SIIM-ISIC Melanoma Classification

27th Place

1st With Context

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Agenda

1. Background
2. Summary
3. Base Models
4. Transformer Models
5. Ensembling
6. Important findings
7. Real world model

Background

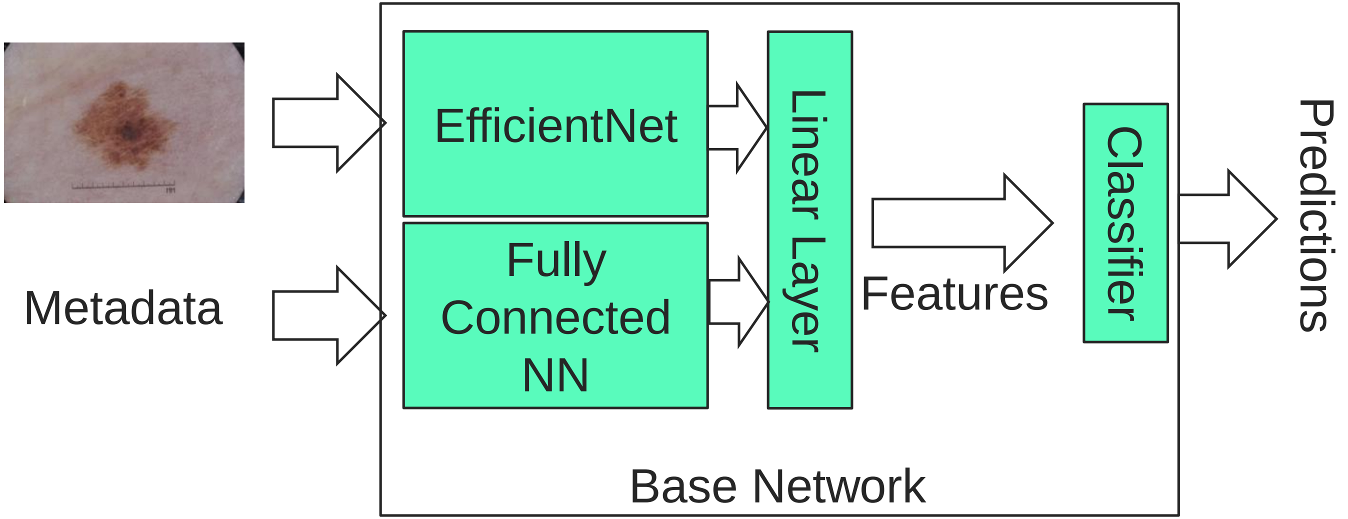
- Yuval Reina
    - BScEE, MBA, COO at Ceragon
    - Hobbyist, Self-Education

- Zahar Chikishev
    - M.Sc. in applied math
    - Kaggler

Summary

Two stage solution:

