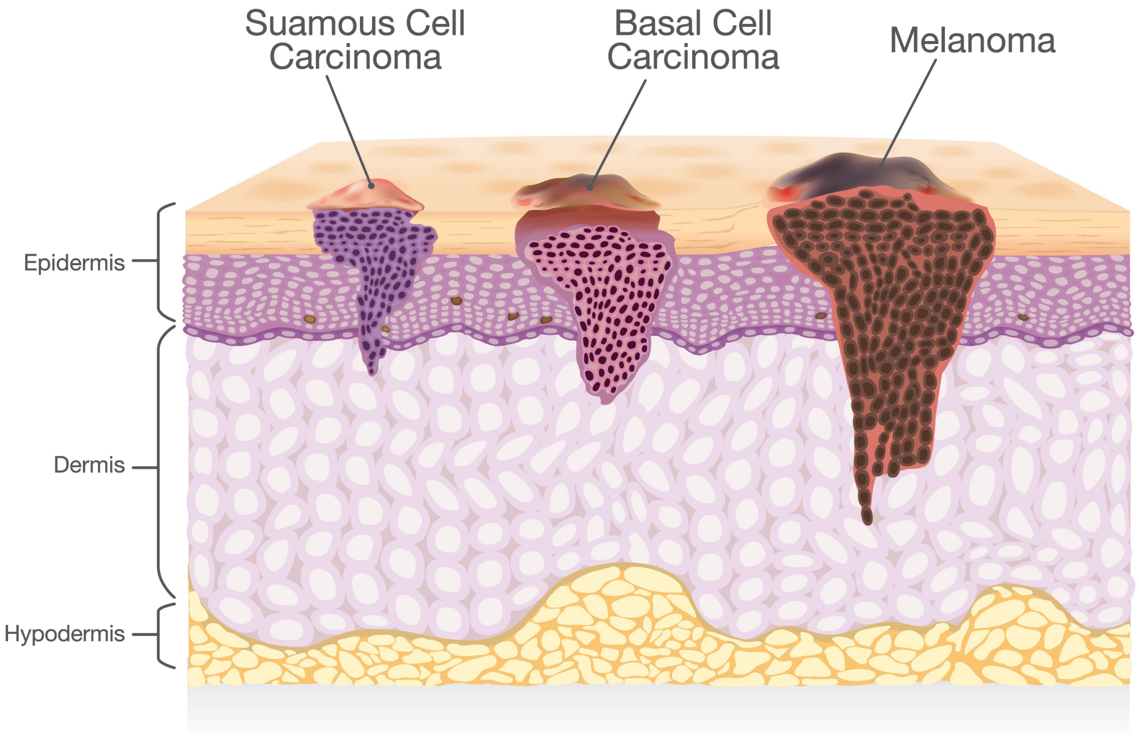
W251 Final Project: Skin Cancer Detection

Computer Vision and Deep Learning Techniques

By: Aditya Bajaj, Gerrit Lensink, Rohit Srinivas, Ruby Han

Introduction

"Skin cancer is the most commonly diagnosed cancer in the United States, and most cases are preventable"



