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Enhancing Melanoma Detection

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Overview: Melanoma Skin Cancer

Deadly if not detected early

Accounts for only 1% of skin cancer but causes majority of skin cancer deaths (American Cancer Society)

Lab Based Detection

Uncertainty from the individual

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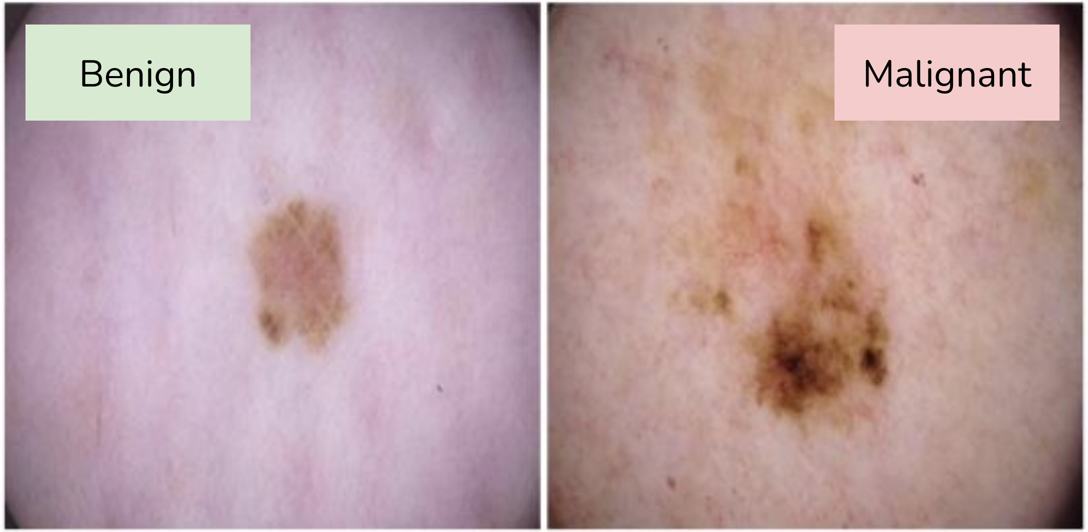
Lab Based Detection
Uncertainty from the individual

Apply Machine Learning methods to the Image Classification problem

Dataset

- Melanoma Skin Cancer Dataset from Kaggle
- 10605 images
  - 5500 benign, 5105 malignant



Methods

Data Exploration

Convolutional Neural Networks

Support Vector Machines

Logistic Regression

Transfer Learning

Data Exploration

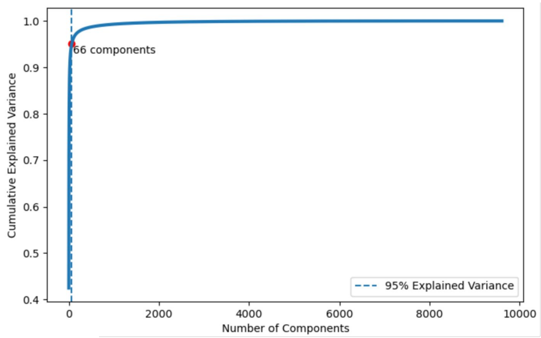
- Images had minimal noise, facilitating precise feature extraction and were balanced.

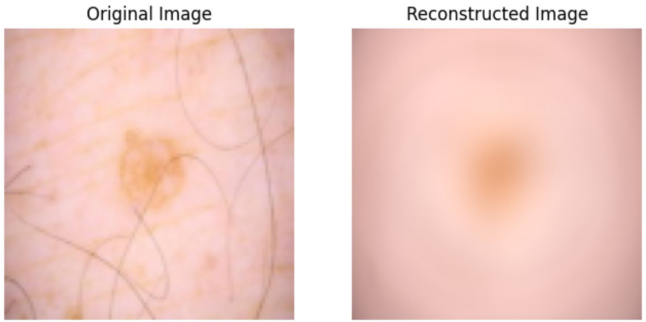
- All images resized to a uniform resolution of 100 x 100 pixels; pixel values normalized to the [0, 1] range to ensure stable model training.

- Implemented random horizontal flips and rotations to mirror real-world variations, enhancing model robustness and generalization capabilities.

