THE GEORGE WASHINGTON UNIVERSITY
WASHINGTON, DC

Acute Lymphoblastic Leukemia (ALL) Classification:
Kaggle Competition

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Overview

Goal: Experiment with several convolution neural networks (CNNs) in order to find the model that best distinguishes between Normal and Leukemia blast (cancer) cells

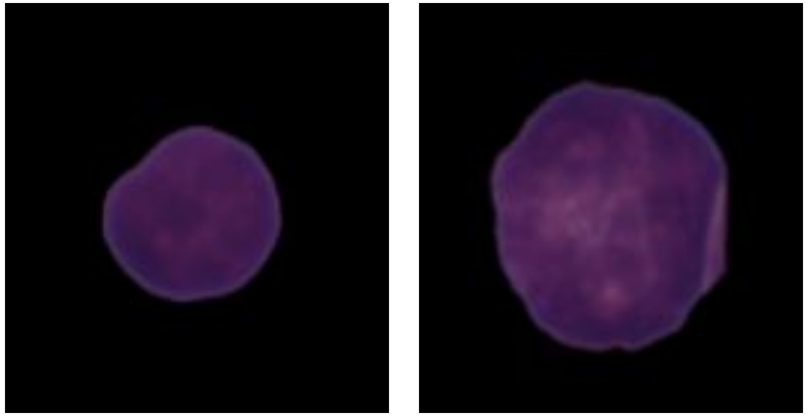
- Introduce the machine learning application
- Describe the dataset
- Model Experimentation
  - Base Model
  - Individual Model Experiment Descriptions
- Best Model
- Summary
- References

Introduction

- **Goal:** Experiment with several convolution neural networks (CNNs) in order to find the model that best distinguishes between Normal and Leukemia Blast (cancer) cells
- **Motivation:** Interest in becoming more familiar with CNN networks for image classification and applying machine learning skills to health care
- **Roadmap:** Based on their F-1 and Cohen Score, a best model will be chosen
- **Framework:** PyTorch, pre-trained networks that we will use as a baseline comparison
- **Background Information:** Introductory papers and previous Kaggle code
- **Models:** VGGNet16_19, EfficientNetB0_B3_B4_B5_B7, GoogleNet, DenseNet161_121_169, ResNet152

Dataset

- 15,135 images from 118 patients with two classes: Normal and Leukemia Blast (cancer) cell
- 10GB of data
- Train, Validation, Test: 10,661 | 1,867 | 2,586
- Expert oncologist annotated the ground truth labels of the data, staining noise & illumination errors



Base Model: One Convolution Block

One Convolution, Batch Normalization, Global Pooling, and Linear layer

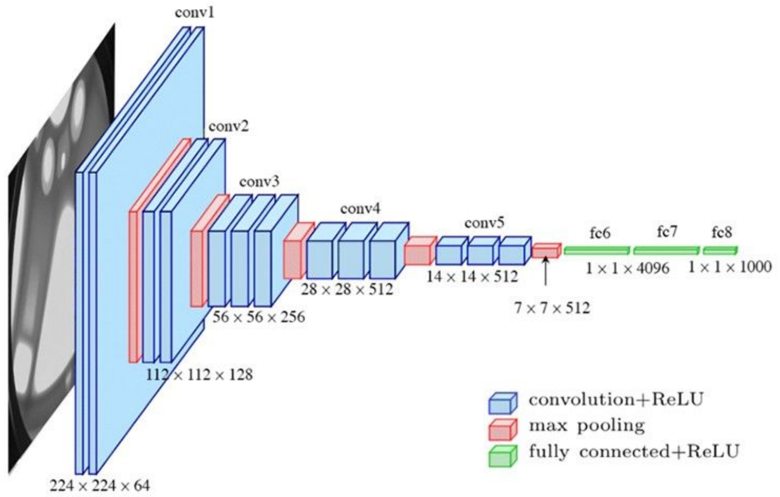
- **Image Size:** (100,100)
- **Batch Size:** 60
- **Epoch:** 1
- **Learning Rate:** 0.001
- **Data Augmentation:** None
- **Class Imbalance:** None
- **Accuracy: 63.6%**