Depicts cancer cell type growth on human skin

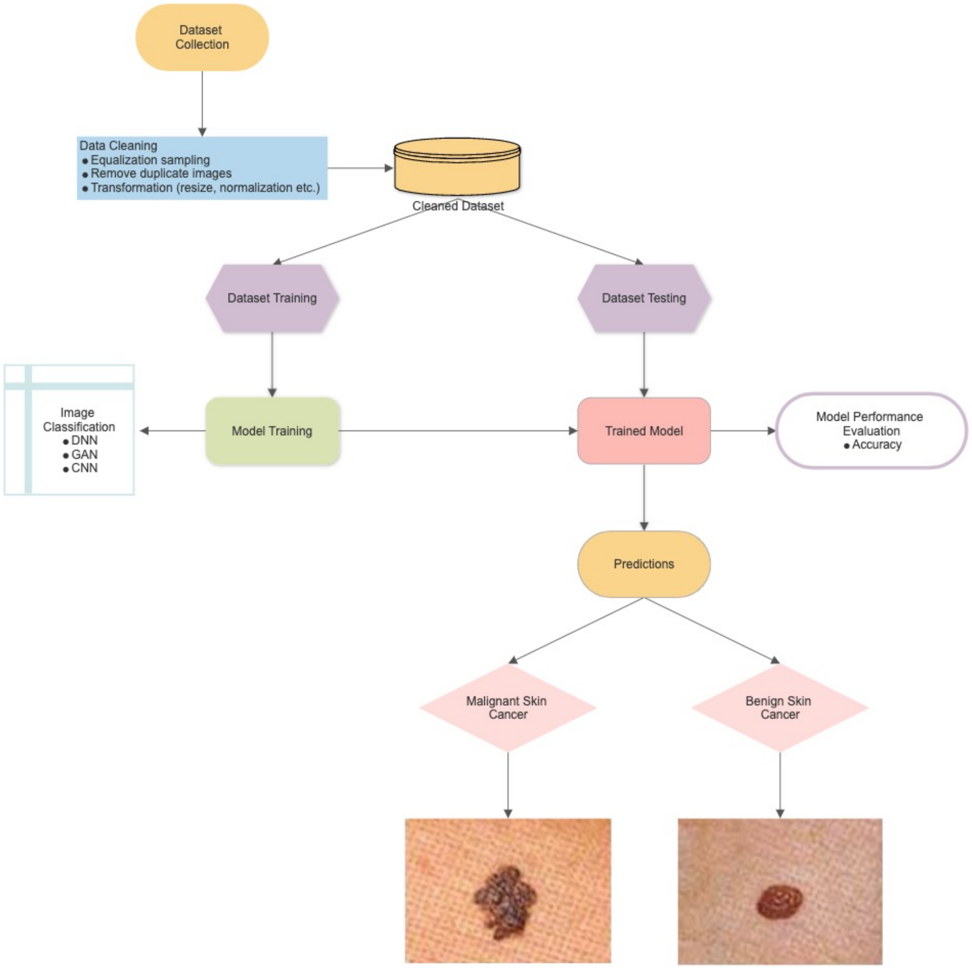
Motivation:

- Skin cancer greatly affects quality of life, and it can be disfiguring or even deadly.
- The number of Americans who have had skin cancer at some point in the last three decades is estimated to be higher than the number for all other cancers combined, and skin cancer incidence rates have continued to increase in recent years.
- Each year in the United States, nearly 5 million people are treated for all skin cancers combined, with an annual cost estimated at $8.1 billion.
- Despite efforts to address skin cancer risk factors, such as inadequate sun protection and intentional tanning behaviors, skin cancer rates, including rates of melanoma, have continued to increase in the United States and worldwide.
- Melanoma is responsible for the most deaths of all skin cancers, with nearly 9,000 people dying from it each year.

Goal

Our aim is to introduce an automated system which will be able to detect skin disease class in dermoscopic images in this paper.

