TITLE GOES HERE

subtitle

We can use the above blocks as separators for different sections of the poster. I’ll make multiple slides to show examples of different formats we can use and choose a random color divider (we can decide together later) - Isabelle
PS: of course we can use different formats. I just wanted to get started and we can discuss later on specifics (:

I like this color pallet btw ^ -minnie

Title of Project

Short description of our motivation

Minnie Liang, Isabelle Hu, Preeti Gomathinayagam, Mohammad Masoud

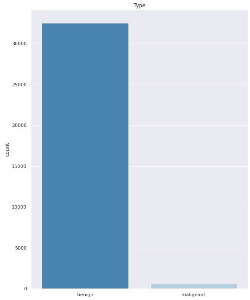
Deep Learning Techniques for Melanoma Classification

Minnie Liang | Preeti Gomathinayagam | Mohammad Masoud | Isabelle Hu

Motivation

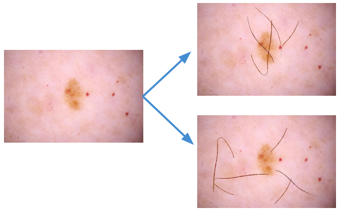
-Gives people much faster feedback on their skin lesions than seeing a dermatologist, which on average has a 38 day wait time.
-Help combat the dermatologist shortage issue, as recent studies have shown that there are around 3.3 derms for every 100,000 people, which means there simply aren't enough doctors to treat all patients.
-Help decrease the number of unnecessary bookings to a dermatologist, allowing crucial patients to be seen in a timely manner.

Dataset



ISIC 2020 Challenge Dataset
-Composed of 33,126 images with gender, age, anatomical site, diagnosis, and benign/malignant classification
-Preprocessed the features to remove unnecessary information (diagnosis) and NaN values (when gender was not given)
-Heavily imbalanced as only around 17.6% of the data is malignant.

Image Augmentation



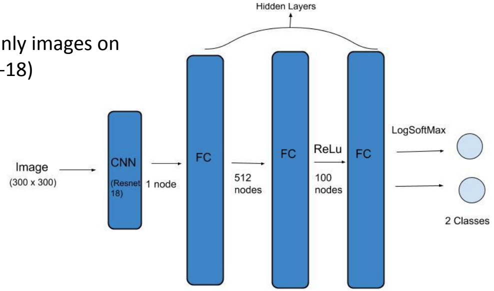
-Augmented the number of malignant images twice to help balance the data.
-Added a random number of hairs at random positions to each malignant image

Representation of Additional Features

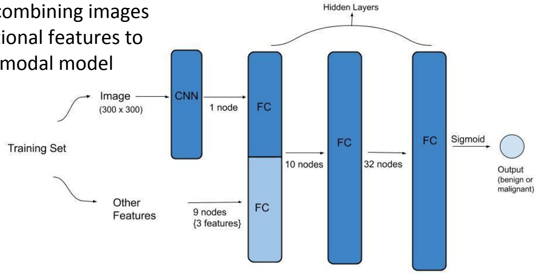
-Additional features: gender, age, anatomical site of skin lesion
-Represented by a one hot vector of size 9
-First position is gender: 1 if male, 0 if female
-Second position is age: rounded to the nearest 5 and divided by the max age (90)
-Last 7 positions represents the site of the lesion in the respective order [head/neck, lower extremity, oral/genital, palms/soles, torso, upper extremity, nan]
-Ex: [1, 0.2777777777777778, 0, 0, 0, 0, 1, 0, 0] represents an approximate 25 year old male with a skin lesion on the torso

Models

Predicted using only images on one CNN (Resnet-18)



Predicted by combining images with the additional features to create a multimodal model