VGGNet 16, 19

Very Deep Convolutional Networks for Large-Scale Image Recognition

Karen Simonyan and Andrew Zisserman - Adding more (convolution) layers (depth), the model performance increases

- **Data Augmentation:** Horizontal Flip, Vertical Flip, with probability
- **Image Size:** (128,128)
- **Batch Size:** 512
- **Epochs:** 20
- **Learning Rate:** 0.001
- **Class Imbalance:** None
- **High Accuracy:** (58.3%), (59.2%)

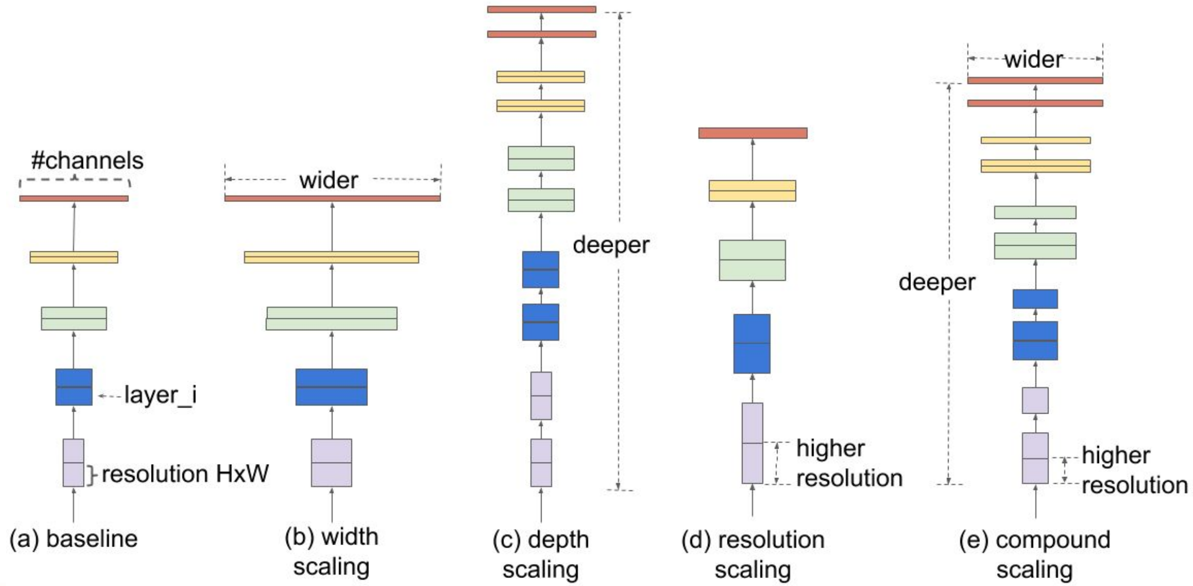


EfficientNet B4, B5

EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

Mingxing Tan and Quoc V. Le - Model Scaling: depth, width, resolution

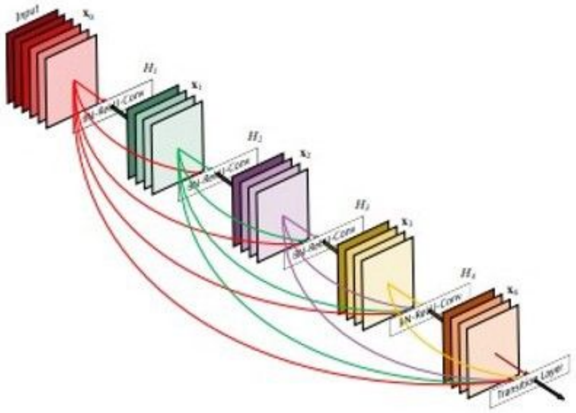
- **Data Augmentation:** Horizontal Flip, Vertical Flip, Brightness, Contrast
- **Image Size:** (300,300)
- **Batch Size:** 32
- **Epoch:** 7
- **Learning Rate:** 0.001
- **Class Imbalance:** Oversampling
- **High Accuracy:**(63.8%), (62.8%)

