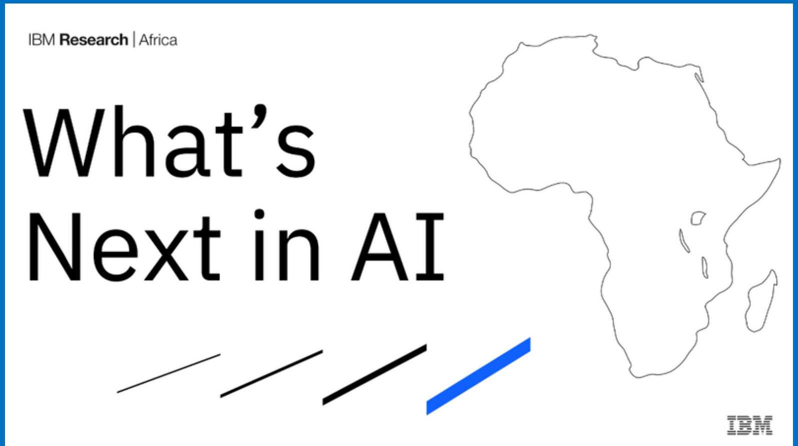


Representation Analysis in Academic Materials

Girmaw Abebe Tadesse, PhD
Research Scientist – AI Science Team

girmaw.abebe.tadesse@ibm.com

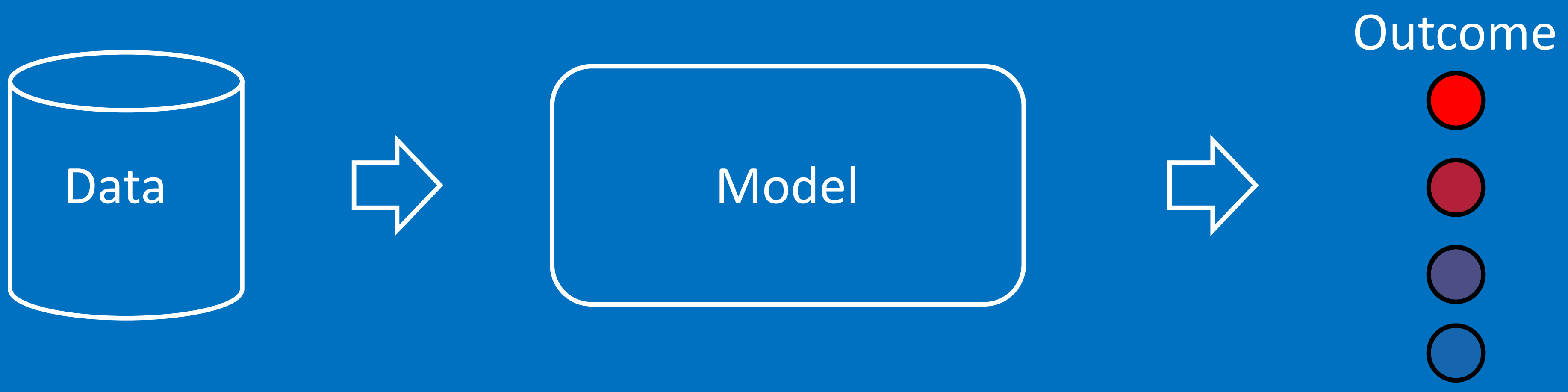
@girmaw_abebe

18 August 2021

Outline

- Challenges of learning from data
- Healthcare: dermatalogy as a use case
- Problem formuation
- Proposed approach
  - Results
- Conclusion

