Skin Cancer Detection with 3D Total Body Photos

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Project Overview and Objectives

- **Objective:** Develop AI algorithms to **differentiate malignant from benign** skin lesions.
- **Inspiration:** ISIC2024 Kaggle Competition.

Context

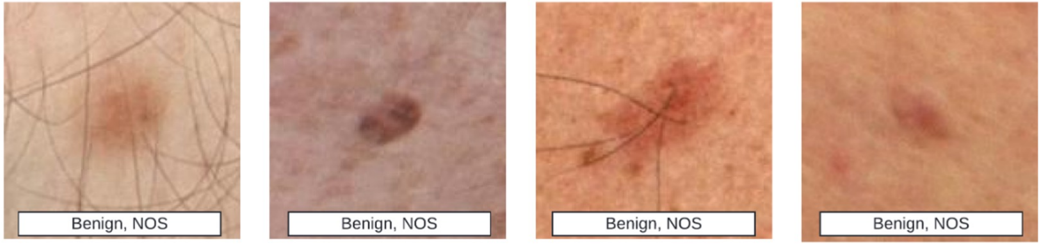
- **Problem: Skin cancer can be fatal if undiagnosed**; many underserved populations lack access to specialized dermatologic care.
- **Solution: AI algorithms to analyze lower-quality images**, similar to smartphone photos used in telehealth
- **Task: Create a binary classifier for skin cancer** using 3D total body photos (TBP) with single-lesion crops.
- **Benefit: Enhances triage and early detection of skin cancer**, especially in settings with limited specialized care.

Melanoma vs Benign Lesion Classification

Highly imbalanced large dataset**,** 401k Images in total, 1042 Patients

Melanoma (393 images, 0.01%)

Benign (400, 666 images, 99.99%)



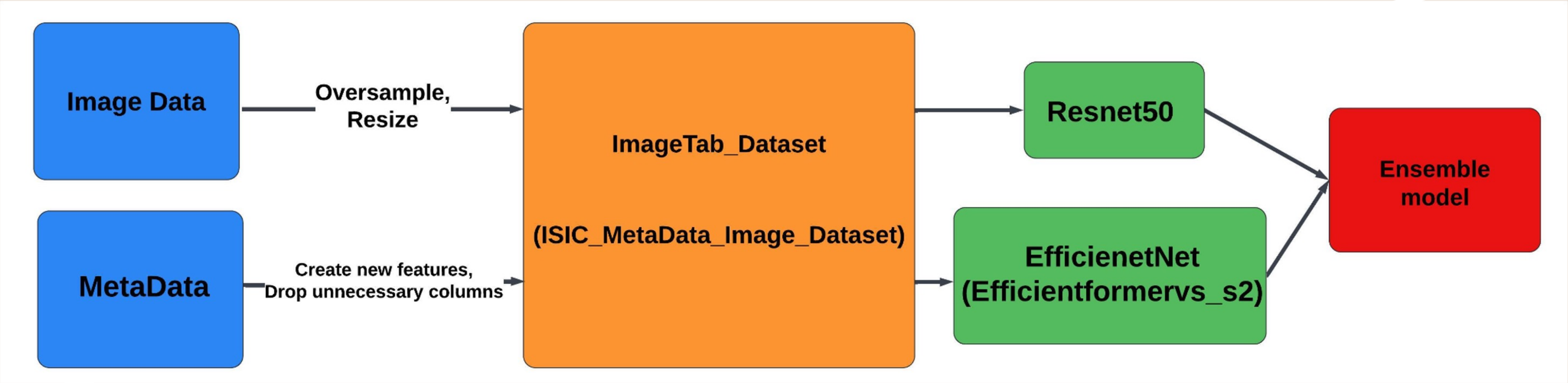
Exploratory Data Analysis (EDA)

- **Images (jpeg and hdf5):** Examined image sizes and reviewed examples of melanoma and benign images.
  - Images vary in size, with a broad range of dimensions:
    top 5: 133x133 - ~21k, 131x131 - ~21k, 129x129 - ~20k, 135x135 - ~20k, 137x137 - ~19k.
    Standard size chosen: 137x137.

