

Dermatologist level classification of skin-cancer with deep neural networks

CS 273B

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Motivation

- 5.4M non-melanoma skin cancer cases each year
- 20% of adults will get skin cancer
- 10K deaths from melanoma
- \$8.1B in US healthcare costs
- Stage I has > 98% survival rate
- Stage IV has < 12% survival rate

Background Work

- ImageNet Google Inception v3
- Microscopy techniques
- ML for diagnosis of melanoma + skin cancers
 - k-Nearest Neighbors
 - PCA
 - SVM

Goal

AI assisted dermatology

Early detection is critical for malignant skin cancers

Smartphone enabled diagnostic tool at dermatologist-level accuracy

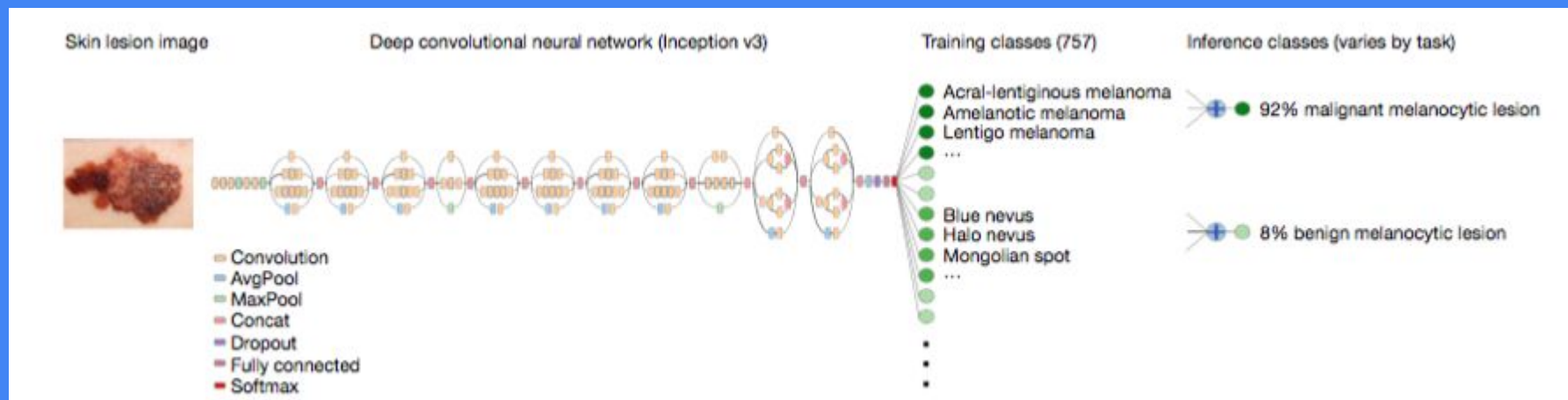
Dataset

- > 130K images of skin
- From: 18 different clinician-curated, open-access online repositories, as well as from clinical data from Stanford University Medical Center
- ISIC Dermoscopic Archive, Edinburgh Dermofit Library, Stanford Hospital, Google Images
- Labelled by hand and verified with biopsy
- 757 disease classes, 2,032 distinct diseases