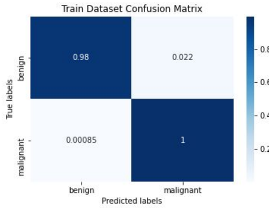


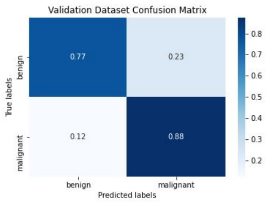
Experiments

-Tried two different CNN's: Resnet-18 and VGG16
-Compared implementing only a CNN versus CNN with metadata

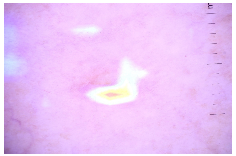
Results

-For the Resnet-18 CNN with metadata, the training and validation datasets gave the following confusion matrices, and a 0.7330 accuracy on the test dataset





-Using Resnet-18 compared to VGG16 did not make much of an impact. (73.15% test accuracy on Resnet-18 and a 74.35% test accuracy on VGG16)



-Constructed gradCAM photos of the skin lesions to see which areas of the image were influencing the model's decision in benign/malignant classification.

References

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Dec 2015.

Yuexiang Li and Linlin Shen. Skin lesion analysis towards melanoma detection using deep learning network. Sensors, 2018.

Advanced Dermatology Skin Cancer Associates. There's a reason you have to wait so long for a dermatologist appointment, Aug 2018.

Diane Mapes. The dermatologist won't see you now, Mar 2007.

Multimodal Multi-Class Classification of Lung Diseases

Daniel Lee, Haripriya Mehta, Felipe Moreno
Harvard, MIT

Massachusetts Institute of Technology®

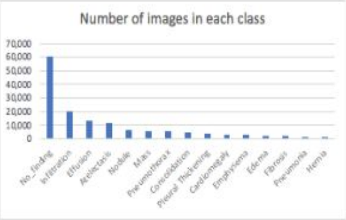
Motivation

- Confirm radiologists' results and potentially identify findings that may have been overlooked

- Goals of this project:
  - Identify slow changes
  - Ease the lack radiologists in developing countries
  - Can be applied to more complex dataset (CT, MRI)

Dataset

NIH Chest Dataset
- Composed of over 11,000 images, patient age and gender data
- Each image can show no disease/1 disease/multiple diseases
- Processed data as some features did not make sense (age of 414)
- 14 classes (13 diseases and 1 no-disease)
- Highly Imbalanced Dataset with about half the images having no-disease



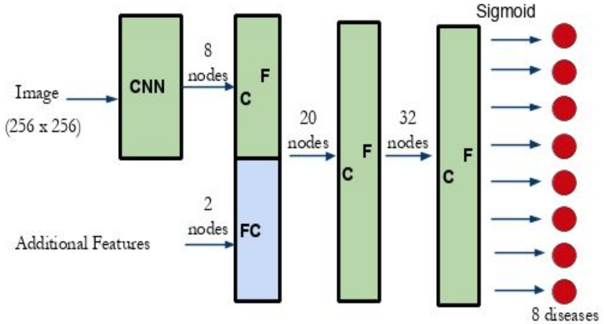
Focused on 8 diseases (Infiltration, Effusion, Atelectasis, Nodule, Mass, Pneumothorax, Cardiomegaly and Pneumonia) omitting under represented categories and 1 non-disease

Paper citation or references

Representation of Additional Features

Additional Features (gender and age):
- Represented by one-hot vector of size 12
- First two positions represent Male, Female
- Last ten position represent age intervals [1, 10], [11, 20], … , [91, 100]
- Example: [1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0] encodes a Male Patient aged between 31 and 40 years.

Multimodal Multi-class Classifier



Each output represents the individual probability of a disease being expressed.

Binary Cross Entropy Loss
- Diseased labeled images were upsampled to further balance the data.

Used single modal (CNN only) as baseline

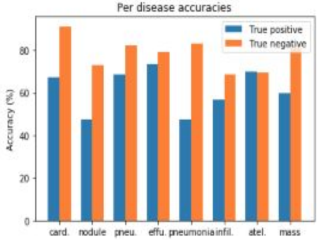
Results

- Highest accuracy achieved by ResNet as compared to AlexNet & VGG
- Augmented data using rotations, scaling and translations applied to training data to improve generalization.