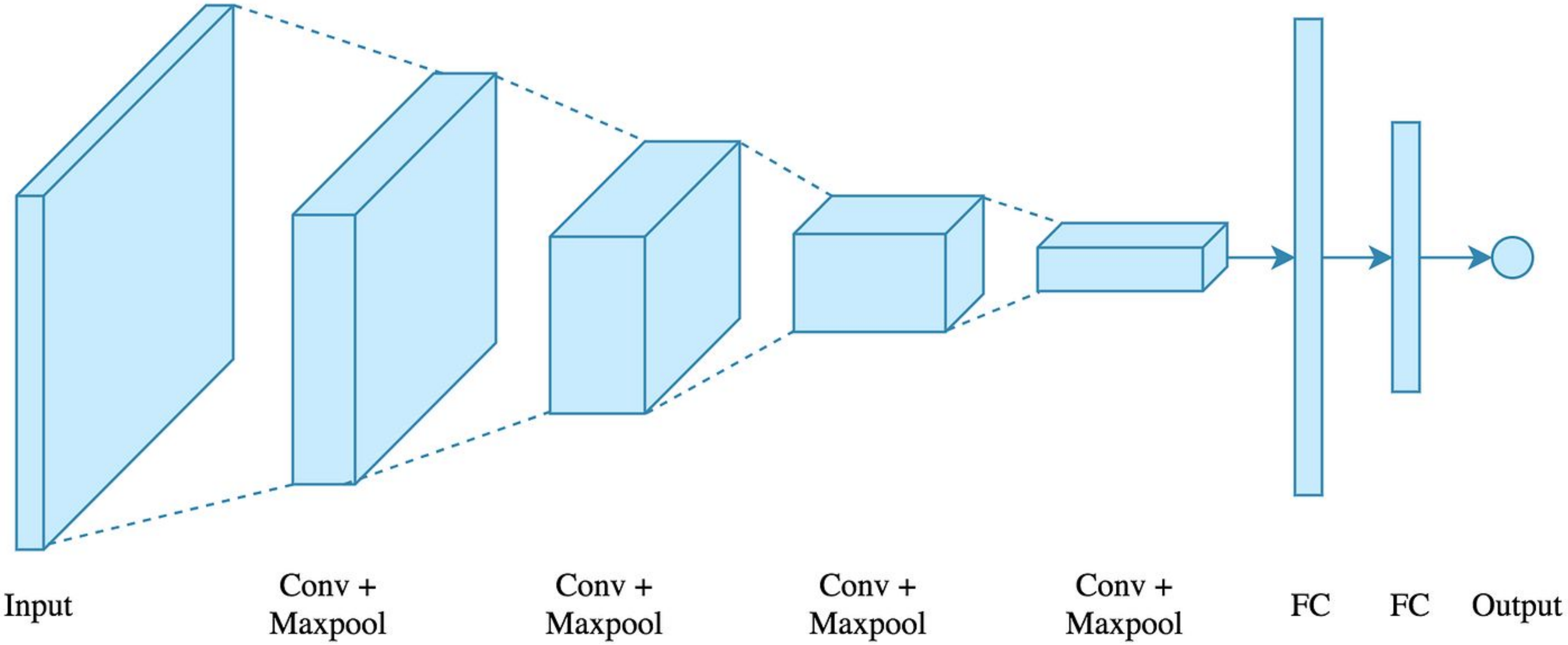
Dimensionality Reduction

- Applied PCA to manage high dimensionality of image data.
- Efficient Feature Reduction: Reduced from 9,605 features to 66, retaining 95% of original variance.
- Enhanced Model Efficiency: Significant dimensionality reduction speeds up training without losing critical information.





CNN


Input
Conv +
Maxpool
Conv +
Maxpool
Conv +
Maxpool
Conv +
Maxpool
FC
FC
Output

CNN Model Architecture

- Input (100x100x3)
- CNN Layer 1 (16 filters), ReLU, MaxPool (2x2)
- CNN Layer 2 (32 filters), ReLU, MaxPool (2x2)
- Flatten
- Fully connected layer (flatten dimension to 512)
- Fully connected layer (512 to 2)
- Output: max of the two outputs

Hyperparameter Optimization

- CNN Layers
  - **[16, 32]**, [16, 32, 64], [16, 32, 64, 128, 256]
- 3, 5, and **10** training epochs
- Tried all 9 combinations
- Could have optimized on more values
  - Linear layers, size of max pooling, etc.