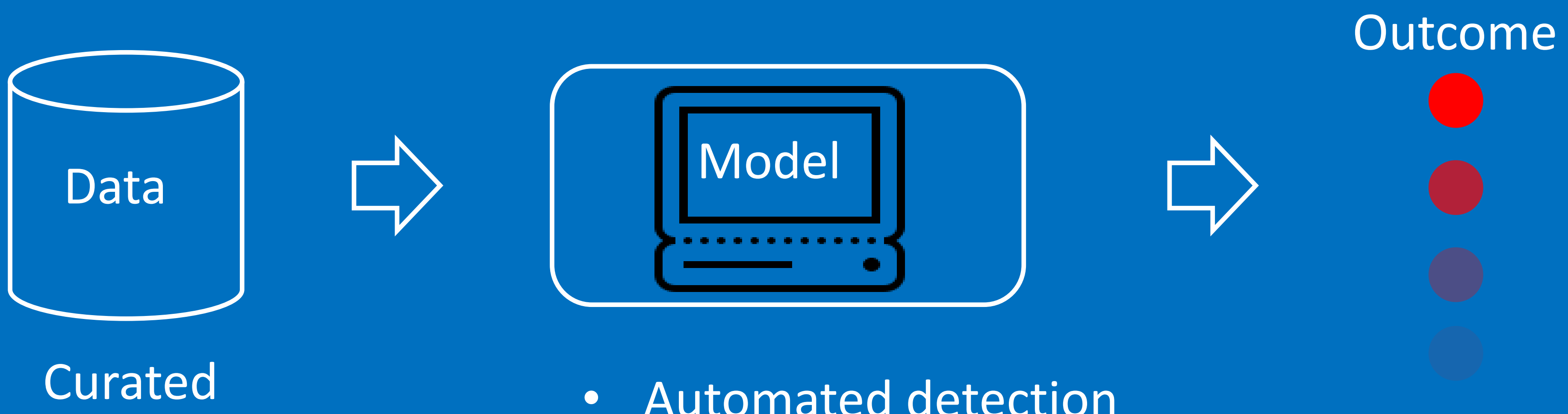
Challenges of learning from data



Questionable data
E.g., Lack of representation

Questionable inference
E.g., Bias

Challenges of learning from data



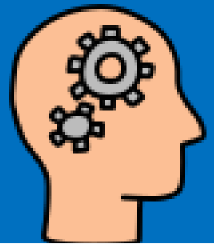
- Automated detection
- Re-training/Correction
- ….

Challenges of learning from data

Data

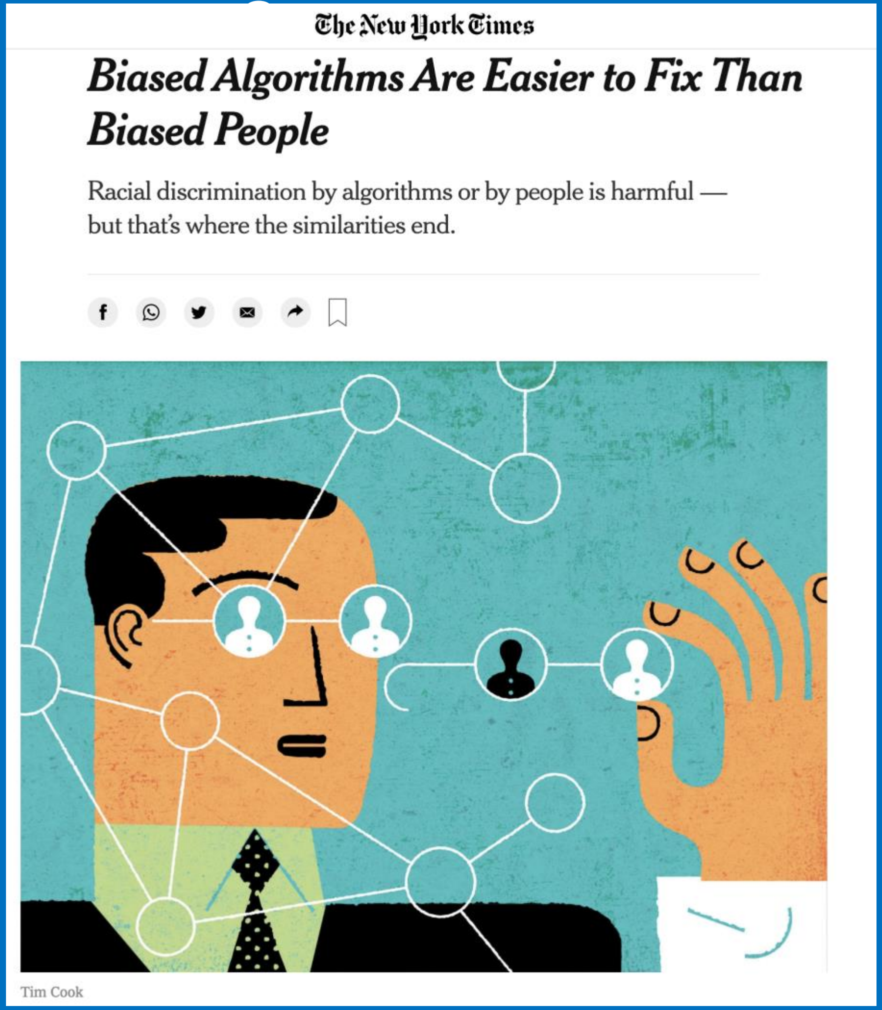
- Traditional
- Complex

Model



- Detection?
- Correction?