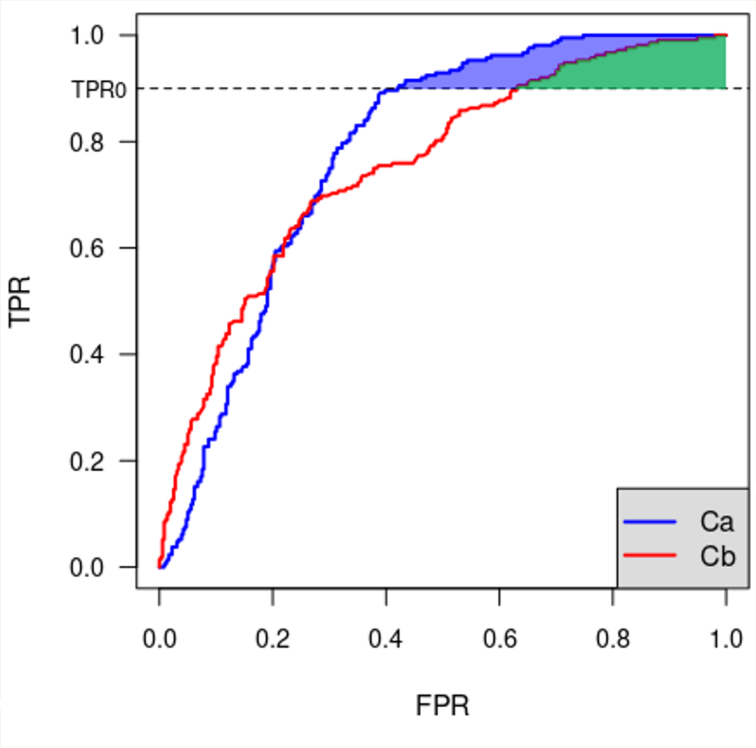
- **Meta Data (csv)**
  - 401059 Rows, 55 columns
  - **Missing Values:** 3k for age, 12k for sex, and 6k for anatomical site general.
    NAN values are replaced with the mode of the respective feature.
  - **Feature Types:** Includes both categorical and continuous variables.
- **Train-Test Split:** Stratified split ensures a balanced representation of both target classes in each set.
- **Feature Importance:** A Random Forest model computes feature importance scores.

Ensemble Model

Fastai | **PyTorch**



Evaluation



- Evaluated on partial area under ROC curve (pAUC) above 80% TPR.
- Other surrogate loss functions: Focal Loss, MSE Loss, Binary Cross Entropy Loss
- Results on 28% of hidden test set, which contains approximately 500k images

Results

Oversampling	Image model	Epochs	Loss function	Valid score*	pAUC
100k:10K	Resnet50 +Efficient_v2	0+5 0+5	CrossEntropy	0.0025	0.140
No	Resnet	0+1	CrossEntropy	0.0064	0.133
10k:1k	Resnet50	5+2	CrossEntropy	0.108	0.127
100k:10k	Resnet50	7+3	pAUC	0.962	0.018
100k:10k	Resnet50 +Efficient_v2	5+2 5+2	CrossEntropy	0.088	0.090
No	Pytorch ResNet50	22	FocalLoss	0.0043	0.126
No	Pytorch ResNet50 + EfficientNet (Ensemble)	22+11	FocalLoss	-	0.126

Conclusion

- The FastAI ImageTab model delivered the best performance.
- **Challenges:** High RAM usage for DataLoader (slow training and requires lots of memory), Possible overfitting
- **Advantages of our work:** We explored multiple approaches and leveraged various pretrained models, which saved time and yielded good results.
- **Future work:**
    - We plan to explore other ensemble models and techniques to improve image quality, such as hair removal.
    - Why does more training lead to a lower score, despite overfitting penalties?
    - Find more efficient ways to overcome the RAM requirements in the pytorch code.