- Base model for feature extraction per image



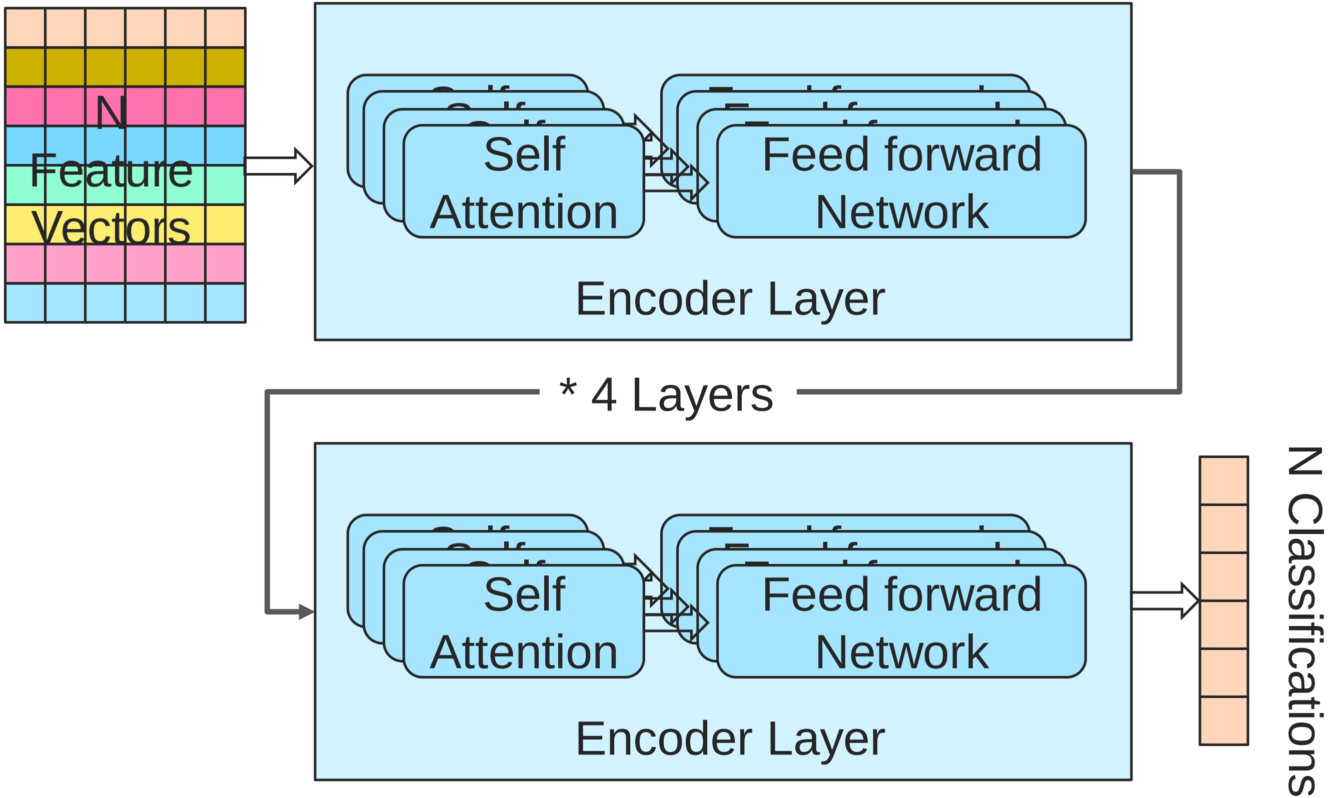
Pre – trained models:

- EfficientNet B3, B4, B5, B6, B7

Summary

Two stage solution:

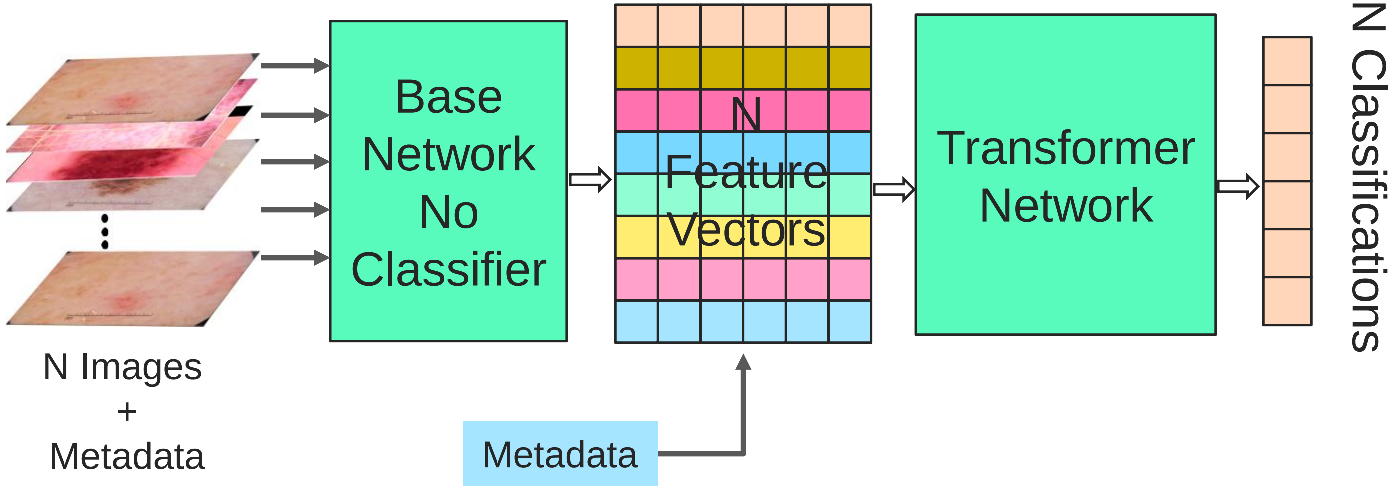
- Transformer model for context learning