SVM: Motivation

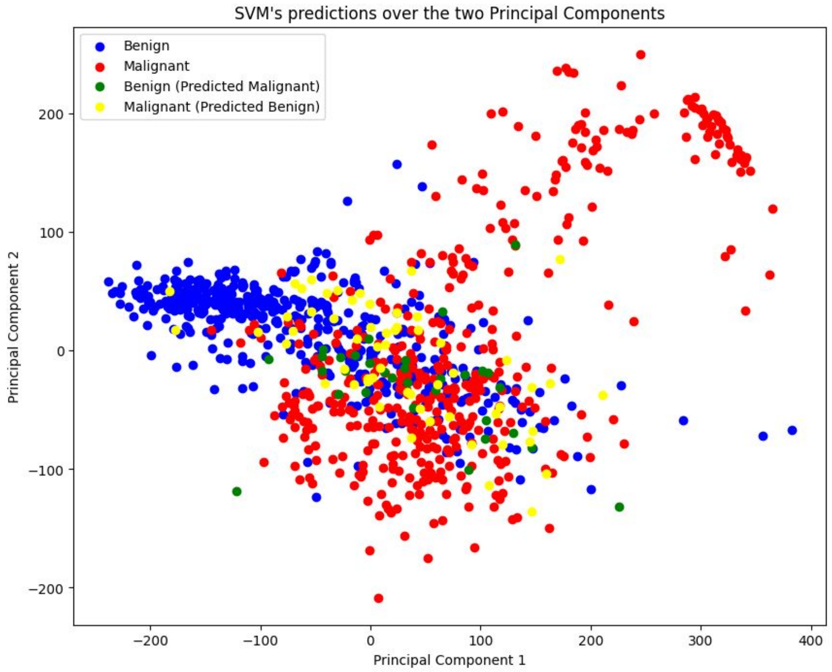
- Kernel functions
  - Better at handling higher dimensional data compared to other supervised learning models

- Advantages over deep learning
  - Has shown promises in situations where training samples availabilities are limited
  - Better interpretability
  - Computational efficiency

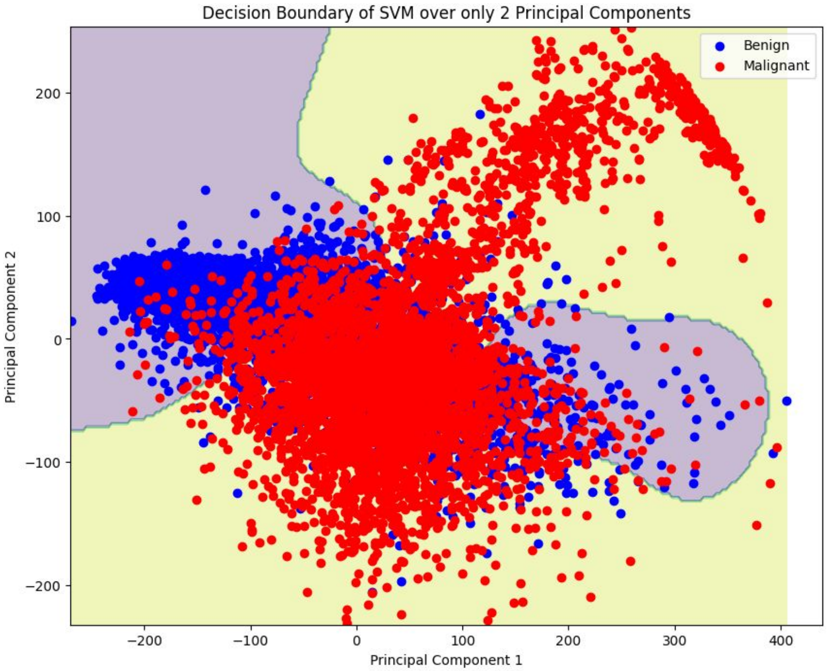
SVM: Training Process

- PCA
- Split full training set into training and validation
- RBF performed much better than linear kernel
- Grid search for hyperparameters
  - 10 values of C logarithmically spaced between 1E-2 and 1E10
  - 8 values of gamma logarithmically spaced between 1E-9 and 1E3, along with “auto” and “scale”
  - Used 5-fold cross-validation for evaluation
  - Best parameters: C=4.64, gamma: 'scale'