Biased domain-experts?



The New York Times

Biased Algorithms Are Easier to Fix Than Biased People

Racial discrimination by algorithms or by people is harmful — but that's where the similarities end.

Tim Cook

Healthcare, specifically dermatology as a use case

The New York Times

https://www.nytimes.com/2020/08/30/health/skin-diseases-black-hispanic.html

Dermatology Has a Problem With Skin Color

Common conditions often manifest differently on dark skin. Yet physicians are trained mostly to diagnose them on white skin.

Research Letter FREE

December 2017

Addressing Minority Representation in Dermatology

Answering a Call to Action Through Structured Mentorship and Instruction

Shawn G. Kwatra, MD[1]; Alice He, MD[1]; Manisha J. Loss, MD[1]; et al

Author Affiliations | Article Information

JAMA Dermatol. 2017;153(12):1329-1330. doi:10.1001/jamadermatol.2017.3224

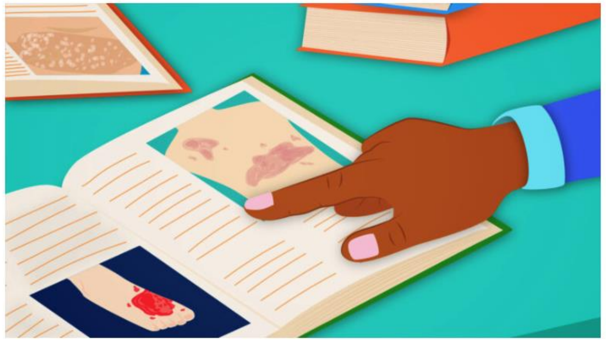
Recent attention has been called to the insufficient representation in dermatology of African American and Hispanic individuals, which comprise the major populations underrepresented in medicine (UIM).[1,2] There have been 2 recent calls to action to increase UIM populations in dermatology, a task that necessitates action.[1,2]

https://jamanetwork.com/journals/jamadermatology/fullarticle/2652680#.Xx7ozd64Hts.twitter

HEALTH

Dermatology faces a reckoning: Lack of darker skin in textbooks and journals harms care for patients of color

By USHA LEE MCFARLING / JULY 21, 2020 Reprints



HYACINTH EMPINADO/STAT

https://www.statnews.com/2020/07/21/dermatology-faces-reckoning-lack-of-darker-skin-in-textbooks-journals-harms-patients-of-color/

Consequences

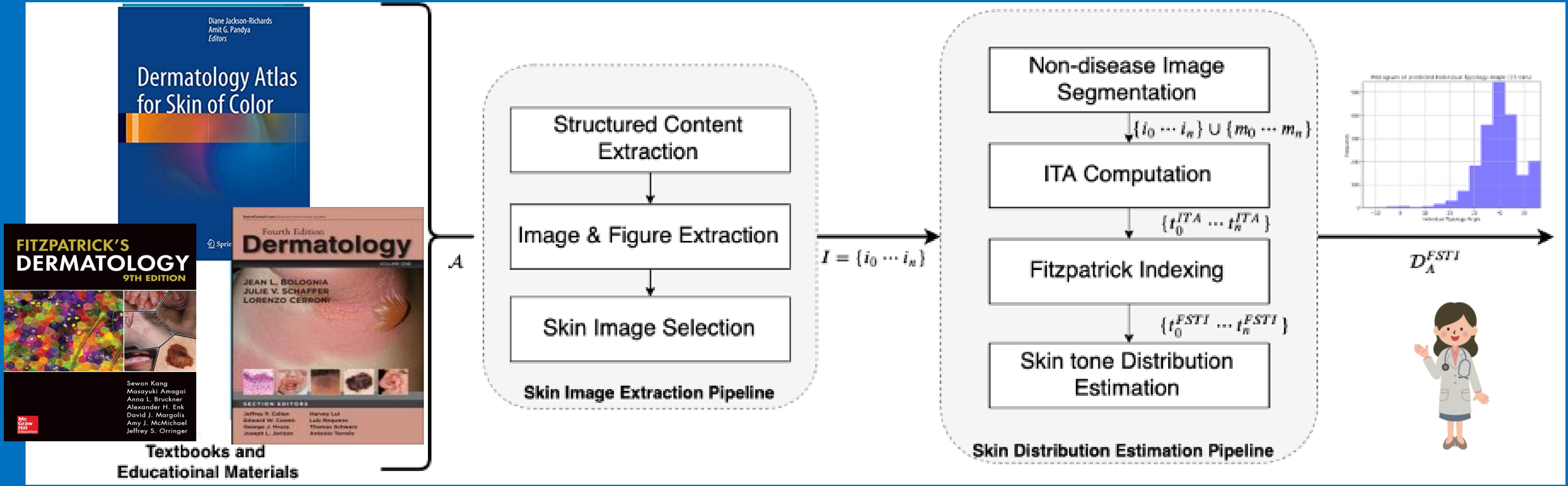
- Lack of expert access
- Delayed diagnosis
- Increased morbidity
- Increased mortality

Question?

