Major Project

Melanoma Detection: An Automated Approach

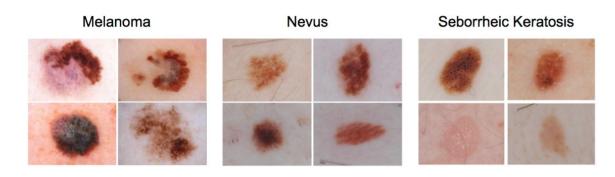
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Challenge 2017

- International Skin Imaging Collaboration (ISIC)
- Two binary classification tasks:
 - In the first, distinguish between (a) melanoma and (b) nevus and seborrheic keratosis.
 - In the second, distinguish between (a) seborrheic keratosis and (b) nevus and melanoma.
- 2000 images are provided as training data, including 374 "melanoma", 254 "seborrheic keratosis", and the remainder as benign nevi (1372).



Literature Review

Lequan, Hao	RoR	Resnet	Deep Transfer Learning	Sparse Coding
 Dataset: ISBI 2016 Skin Lesion Analysis Towards Melanoma Detection Challenge dataset. 2 stage framework- FCRN for lesion segmentation + Deep Residual network for classification 	Dataset: benchmark datasets CIFAR-100 Uses residual mapping function in two layers Two methods of stochasic depth and linear decay weightage	Dataset: International Skin Imaging Collaboration (ISIC) dataset Concept of shortcut connections using identity function Image is resized and randomly cropped in a 10-crop testing style Plan 18 and 34-layer nets are evaluated	 Dataset: International Skin Imaging Collaboration (ISIC) dataset Uses pre-trained Caffenet model from the ILSVRC The preprocessing step involves resizing the image and Subtract the model's input mean image to "centralize" Classifier: Non-linear SVM using a histogram intersection 	 Dataset: International Skin Imaging Collaboration (ISIC) dataset Unsupervised methods - learns a dictionary of sparse codes SPAMS sparse coding dictionary learning algorithm- based on stochastic approximations. Images are rescaled to pixel extraction of 8x8 patches, to learn 2 dictionaries (color/gray) Classifier: Non-linear SVM using a histogram intersection kernel

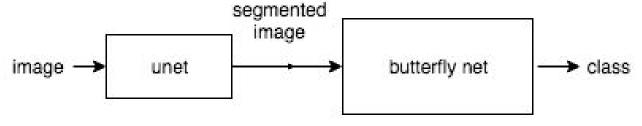
Algorithm

Concept

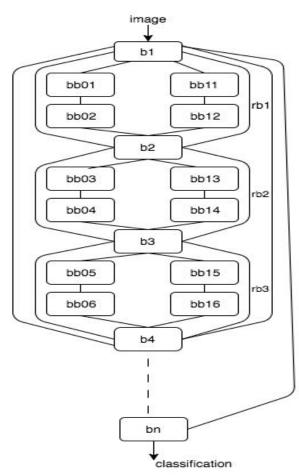
- Widening the network to increase the learning parameters
- Each layer is an ensemble of 2 networks
- Weighted-Identity function + multi layer shortcuts
- Images are segmented

Characteristics

- Wider model (equivalent of a 100+ layer model)
 - Keras limitation (depth)
- Saving all weights is not necessary

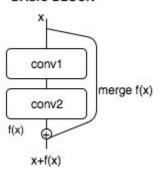


Architecture

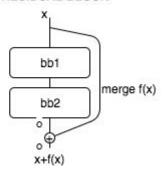


Block Structure

BASIC BLOCK



RESIDUAL BLOCK



Basic block layer ordering

- Batch normalization
- Convolution
- ReLu layer

Butterfly algorithm performs the merge function for each layer parallely and sums the output so it becomes...