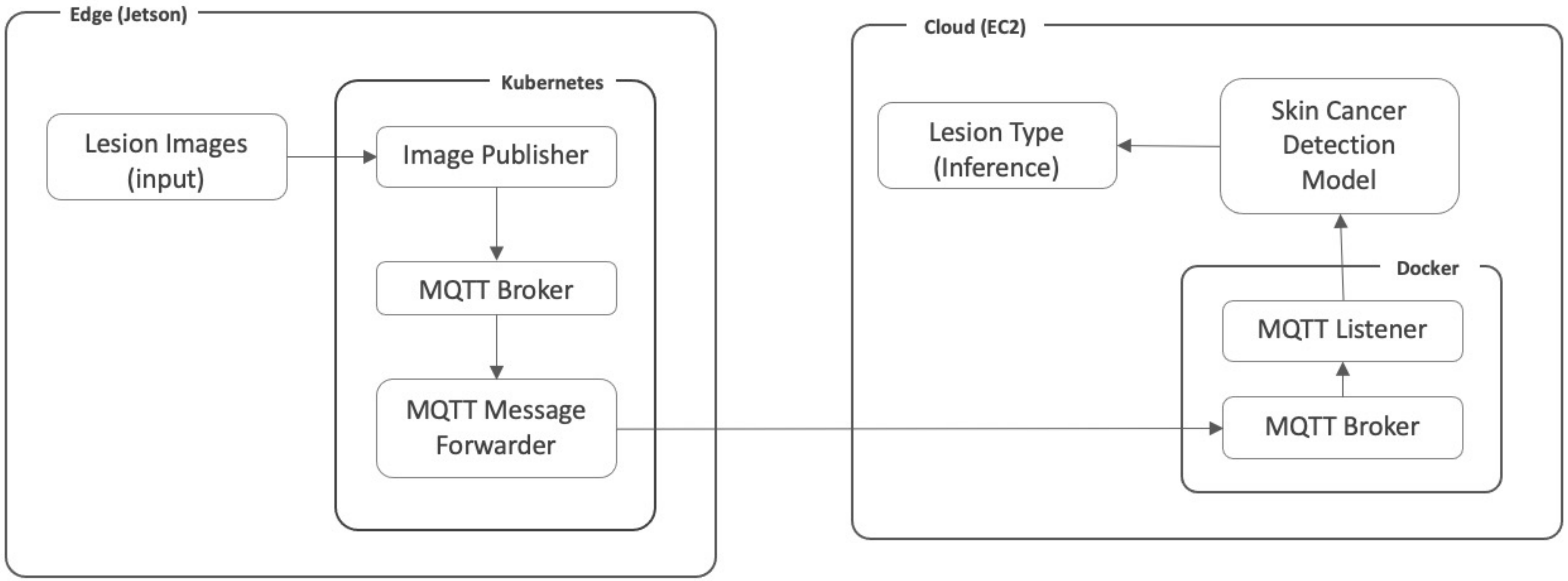
The assignment was defined by International Skin Imaging Collaboration (ISIC) with the purpose of improving melanoma detection. We utilized computer vision and deep learning modelling techniques through transfer learning by considering the imbalanced data in each class of the dataset.



Pipeline

Our work seeks to expand on pre-existing skin cancer detection models by creating an end-to-end pipeline which receives user photos as input on an edge device and returns lesion type from a model deployed in the cloud.

We create this system by passing user images from a Jetson Nano 4GB to our lesion-classification model, trained and deployed in the cloud

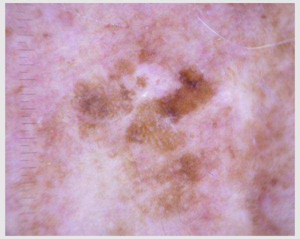


Pipeline: End to End pipeline built to capture images from edge, and processing all the way in the cloud