Global Accuracy:

Model	Global Accuracy	# of epochs trained
Resnet 18 (CNN Only)	Train: 69.8% / Val: 75.7%	20
Resnet 18 (Multimodal)	Train: 73.7% / Val: 77.0%	30

Accuracy Per Disease (ResNet 18; multimodal)



Potential Criticism

Luke Oakden-Rayner
- radiologist cum machine learning specialist
- argues that many images of NIH dataset are mislabeled
- radiologists never saw original images; labels were determined using NLP techniques
- Stanford CheXNet works well because Stanford's own radiologists relabelled the dataset

Conclusion: Our accuracy could be higher given correct labels.

Paper Dreams

Haripriya Mehta Faculty Mentor: **Pattie Maes** Graduate Mentor: **Guillermo Bernal**

MIT EECS
Undergraduate Research and Innovation Scholar

Motivation

- Storyboard artists face "artist's block"
- Can we augment the artist's creativity using deep learning?

Our Storyboarding Tool

- Paper Dreams: creative storytelling tool
- Artist in charge of his/her creative process + conversation with neural net
- Neural net colorizes, recognizes, and draws related sketches with feedback from artist
- Early childhood education and elderly

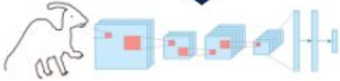
Output

Example Storyboard Panels

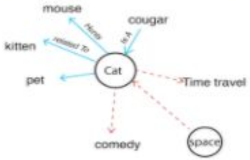
Architecture for Paper Dreams

Artist sketches → Storyboard colorization (Pix2Pix on irasutoya) → Artist faces creative block and is running out of ideas

Sketch Recognition (CNN on Quick, Draw!)



Determine object relation (spaCy on Gutenberg)



← Sketch generation (Sketch-RNN on Quick, Draw!)

← Storyboard colorization (Pix2Pix on irasutoya)

Feedback Loop; artist is inspired to draw some other object

Want to see it in action? Want to contribute? Please scan the QR code.

User

Neural Net

Future Goals

- Sketch generation in the style of the user using VAE or CycleGAN
- Character design where a character can be drawn in a "good" or "evil" manner based on user preference

Preliminary Results

Sketch Recognition

- OpenAI's Reptile - Accuracy: <5%; 1 drawing for each of 15 classes
- CNN with Quick Draw – Accuracy: 85%; 100,000 drawings for each of the 20 classes

Concept Relation

- Relations dictated by cosine similarity using spaCy and trained on Project Gutenberg