Could we automatically identify the representation of skin images in dermatology academic materials across skin tones?

Proposed solution

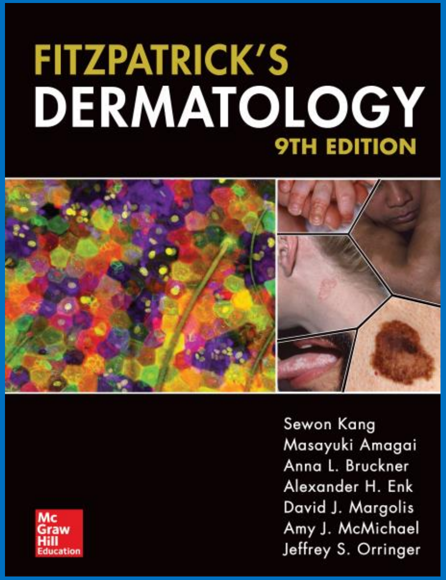
Input ⇨ **Ingestion, Extraction & Detection** ⇨ **Output**

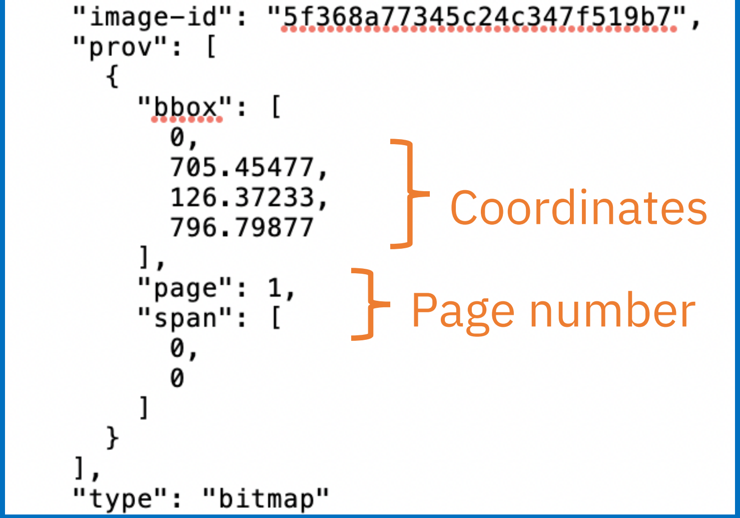


Tadesse et al., Automated Evaluation of Representation in Dermatology Educational Materials, AAAI Trustworthy Workshop, 2021.

Document ingestion: extract images

Corpus Conversion Service





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      705.45477,
      126.37233,
      796.79877
    ],
    "page": 1,
    "span": [
      0,
      0
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  }
],
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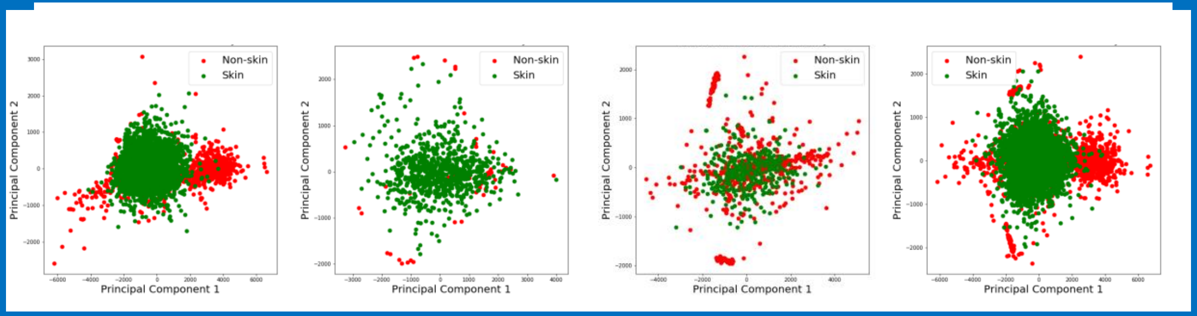
Non-skin images