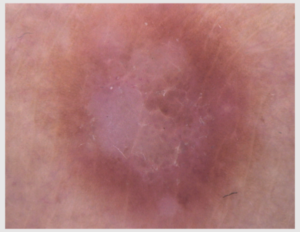
Dataset

benign

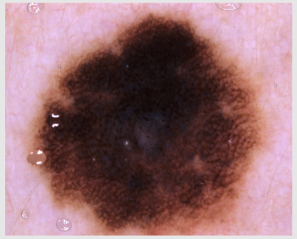
Benign keratosis-like lesions



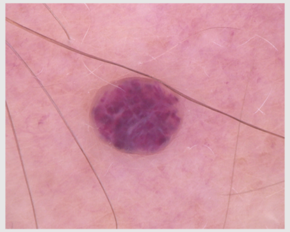
Dermatofibroma



Melanocytic nevi

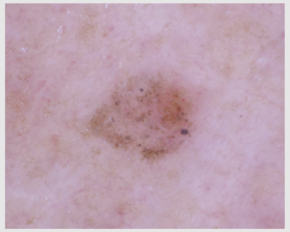


Vascular lesions

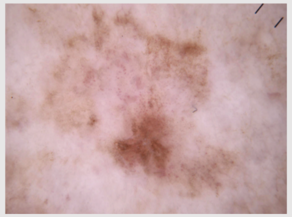


malignant

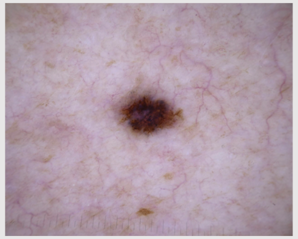
Basal cell carcinoma



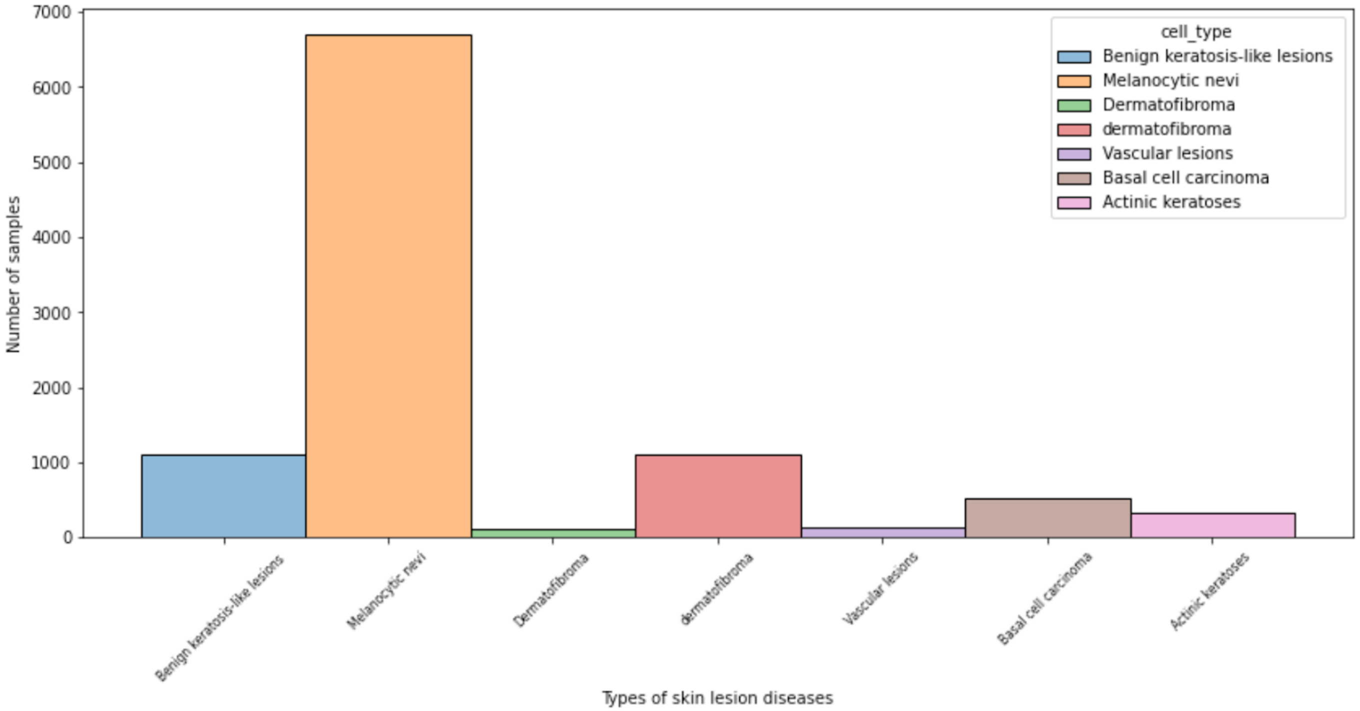
Actinic Keratoses



Melanoma



Distribution of Images (2018 ISIC Dataset):



10,000 observations

- 2,500 images were originally believed to be duplicates.
    - “Duplicate” images were identified as the same lesion, with different resolution or transformation
- Dataset was augmented via equalization sampling to reduce class imbalance