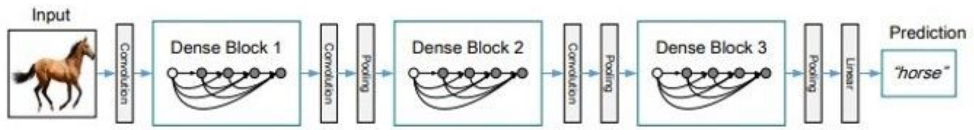


DenseNet121

DenseNet architecture following a pattern of dense blocks of convolution and transition layers

- **Image Size:** (300,300)
- **Batch Size:** 32
- **Epoch:** 2
- **Learning Rate:** 0.0001
- **Data Augmentation:** Random Crop, Horizontal Flip
- **Class Imbalance:** None
- **Accuracy: 65.3%**

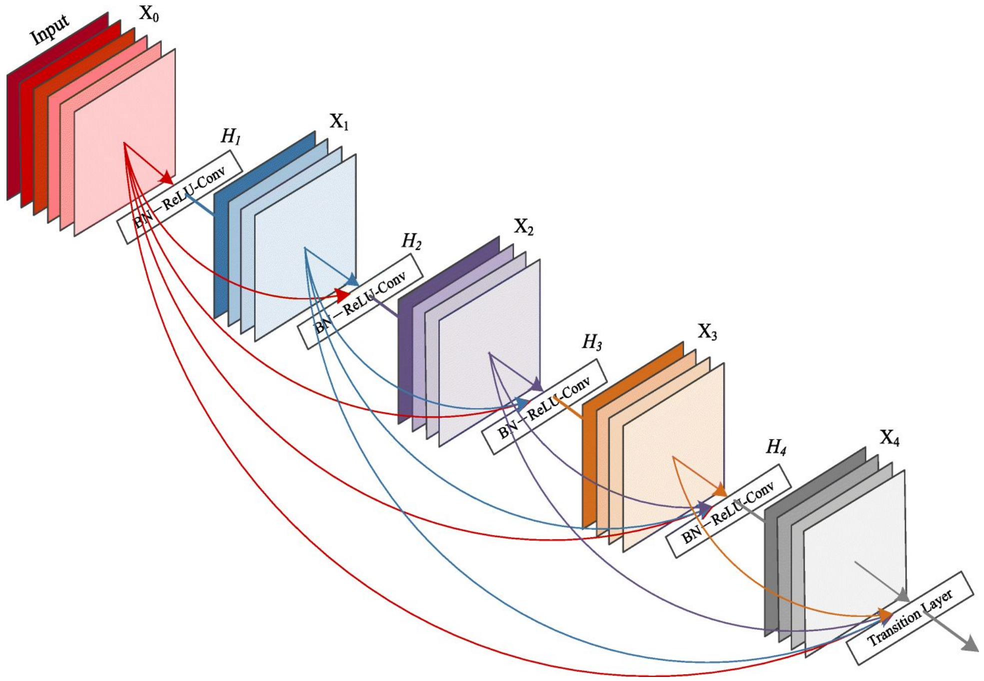




DenseNet161

DenseNet architecture following a pattern of dense blocks of convolution layers and transition blocks