Summary

Two stage solution:

- Base model for feature extraction per image
- Transformer model for context learning



Base Models

As base model we used different types of EfficientNet
B3, B4, B5, B6, B7
Pre-trained on Imagenet using Noisy student algorithem

Loss Functions:

- Cross Entropy on 8 diagnosis classes

Metadata:

- Age
- Sex
- Anatomic site

Number of Features – 256

Base Models – Cont.

Augmentation

- Random resize + crop
- Random rotation
- Random flip
- Random color jitter (brightness, contrast, saturation, hue)
- Cutout - erasing a small rectangle in the image
- Hair - Randomly adding “hair like” lines to the image
- Metadata augmentation

Training

The data was form ISIC 2019 + 2020 competitions

The goal - minimize the loss after the classification layer.

Feature extraction

The feature where extracted by the output of the last layer before the classification layer.

Transformer Model

- The transformer is a stack of 4 transformer encoder as described in Attention Is All You Need with 4 attention heads
- The input to the transformer is N feature vectors from the same patient.
- For simplicity, 32>=N, if the patient has more then 32 images, they are randomly grouped to 32 images groups
- Metadata is embedded and added to the feature vectors

Transformer Training

Two stage training:

1. ISIC 2019 (only 1 image/patient) + ISIC 2020
2. Fine – tune on ISIC 2020 alone

Augmentation

- Feature extraction of base model on 12-16 differently augmented images
- Select different augmented image in every epoch

Loss Functions:

- Cross Entropy on 8 diagnosis classes
- Focal Loss in one model (B5) – similar results

Inference

1. Use the base model to extract 16 sets of features for each image using augmentation
2. Randomly Divide all the images of a patient to groups of size 32 (max)
3. Select one random example for each image in a series and construct to full series.
4. Inference using Transformer network.

TTA - Do the above 32 times (with random selections, and grouping) and average the results

Training And Inference Times

Setup:

- CPU – Intel i9-9920
- RAM – 64G
- GPU – Tesla V100 32G / Titan RTX (20% slower)

Training:

- Base Models: ~ 3 (B3) – 11 (B7) h/fold
- Feature extraction: 4 – 14 h (3 * 3 folds, 12 TTA train 16 Test)
- Transformer: 1h/model
- Total time for all models ~ 2.5W for 1 GPU

Inference:

- Inference base model: ~20 min - 1h /model (for 12xTTA)
- Transformer model: ~ 2min (for 32xTTA)

Ensembling

Ensembling was done by averaging the predictions before Softmax

Without Context Submission:

A. EfficientNet B3 noisy student image size 400*600
B. EfficientNet B4 noisy student image size 400*600
C. EfficientNet B5 noisy student image size 400*600
D. EfficientNet B6 noisy student image size 600*900
E. EfficientNet B7 noisy student image size 400*600

With Context

All the “without context” model +

1. Transformer on features from A.
2. Transformer on features from B.
3. Transformer on features from C using focal loss
4. Transformer on features from D.
5. Transformer on features from E.

Results

With Context Submission:

Private LB - 0.9441

Public LB - 0.9575

Without Context Submission:

Private LB - 0.9430

Public LB - 0.9582

Best Single model :

Transformer on EfficintNet B5

Private LB - 0.9397

Public LB - 0.9602

Simpler and Real World Model

A simpler model would be:

- One base model - EfficientNet B5 for feature extraction
- Transformer model
- Keep 3 * 3 folds
- Keep TTA

In real world, previous images of a patient are already tagged, using this information to predict the current tagging, makes the model a seq2seq model – which is what a full transformer (encoder +decoder) was invented for.

Important and Interesting Findings

- Due to small number of positive examples at the test set it was impossible to get reliable results.

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