Skin vs. Non-skin classification

Staar et al., Corpus Conversion Service: A Machine Learning Platform to Ingest Documents at Scale. KDD. 2018

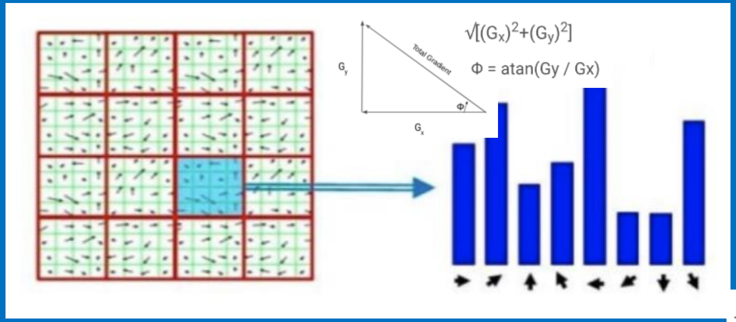
PCA Visualisations: before classification

Pixel intensity values

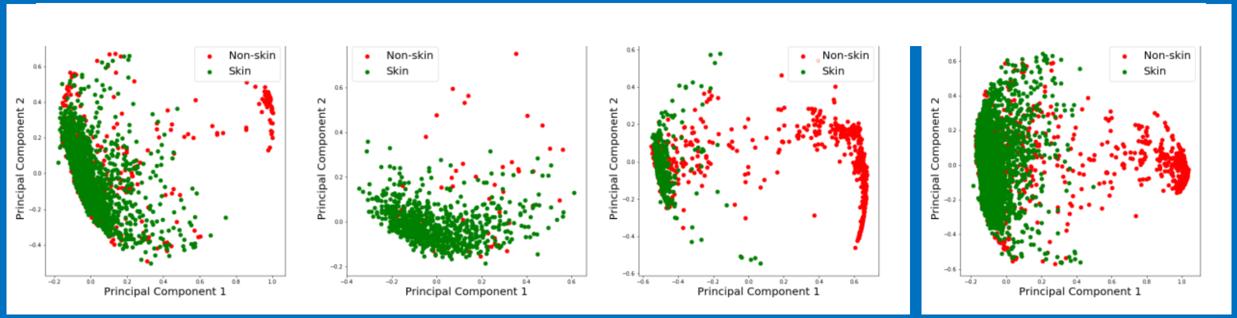


Bologna Atlas Rook All

Histogram of Oriented Gradient (HOG)



$$\mathrm{ITA} = \arctan\left(\frac{\mathrm{L}-50}{\mathrm{b}}\right) \times \frac{180^\circ}{\pi}$$