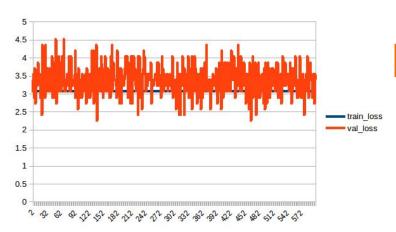
$$(x1+f(x1)) + (x2+f(x2))$$

See __ paper__

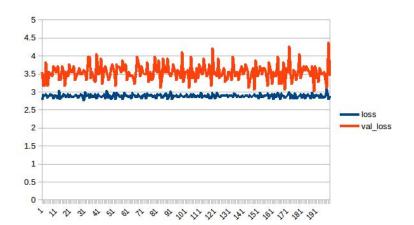
Issues

- 1. Vanishing gradients
 - Delta change in weights approach 0
- 2. Overfitting
 - Higher than necessary # of params
- 3. Diminishing feature reuse
 - Too abstract info in deeper layers
- 4. Internal co variation
 - Distribution of each layer's inputs changes during training, as the parameters of the previous layers change

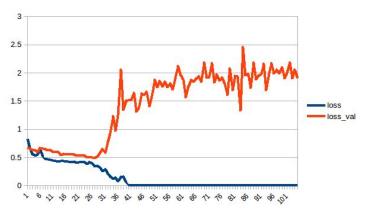
- 1. Shortcut connection
- 2. Forward previous layer through identity shortcuts
- 3. Multi layer connections
- 4. Batch normalization



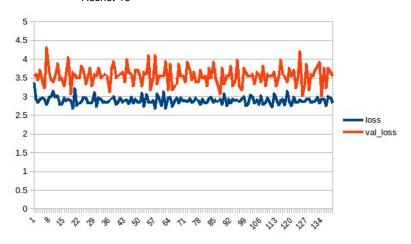
Butterfly Classifier



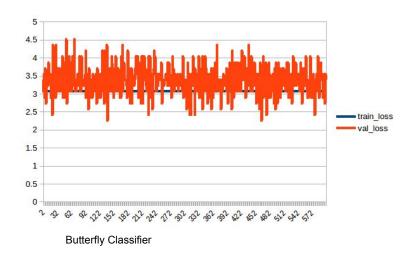
Results

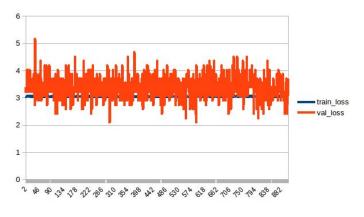


Resnet-18



RoR-SD-20



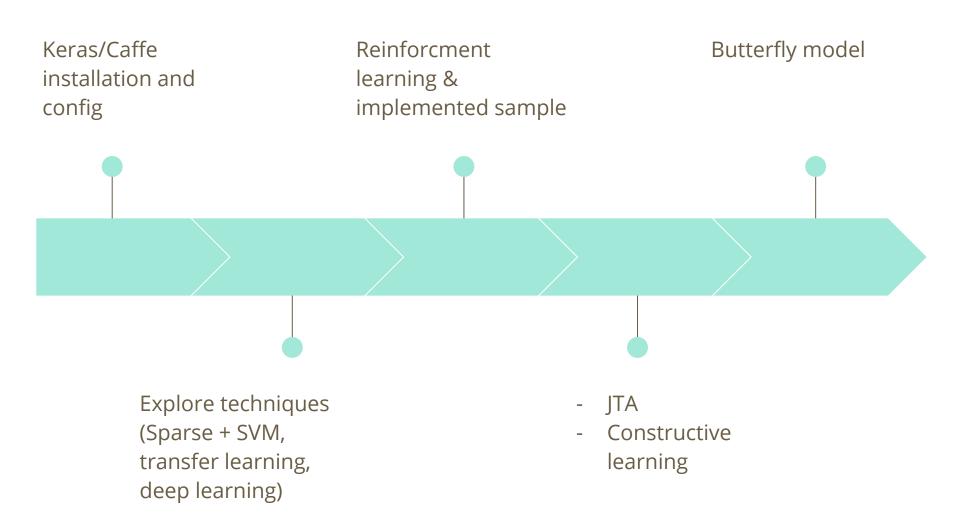


RoR-SD weighted

Accuracy:

Automated Melanoma	ROR-SD	Butterfly GT	Butterfly Unet
85.5%	82%	87%	86%

The End



Challenges in Frameworks

Caffe

 Very limited customization of architecture

Keras

- Issues in saving complicated model
- Issues in matrix multiplication

Extensions on the butterfly model

Modify weightage

Implement equal weightage of all RoR blocks for the butterfly model via linear decay

Image Input

Split the image evenly and feed into the two 'wings' of the model