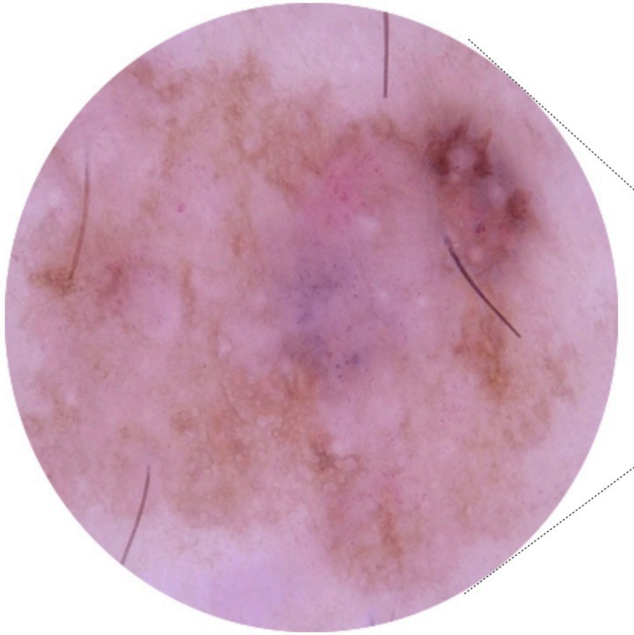
Data Augmentation – Microscopic crop

The data in the dataset consists of images at multiple resolutions, and this causes a class imbalance making this a challenging dataset to classify correctly.

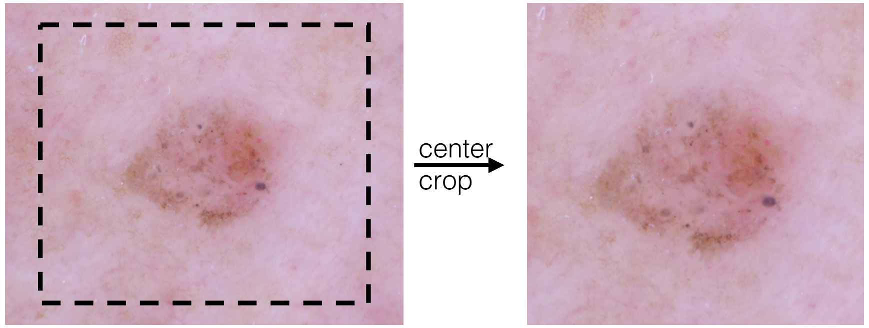
Data Augmentation was necessary to ensure we leverage the best use of deep learning nets to focus on crucial lesion patterns for classification and efficient utilization of computational power.

We reduced information from the image edges through the microscopic crop also resized all the images to a standard 800x600 pixel ratio.

Directly resizing may distort the skin lesion, hence we crop at the center and proportionately resize



Microscopic crop of the “benign keratosis-like lesion” type



Sample crop image of basal cell carcinoma cell type

Achieved two goals:

1. Cropped the images about the image center to focus more on lesion patterns.
2. Images are at multiple resolutions. We reduced the high cost of computations required for processing large resolution images by rescaling.

Data Augmentation – Using DCGAN

- Generated images from complete noise using DCGAN, with five layers. DCGAN was able to generate images around 1500th step.
- Some classes had just around 100 images, and leveraging DCGAN, we were able to increase the number images by 5x.
- Though the output image lacks cohesion and cannot be compared at a pixel level, it can still offer information to compare the sharpness and presence of malignancy markers and their fine-grained details.
- We had an overall better performance across Precision, Recall, and F1-Scores.

Test Dataset – ISIC Challenge

International Skin Imaging Collaboration's (ISIC) goal is to support efforts to reduce melanoma-related deaths and unnecessary biopsies by improving the accuracy and efficiency of melanoma early detection.

Rank <77 total>	Team <77 unique teams>	Approach Name	Manuscript	Used External Data <19 yes>	Primary Metric Value <Balanced Multiclass Accuracy> ↓
1	MetaOptima Technology Inc. MetaOptima Technology Inc.	Top 10 Models Averaged		Yes	0.885
2	DAISYLab DAISYLab	Large Ensemble with heavy multi-cropping and loss weighting		Yes	0.856
3	Medical Image Analysis Group, Sun Yat-sen University Medical Image Analysis Group, Sun Yat-sen University	Emsemble Of SENET and PNANET with DataAugmentation when TEST		No	0.845
4	Li Li	densenet		No	0.815
5	Ask Sina Ask Sina	Approach 3 : Average of Approach 1 and 2		No	0.812
6	RECOD Titans RECOD Titans	Average of 15 Deep Learning Models Trained Only with Challenge Data		No	0.803
7	NWPU-SAIIP NWPU-SAIIP	FV+Res101		No	0.786
8	Wonlab in Sungkyunkwan University, Korea, Republic of Wonlab in Sungkyunkwan University, Korea, Republic of	WonDerM: Skin Lesion Classification with Fine-tuned Neural Networks		Yes	0.785
9	vess vess	Resnext101 & DPN92, Snapshot ensamble, D4 TTA		No	0.784
10	LMU DataMining LMU DataMining	thresholding DF AKIEC MEL VASC BKL		Yes	0.780
11	University of Washington University of Washington	Densenet201		No	0.768