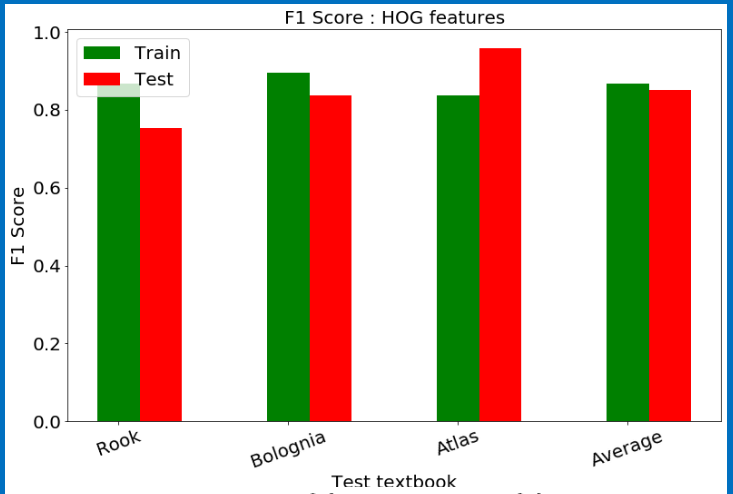


Bologna Atlas Rook All

Skin vs. Non-skin classification

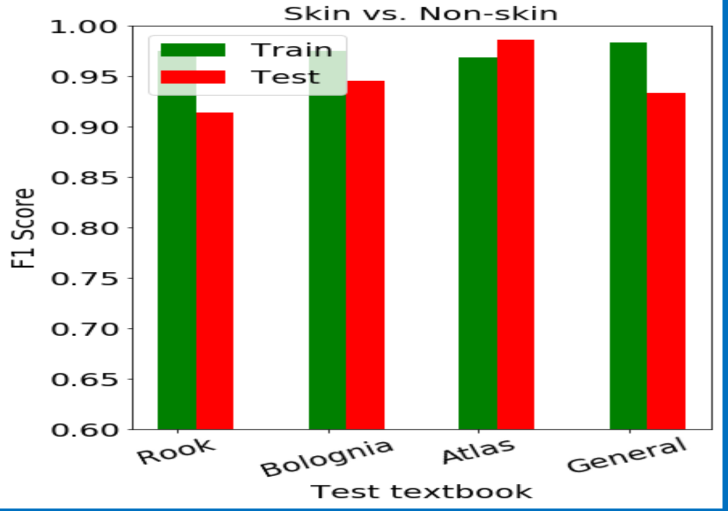
Book	# chapters	# of images	# of skin images
Rook [2]	3	1026	343
Bolognia [1]	160	4526	3225
Atlas [5]	36	880	822
Fitzpatrick [3]	217	21727	1881

One-class SVM



One-textbook-out validation: don’t see the test data during training

XGBoost



Skin tone estimation

Skin images

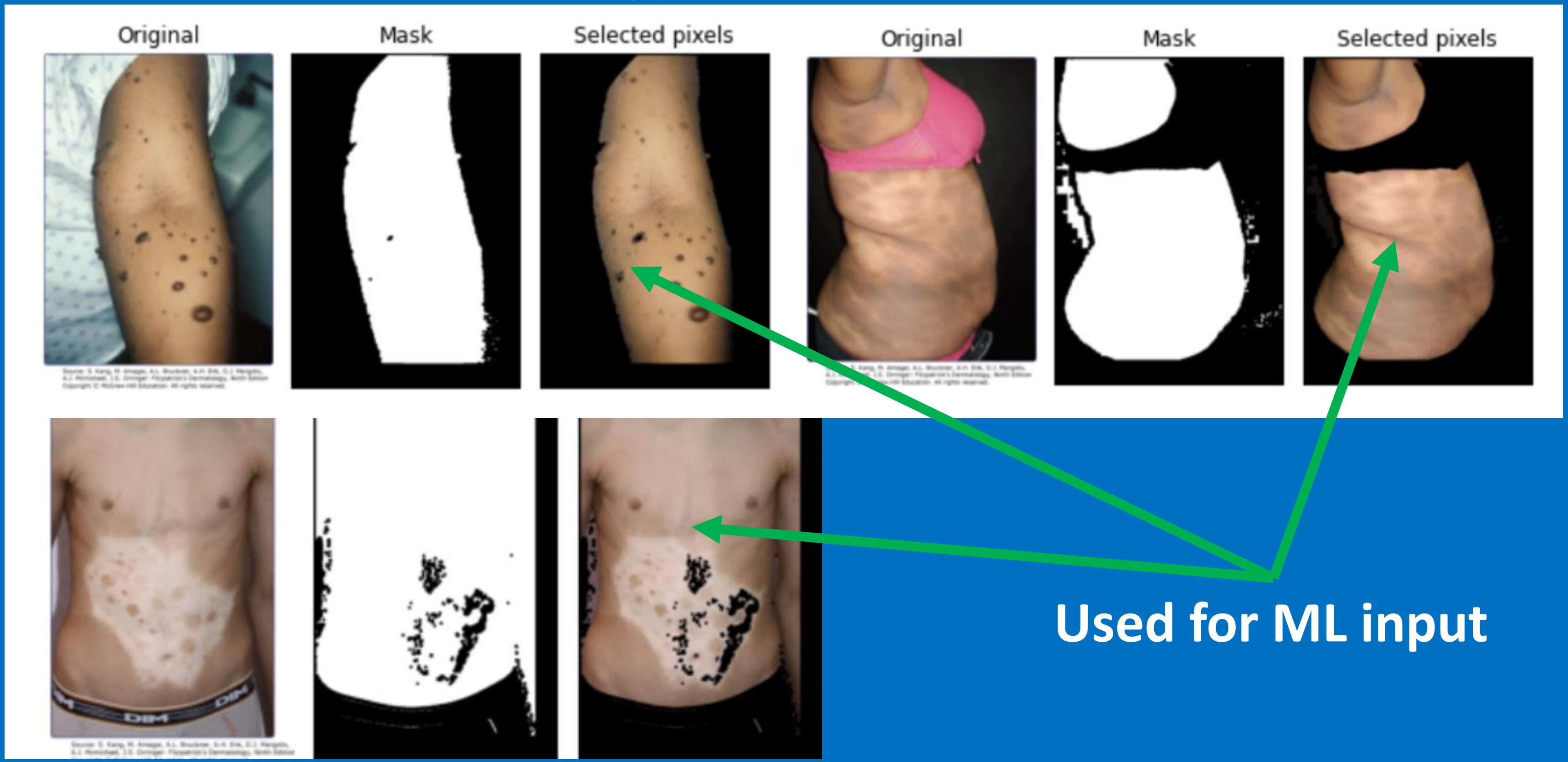
Challenges: non-skin foreground or background parts