Methodology

Label Taxonomy



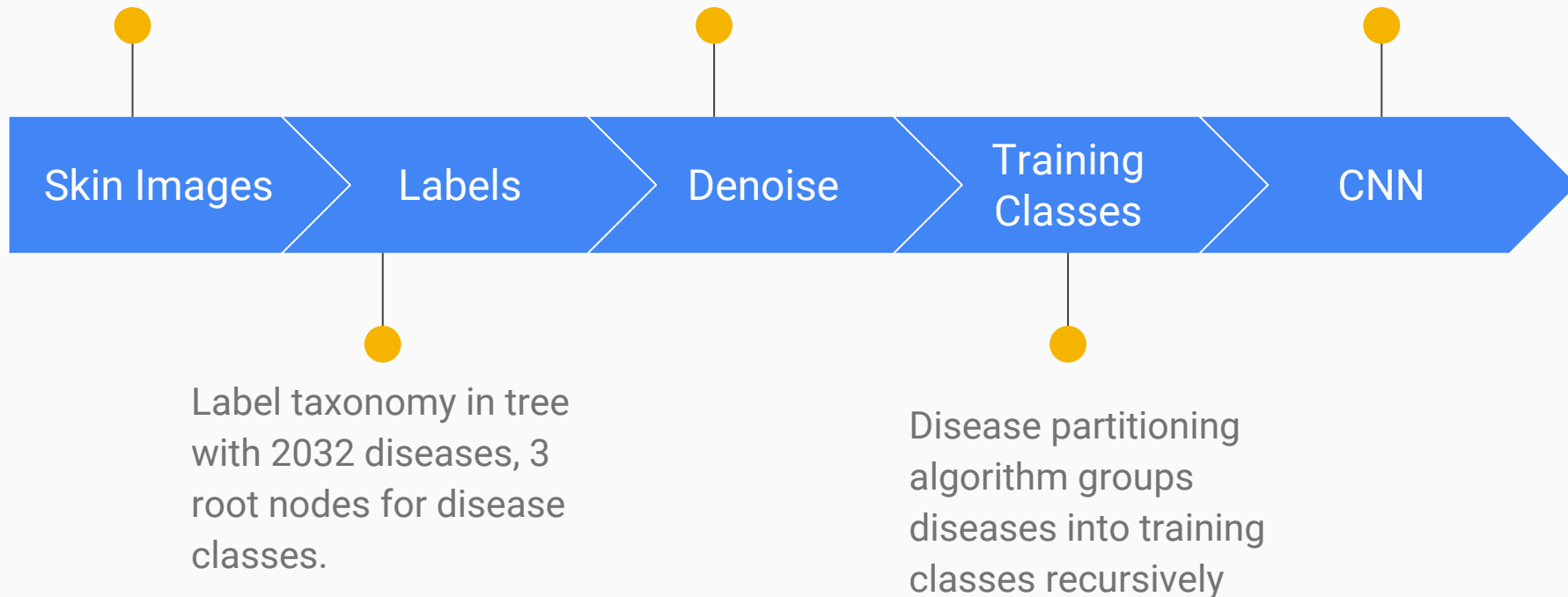


CNN

ISIC Dermoscopic
Archive, Edinburgh
Dermofit Library,
Stanford Hospital

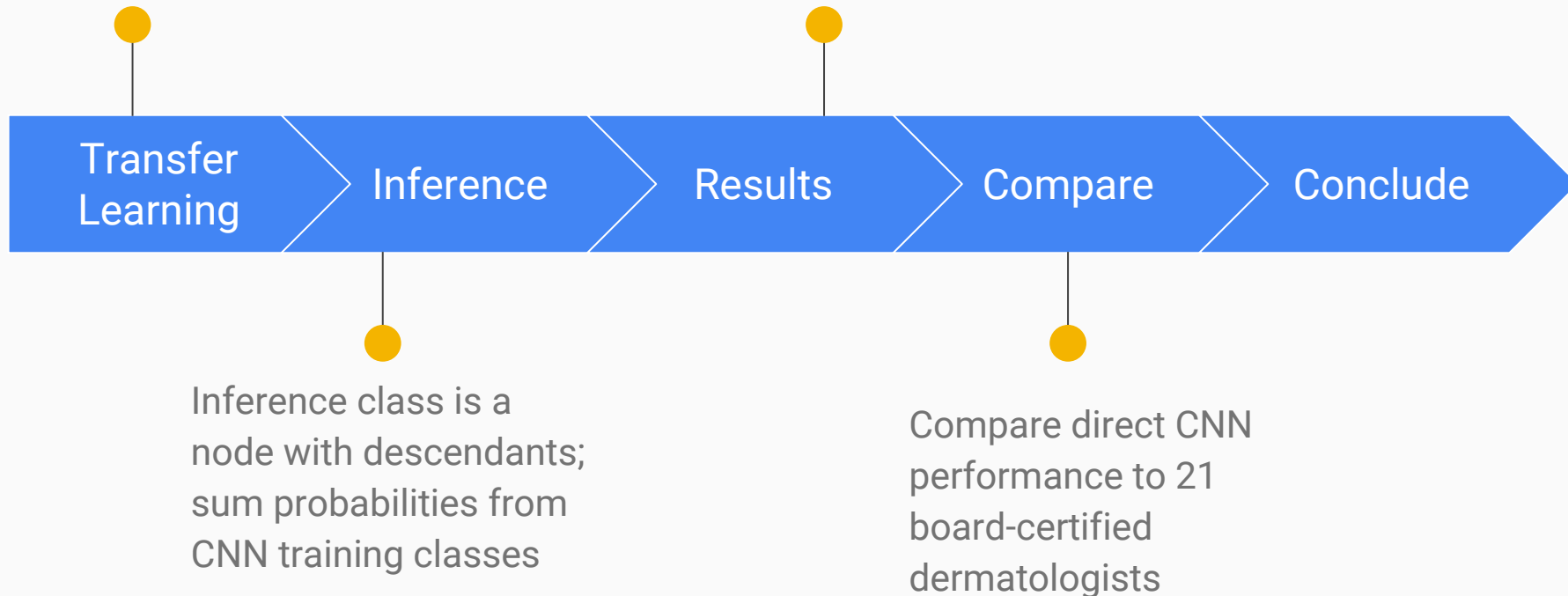
Remove blurry and far
away images; do not
split similar images
between train/validation.