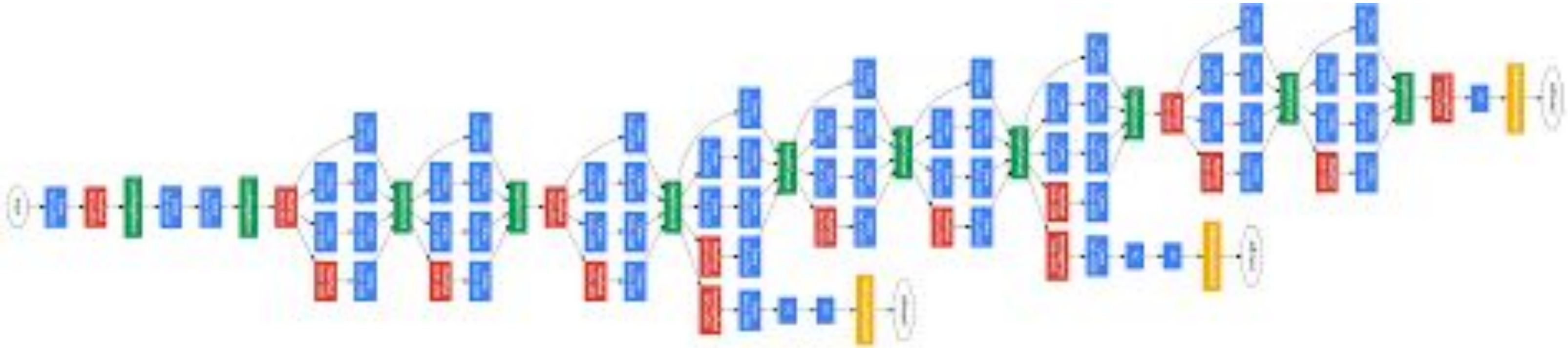
- **Image Size:** (100,100)
- **Batch Size:** 32
- **Epoch:** 5
- **Learning Rate:** 0.0001
- **Data Augmentation:** Random Crop, Horizontal Flip (with Probability)
- **Class Imbalance:** None
- **Accuracy: 70.8%**



GoogleNet

GoogleNet is a pretrained 22 layer convolutional neural network

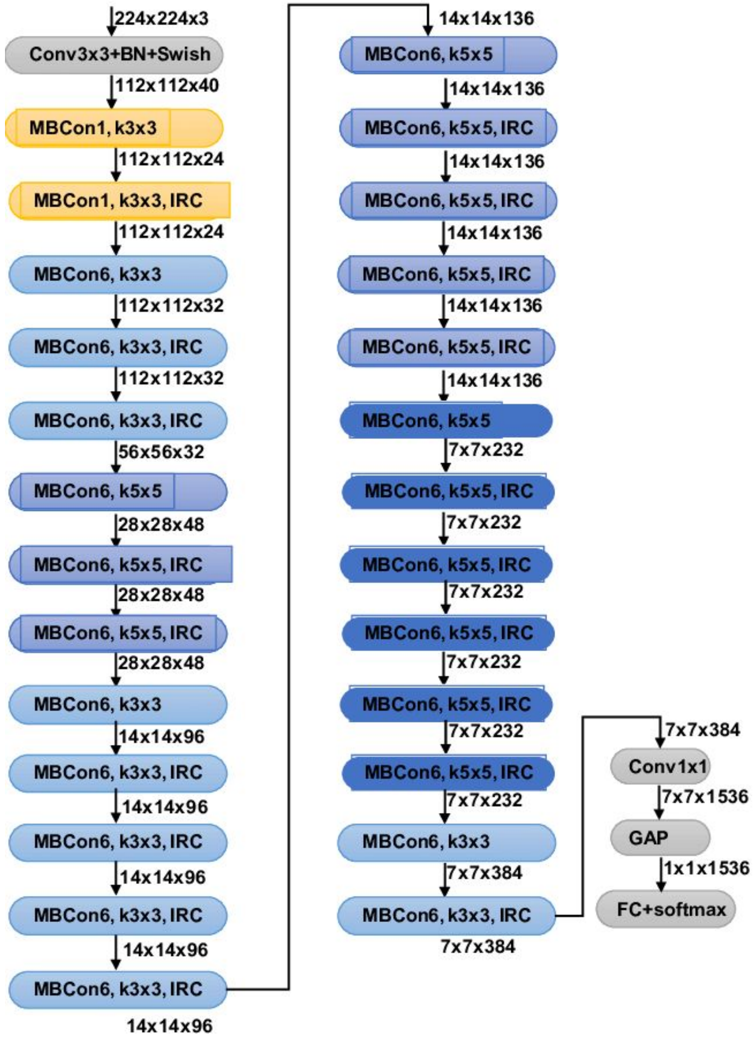
- **Image Size:** (200,200)
- **Batch Size:** 32
- **Epoch:** 10
- **Learning Rate:** 0.0001
- **Data Augmentation:** Random Crop, Horizontal Flip, Vertical Flip (with Probability)
- **Class Imbalance:** None
- **Accuracy: 72.3%**



