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neuromatch academy

# Melanoma classification

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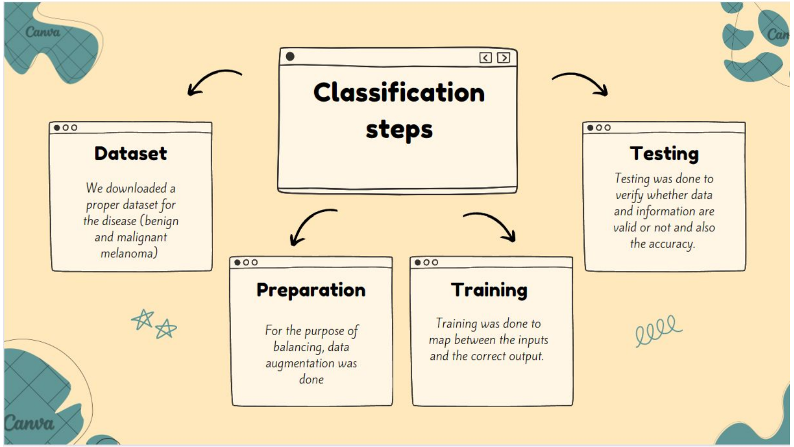
# Problem statements, motivation etc.

- Motivation:

Believing in the importance of using deep learning tools in the field of human health, this project was directed to a kind of medical purpose. This is after knowing the difficulty, pain and length of time it takes to determine the type of skin disease present.

- Problem statement:

The problem that the project deals with revolves around determining the presence of a specific disease in the skin (determining whether it is a malignant or benign tumor) only through the image.




- Steps of classification:

I did this mind map just to focus on the major steps throughout the project.

# Methods, Architecture and Optimizers

## Methods:

### Transfer Learning

Utilised pre-trained models like EfficientNet, ResNet to enhance our CNN's accuracy.

### Data Augmentation

To tackle the data imbalance, we augmented the melanoma images by applying random horizontal and vertical flips.

## Architectures:

### Simple CNN

A custom-built CNN architecture based on LeNet.

### Not-So-Simple-CNN

A custom-designed architecture.

### ResNet

A widely-used pre-trained CNN architecture known for its depth and efficiency.

### TinyVGG

A compact version of the VGG architecture, for smaller datasets.

### EfficientNet

State-of-the-art CNN known fot its scalability and performance.

## Optimizers:

### Stochastic Gradient Descent (SGD)

A classic optimizer used for training neural networks.

### SGD with Momentum

An extension of SGD with added momentum to accelerate convergence.

### Adam

A popular adaptive optimizer combining momentum and adaptive learning rates.

### RAdam

A variant of Adam with improved convergence properties.

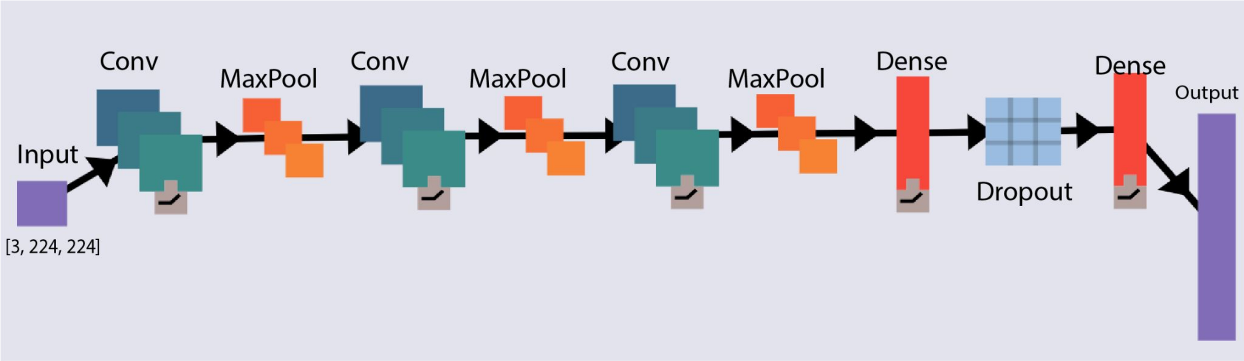
### RMSprop

Similar to the gradient descent algorithm with momentum.