SVM: Plots



SVM's predictions over the two Principal Components
Benign
Malignant
Benign (Predicted Malignant)
Malignant (Predicted Benign)
Principal Component 1
Principal Component 2
200
100
0
−100
−200
−200
−100
0
100
200
300
400



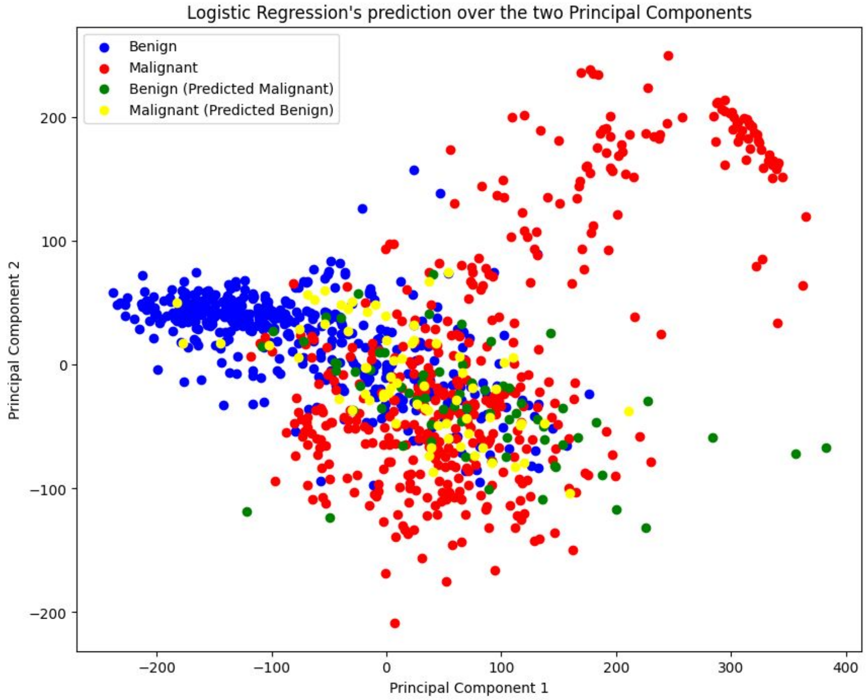
Decision Boundary of SVM over only 2 Principal Components
Benign
Malignant
Principal Component 1
Principal Component 2
200
100
0
−100
−200
−200
−100
0
100
200
300
400