Google Inception v3
CNN architecture from
2014 ImageNet



Remove Inception
v3 classification
layer and retrain
on skin images

9-fold cross validation.
Confusion matrices, saliency
maps, sensitivity-specificity
curves



Validation

Classifier	Three-way accuracy
Dermatologist 1	65.6%
Dermatologist 2	66.0%
CNN	69.5%
CNN - PA	72.0%

Disease classes: three-way classification

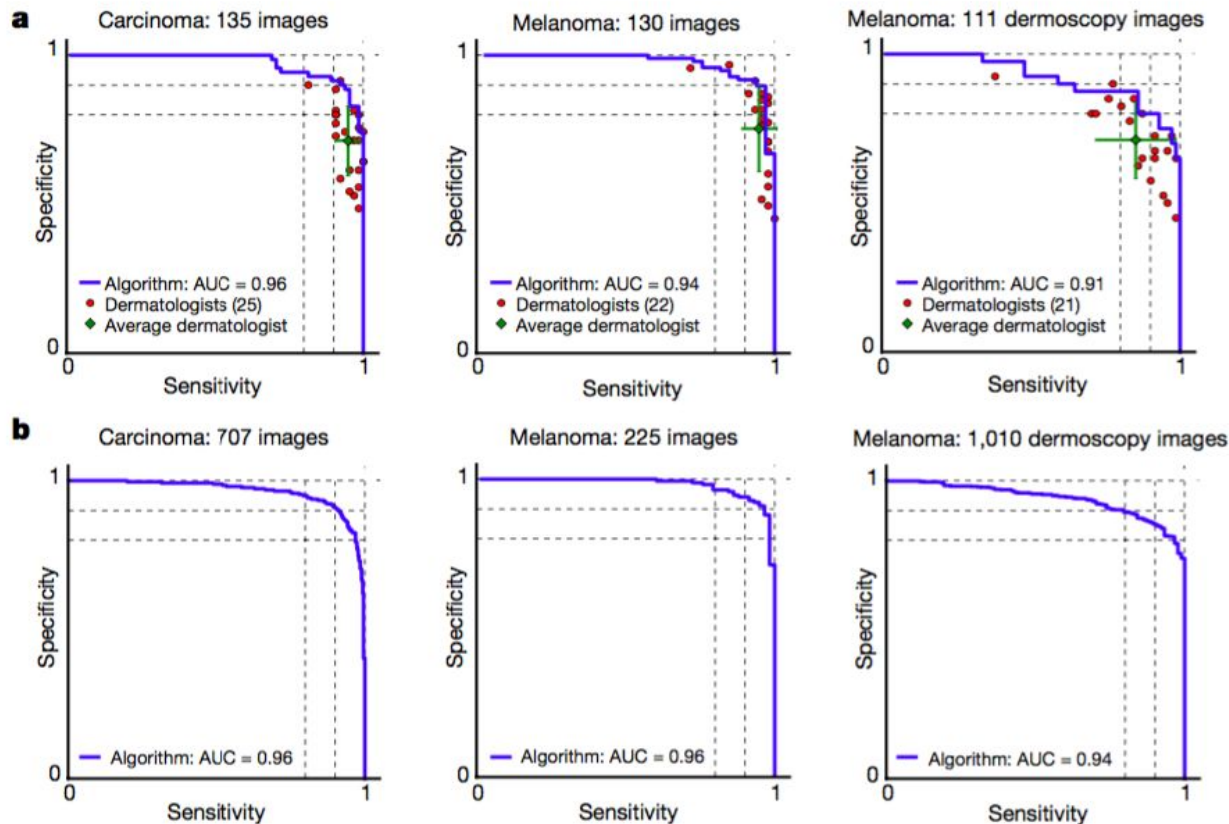
0. Benign single lesions
1. Malignant single lesions
2. Non-neoplastic lesions