Solution: segmentation

Skin image segmentation

- Region based segmentation could suffice for dark vs. light tone outcome[1]
    - pixel intensity, watershed and morphology

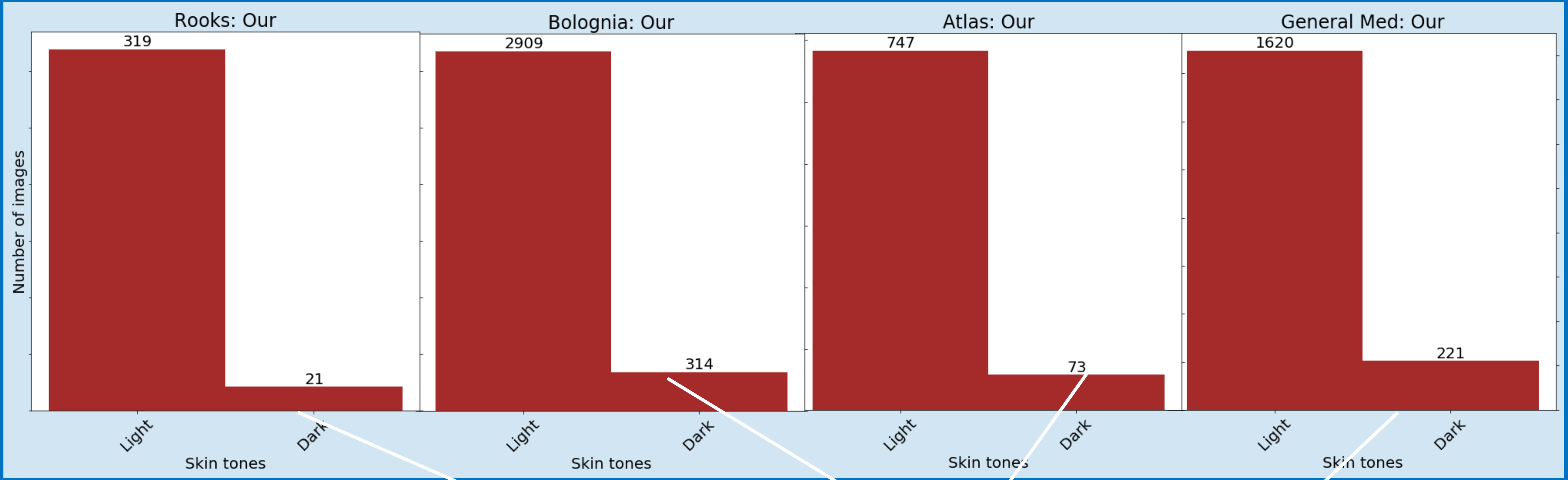
HSV= [(0, 40, 0), (25, 255, 255)]
&
YCbCr = [(0, 138, 67), (255, 173, 133)]



Used for ML input

[1]Frerk Saxen and Ayoub Al-Hamadi. Color-based skin segmentation: An evaluation of thestate of the art. In2014 IEEE International Conference on Image Processing (ICIP), pages4467–4471. IEEE, 2014.

Skin tone estimation

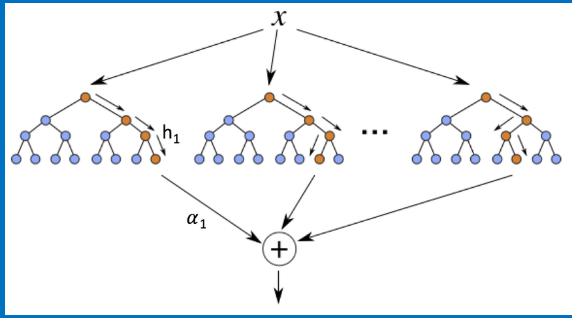


Imbalance represenation

- Question: how good ML methods could detect these skin tones?