All test submissions were done through ISIC's portal

- Test dataset was made available through Harvard Dataverse
- Test submission notebook was created to automate results submission through the project
- Validation accuracy was observed to be 10%-20% higher than test accuracy
- Test dataset may have been more balanced than training dataset

Model Training

Convolutional neural networks (CNNs) have superior performance when it comes to image classification.

CNNs have three main layers but it is the convolutional layers which extract information from the image. The earlier convolutional layers focus on simple features such as colors, edges etc. and the later layers recognize the larger elements or shapes.

Model	Epochs	Loss Function	Optimizer	Additional Features	Test Accuracy
DenseNet121	10	Cross Entropy Loss	Adam		65%
DenseNet201	10	Cross Entropy Loss	Adam		63%
DenseNet201	300	Cross Entropy Loss	Adam		64%
DenseNet201	10	Cross Entropy Loss	Adam	Under/Oversampling	54%
DenseNet201	10	Cross Entropy Loss	Adam	Image Augmentation	56%
DenseNet121	10	Cross Entropy Loss	SGD	Balanced class weights	69%
DenseNet121	10	Cross Entropy Loss	SGD		70%
DenseNet201	10	Cross Entropy Loss	SGD		71%
EfficientNetB7	4	Cross Entropy Loss	SGD		78%
EfficientNetB7	10	Cross Entropy Loss	SGD		75%

* Not an exhaustive list - other model/parameter/architecture combinations removed for brevity

Final Model

	Precision		Recall		F1		Accuracy		
Class	Base	Final	Base	Final	Base	Final	Base	Final	Support
AKIEC	65%	88%	67%	77%	66%	82%	65%	78%	30
BCC	76%	77%	91%	94%	83%	85%			35
BKL	74%	82%	73%	64%	74%	72%			88
DF	71%	70%	62%	88%	67%	78%			8
NV	98%	97%	93%	97%	95%	97%			883
VASC	90%	75%	69%	92%	78%	83%			13
MEL	32%	47%	59%	57%	41%	51%			46

- Accuracy improved by ~15%⇧
- Class imbalance at inference time reduced
  - Precision, Recall, and F1 more ⇧ balanced across classes
- Inference time for 10 randomly selected images: less than 1 second ⇩

Next Steps

- GAN images with Efficient Net
- GAN vs oversampling/under sampling
- Pruning Efficient Net to reduce model load time
- Exploring eternal sources of data
- Connect lesion detection software to webcam, allowing real-time classification

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Questions?