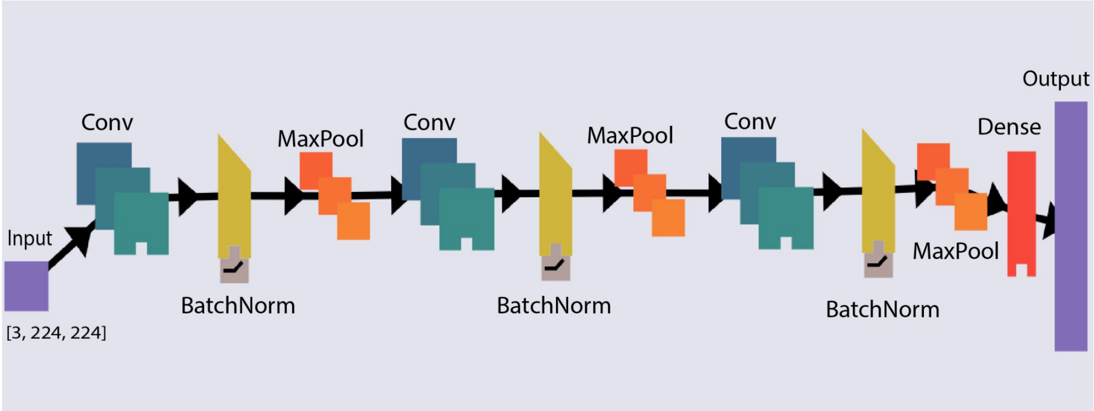
### L2 Regularization and Early Stopping

L2 adds a penalty term to the loss function.
Early Stopping halts training when the model's performance on a validation set starts to degrade.

# “Simple CNN”




# “Not-So-Simple CNN”



# Main findings

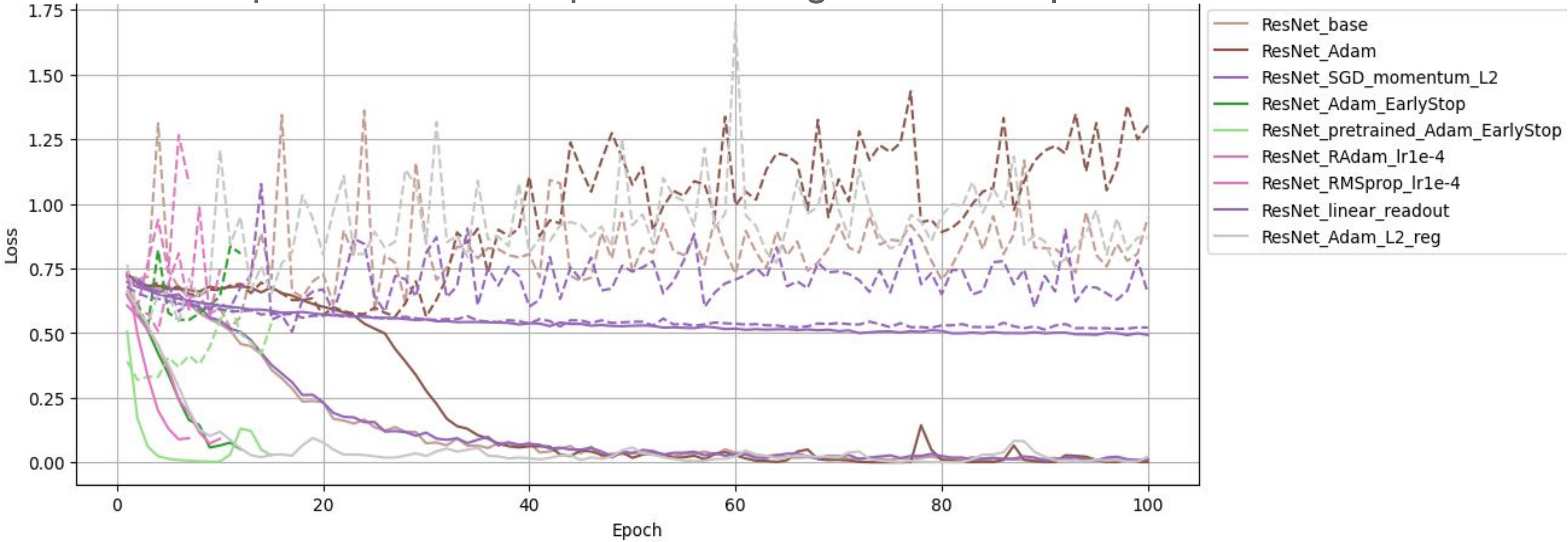
- Overfitting

  Most models were overfitting, even with L2 regularization

- Performance

  Simpler architecture performs as good as complex ones

| Model | Accuracy |
|---|---|
| ResNet18 (pretrained) | 92.4% |
| EfficientNet (pretrained) | 90.3% |
| Not-So-Simple-CNN | 83.6% |
| EfficientNet | 78.1% |
| ResNet18 | 77.1% |
| SimpleCNN | 74.8% |
| TinyVGG | 72.1% |



# Conclusion

- EfficientNet and ResNet with transfer learning produced the most accurate results in classifying benign and malignant skin cancer.

- Models without transfer learning were overfitting due to insufficient data.

- Our custom-built CNN models' performance was comparable to pre-trained models.

- Regularization methods and optimizers did not change the performance since the dataset was small.

# Acknowledgement


Thank you to:

- 🦖 Our TA Parsa Zahedi
- 🦖 Our project TA Mina Rezaie
- 🦖 Our mentor Joseph Akinyemi
- 🦖 Our podmates
- 🦖 And to NMA organizers

This was an amazing experience!!!