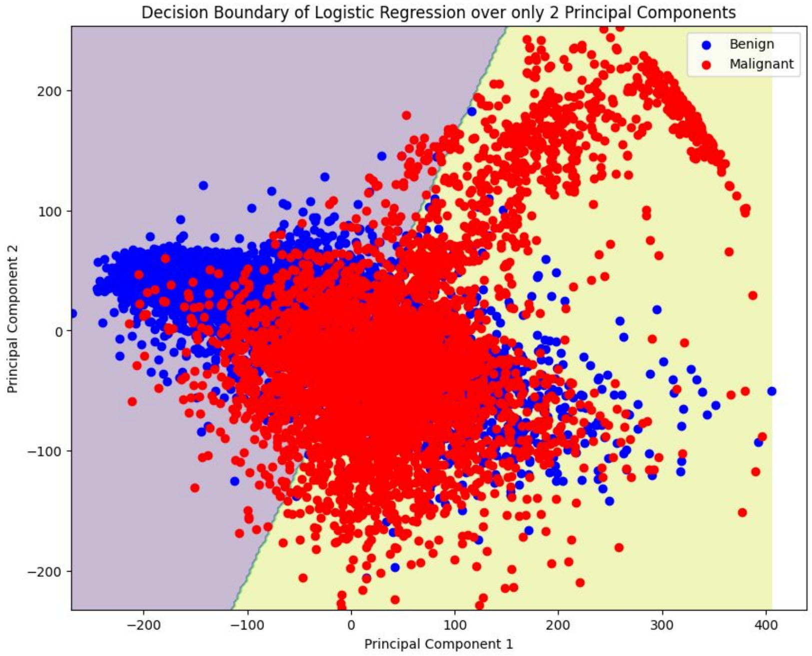
Logistic Regression

- A baseline model for us to compare to

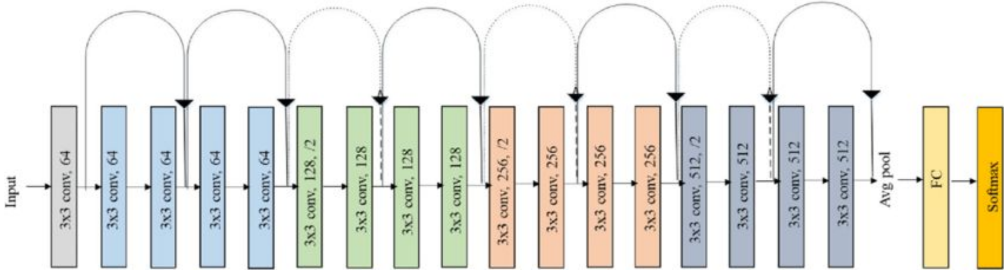
- Also used PCA and grid search for consistency
    - C is logarithmically spaced between 1E-10 and 1E10
    - 5 fold CV

Logistic Regression





Transfer Learning: ResNet-18



- Residual Networks use the Residual Learning Block
  - Gets rid of the vanishing gradient descent problem
- Trained on the ImageNet data set
  - Trained for versatility in image processing

Transfer Learning: Details

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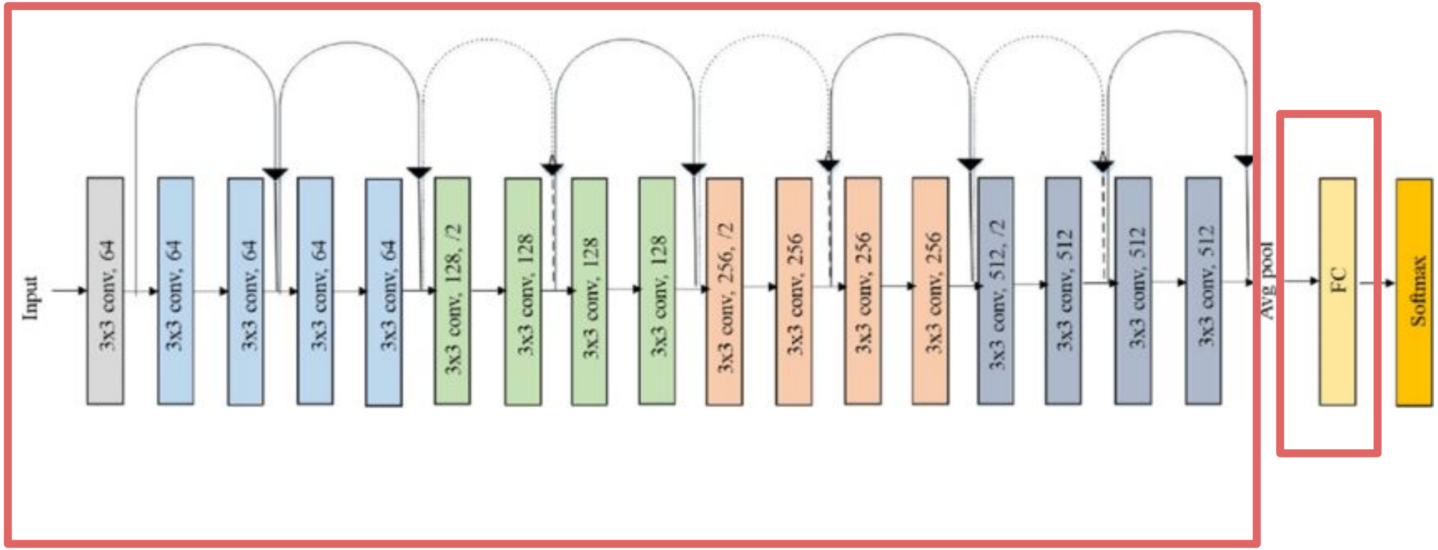
Freeze Model Weights

Replace Fully Connected Layer is just 2 units



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Results

Model	Accuracy	Precision	Recall	F1-Score
CNN	0.917	0.917	0.917	0.917
SVM	0.89	0.89	0.89	0.89
Logistic Regression	0.86	0.86	0.86	0.86
Transfer Learning (ResNet-18)	0.899	0.90	0.899	0.8986

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