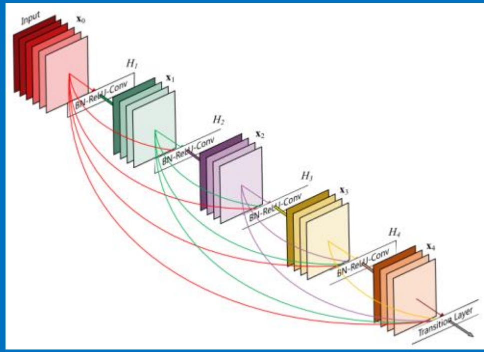
Skin tone estimation: classification

Tree-based Baselines



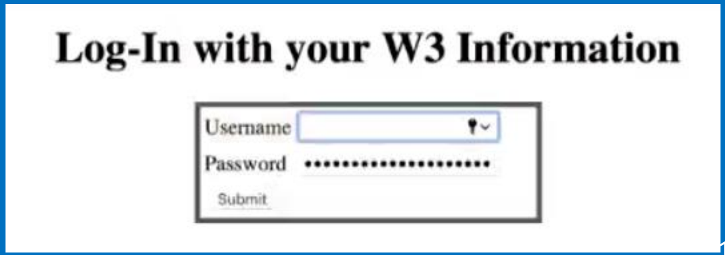
VS.

ResNet (Deep Learning)



Model	Raw Masked Pixels				Feature Vectors (HOG)				Feature Vectors (HOG + ITA)			
	Accuracy	F1-score	Precision	AUC	Accuracy	F1-score	Precision	AUC	Accuracy	F1-score	Precision	AUC
Random Forest	0.901 ± 0.003	0.861 ± 0.005	0.869 ± 0.022	0.746 ± 0.070	0.907 ± 0.005	0.875 ± 0.012	0.893 ± 0.006	0.819 ± 0.044	0.906 ± 0.004	0.880 ± 0.015	0.889 ± 0.007	0.830 ± 0.043
Extra Trees	0.900 ± 0.004	0.863 ± 0.005	0.878 ± 0.019	0.773 ± 0.055	0.905 ± 0.004	0.869 ± 0.011	0.890 ± 0.009	0.826 ± 0.039	0.907 ± 0.005	0.878 ± 0.016	0.889 ± 0.011	0.839 ± 0.027
Ada Boost	0.885 ± 0.008	0.870 ± 0.009	0.862 ± 0.011	0.774 ± 0.029	0.897 ± 0.006	0.885 ± 0.007	0.879 ± 0.009	0.814 ± 0.026	0.900 ± 0.006	0.888 ± 0.007	0.883 ± 0.009	0.820 ± 0.022
Gradient Boosting	0.898 ± 0.005	0.870 ± 0.005	0.869 ± 0.015	0.767 ± 0.049	0.905 ± 0.004	0.888 ± 0.009	0.885 ± 0.008	0.847 ± 0.023	0.906 ± 0.003	0.890 ± 0.009	0.889 ± 0.007	0.847 ± 0.028
Pretrained Resnet	$\mathbf{0.948 \pm 0.003}$	$\mathbf{0.953 \pm 0.002}$	$\mathbf{0.961 \pm 0.001}$	$\mathbf{0.889 \pm 0.011}$	NA	NA	NA	NA	NA	NA	NA	NA

- Next step: Wrap up the system into a standalone tool



Conclusion: Data-centric - the way forward!

GOOD

~~BIG~~ DATA

Andrew Ng

Google's New Dermatology App Wasn't Designed for People With Darker S

The company trained the system to recognize different skin conditions. But like Google itself, the app's data has a diversity problem.

The New York Times

Biased Algorithms Are Easier to Fix Than Biased People

Racial discrimination by algorithms or by people is harmful — but that's where the similarities end.

Tim Cook

Thanks! - Asante! - አመሰግናለሁ!

Team

Girmaw Abebe Tadesse
Research Scientist
Challenge lead

CHINYERE AGUNWA
Research Staff Member

Peter Staar
Principle RSM; Manager ...

Celia Cintas
Research Scientist

Kush Varshney
Distinguished Research ...

Kenya Andrews

Hannah Kim

Interns

External collaborators: Roxana Daneshjou, Dermatology Clinical Scholar, Institute for Human-Centered Artificial Intelligence (HAI), Stanford University James Zou, Assistant Professor, Biomedical Data Science, Institute for Human-Centered Artificial Intelligence (HAI), Stanford University Ademide Adelekun, Resident Physician, University of Pennsylvania Jules B. Lipoff, Assistant Professor of Clinical Dermatology, University of Pennsylvania Ginikanwa Onyekaba, MD Candidate, University of Pennsylvania Veronica Rotemberg, Dermatologist, Memorial Sloan Kettering Cancer Center

IBM

Stanford University

Penn University of Pennsylvania

Memorial Sloan Kettering Cancer Center

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