EfficientNet_B3

EfficientNet is a CNN model that focuses on balancing network depth, width and resolution to enhance performance.

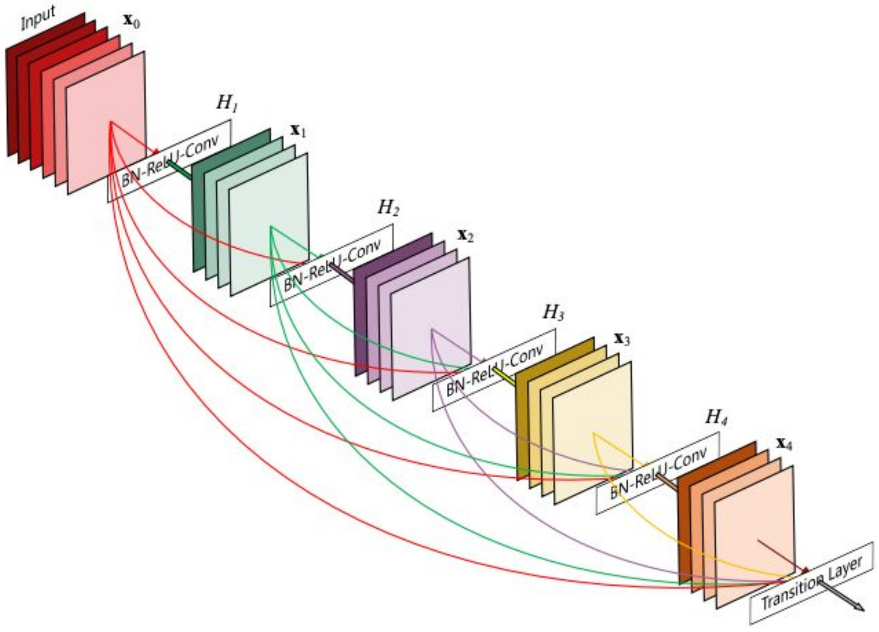
- **Image Size:** (200,200)
- **Batch Size:** 32
- **Epoch:** 10
- **Learning Rate:** 0.001
- **Data Augmentation:** Random Crop, Horizontal Flip, Vertical Flip, Gamma, Brightness, Contrast
- **Class Imbalance:** Class Weights
- **Accuracy: 74.5%**



DenseNet169

Densely Connected Convolutional Networks

Gao Huang et al.



- **Image Size:** (300,300)
- **Batch Size:** 32
- **Learning Rate:** 0.001
- **Data Augmentation:** Horizontal Flip, Vertical Flip, Normalization
- **Class Imbalance:** Oversampling -- minority class duplication
- **F-1:** 73.7% | **Accuracy:** 75.0% | **Cohen:** 40.8%