References

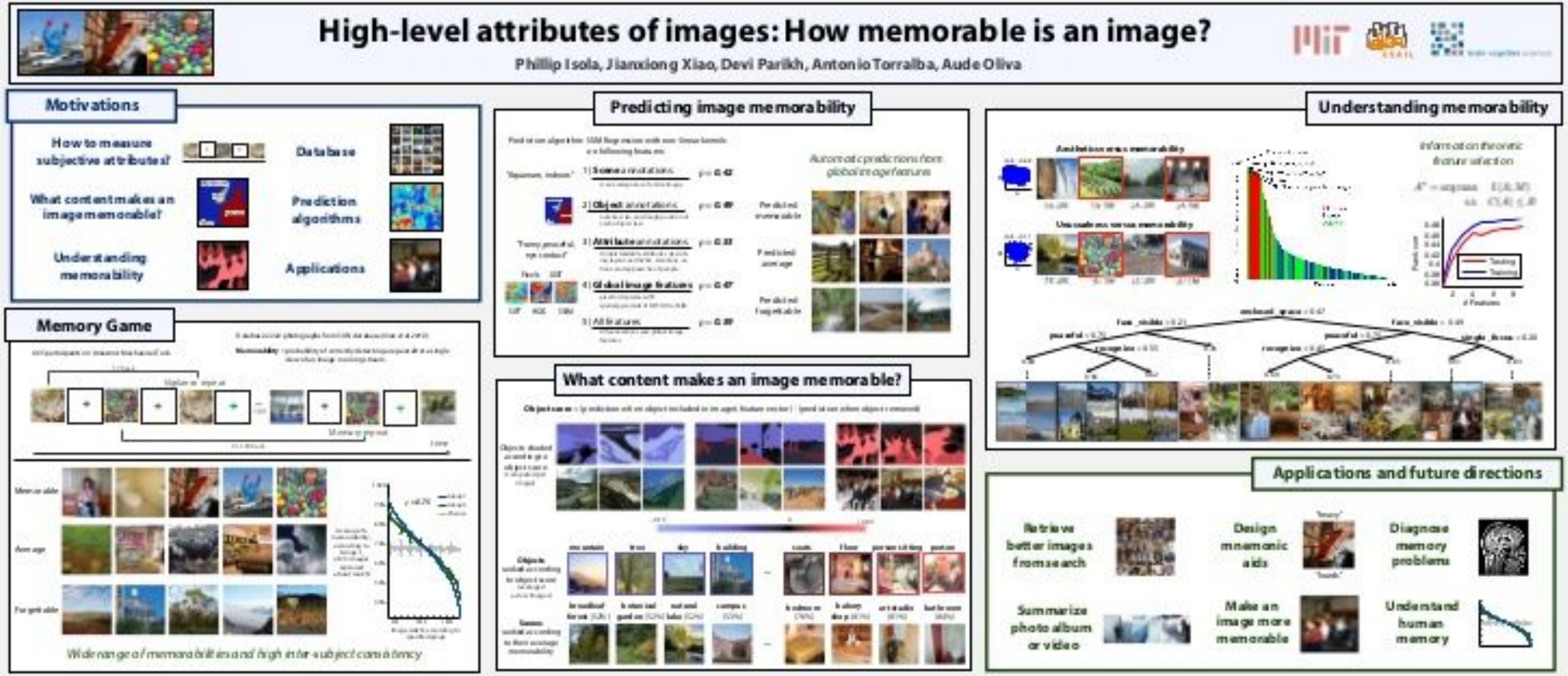
Phillip Isola, Jun-Yan Zhu, Tinghui Zhou and Alexei A. Efros. Image-to-Image Translation with Conditional Adversarial Networks, 2016; arXiv:1611.07004.

David Ha and Douglas Eck. A Neural Representation of Sketch Drawings, 2017; arXiv:1704.03477.

OpenAI. "Reptile: A Scalable Meta-Learning Algorithm." *OpenAI Blog*, OpenAI Blog, 5 Apr. 2018, blog.openai.com/reptile/.

"SpaCy - Industrial-Strength Natural Language Processing in Python." *SpaCy - Industrial-Strength Natural Language Processing in Python*, spacy.io/.

"Concept Of Brain With Gears Logo Vector." *Human Okay Hand Sign (Ok Hand Symbol, Ok Symbol, Ok Sign Icon)*, www.canstockphoto.com/concept-of-brain-with-gears-logo-21221445.html.


High-level attributes of images: How memorable is an image?
Phillip Isola, Jianxiong Xiao, Devi Parikh, Antonio Torralba, Aude Oliva
Motivations
How to measure subjective attributes?
Database
What content makes an image memorable?
Prediction algorithms
Understanding memorability
Applications
Memory Game
Memorable
Average
Forgettable
Wide range of memorabilities and high inter-subject consistency
Predicting image memorability
1) Scene annotations
2) Object annotations
3) Attribute annotations
4) Global image features
5) All features
Automatic predictions from global image features
Predicted memorable
Predicted average
Predicted forgettable
What content makes an image memorable?
Understanding memorability
Applications and future directions
Retrieve better images from search
Design mnemonic aids
Diagnose memory problems
Summarize photo album or video
Make an image more memorable
Understand human memory