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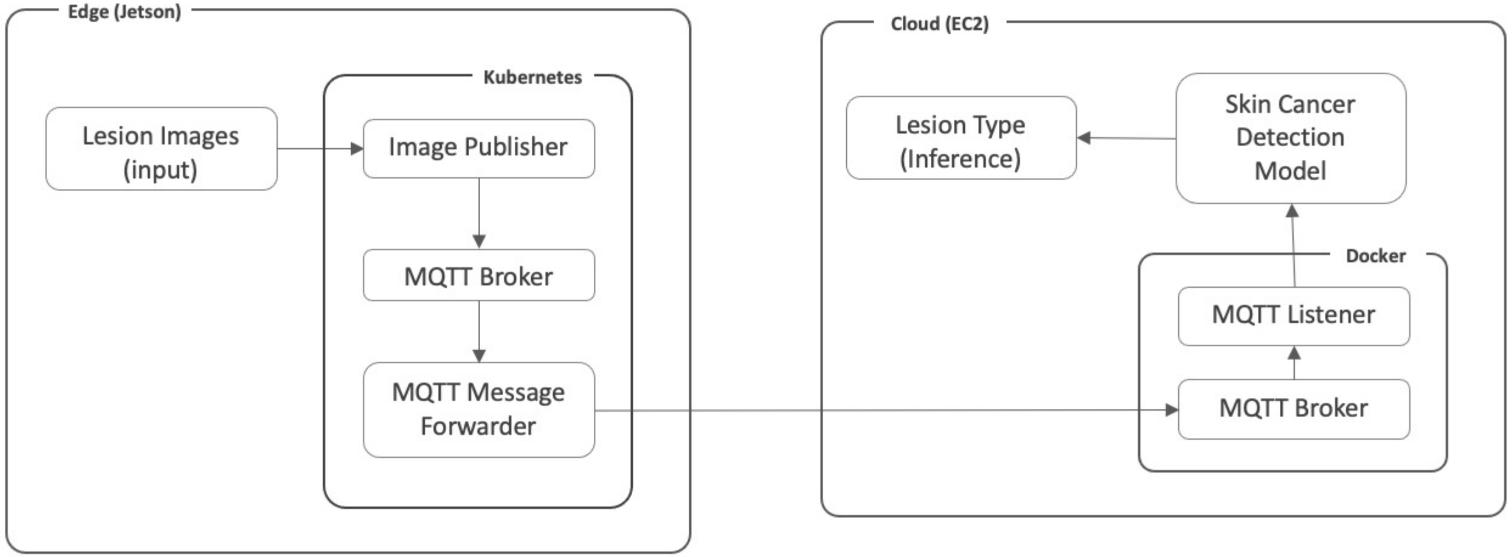
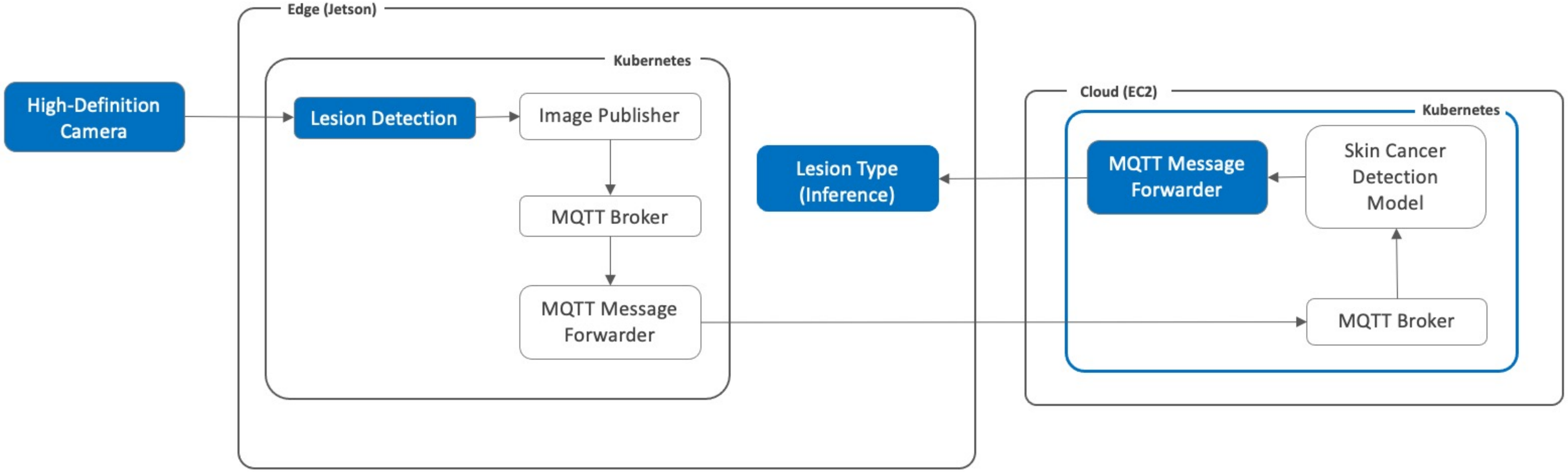
Appendix

Pipeline Improvements





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