ResNet152

Deep Residual Learning for Image Recognition

Kaiming He, Ziangyu Zhang, Shaoqing Ren, Jian Sun

GoogleNet

Going Deeper with Convolutions

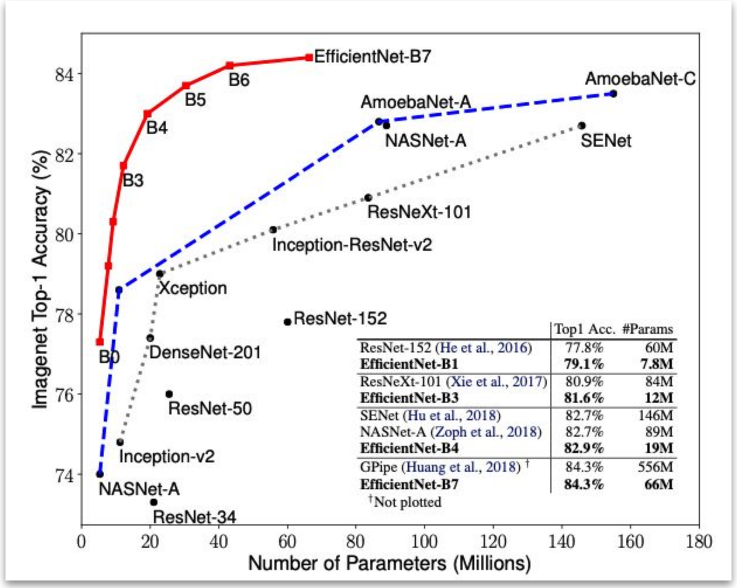
Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich

- **Image Size:** (300,300)
- **Batch Size:** 32
- **Learning Rate:** 0.001
- **Data Augmentation:** Horizontal Flip, Vertical Flip, Normalization
- **Class Imbalance:** Oversampling
- **F-1:** 68.3% | **Accuracy:** 68.3% | **Cohen:** 30.2%

- **F-1:** 75.8% | **Accuracy:** 75.3% | **Cohen:** 48.0%

EfficientNet_B0

- **Image Size:** (300,300)
- **Batch Size:** 32
- **Learning Rate:** 0.001
- **Data Augmentation:** Horizontal Flip, Vertical Flip, Normalization, Center Cropping
- **Class Imbalance:** Oversampling
- **F-1:** 77.6% | **Accuracy:** 77.6% | **Cohen:** 42.2%



Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels $\hat{C}_i$	#Layers $\hat{L}_i$
1	Conv3x3	224×224	32	1
2	MBConv1, k3x3	112×112	16	1
3	MBConv6, k3x3	112×112	24	2
4	MBConv6, k5x5	56×56	40	2
5	MBConv6, k3x3	28×28	80	3
6	MBConv6, k5x5	28×28	112	3
7	MBConv6, k5x5	14×14	192	4
8	MBConv6, k3x3	7×7	320	1
9	Conv1x1 & Pooling & FC	7×7	1280	1

Conclusion

How we did: Competitive compared to benchmarks

- Prellberg & Kramer (2020): 88%
- Ashish Goswami: 93%

2 Approached: Data augmentation and pretrained network selection

Our Best Model(s) used Baseline EfficientNet

- Needed to capture more granular image features
- Faster & more accurate

Future Work includes testing with customized learning rates

References

Acute Lymphoblastic Leukemia Classification from Microscopic Images using Convolutional Neural Networks (2020 paper)
Acute Lymphoblastic Leukemia Detection from Microscopic Images Using Weighted Ensemble of Convolutional Neural Networks (2021 paper)
C_NMC_2019 Dataset: ALL Challenge dataset of ISBI 2019 (C-NMC 2019)
Best deep CNN architectures and their principles: from AlexNet to EfficientNet
Committed Towards Better Future: EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks
EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks (2020)
Very Deep Convolutional Networks for Large-Scale Image Recognition Karen Simonyan, Andrew Zisserman (2014)
Kaggle Competition Link
VGGNet Image Link
EfficientNet Image Link (Slide 7)
EfficientNet_B3 image Link
GoogleNet Image Link
DenseNet161 Image Link
Dense121 Image Link

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