Classifier	Nine-way accuracy
Dermatologist 1	53.3%
Dermatologist 2	55.0%
CNN	48.9%
CNN - PA	55.3%

Disease classes: nine-way classification

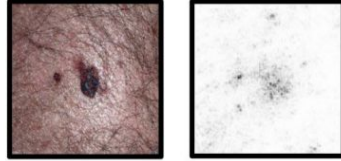
0. Cutaneous lymphoma and lymphoid infiltrates
1. Benign dermal tumors, cysts, sinuses
2. Malignant dermal tumor
3. Benign epidermal tumors, hamartomas, milia, and growths
4. Malignant and premalignant epidermal tumors
5. Genodermatoses and supernumerary growths
6. Inflammatory conditions
7. Benign melanocytic lesions
8. Malignant Melanoma

Main Results



Main Results

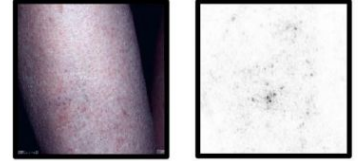
a. Malignant Melanocytic Lesion



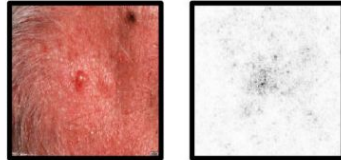
d. Benign Melanocytic Lesion



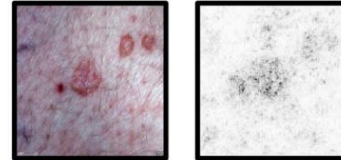
g. Inflammatory Condition



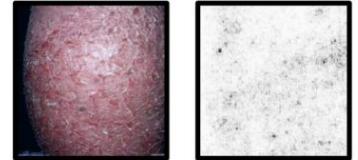
b. Malignant Epidermal Lesion



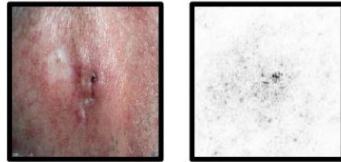
e. Benign Epidermal Lesion



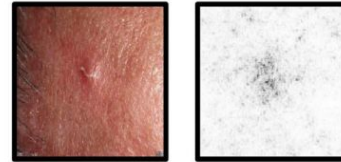
h. Genodermatosis



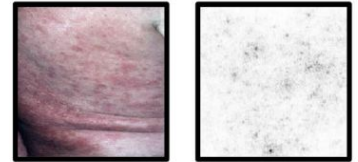
c. Malignant Dermal Lesion



f. Benign Dermal Lesion



i. Cutaneous Lymphoma



Strengths

91% AUC minimum for CNN sensitivity-specificity curve

Significant advance compared to previous methods that use PCA, k-nearest-neighbors, or other regression based models

Weaknesses

Binary classification does not translate to real world

Dermatologists use other modalities to diagnose - results do not imply that CNN outperforms dermatologist diagnosis

Issues

Test set includes “gold standard biopsy proven images”, but the training set does not

Paper hopes to be able to aid in the diagnosis skin cancer in stage I; however no results support this specific claim

Extensions: Deploy solution to the real world

Classifier should be more general

Should be capable of being deployed in the field (robust to lower quality images, capable of rejecting images that are too blurry)

Ideally do the processing locally (on the mobile device) as opposed to sending it to the server

Extensions: New Analysis

Analyze the performance of the classifier on other skin diseases in the taxonomy commonly misdiagnosed by dermatologists

Analyze the sensitivity/specificity of the classifier on identifying images from different stages (I, II, III, IV) of skin cancer as compared to dermatologists

Extensions: New Algorithms

Additional data augmentations (the authors only use random reflections/rotations)

Benchmark the performance on different architectures (ResNet V2, etc)

Questions?