Melanoma Detection Using CNNs

- Skin cancer is the most common form of cancer, with melanoma being the deadliest type.
- Early and accurate detection of melanoma is crucial for successful treatment.
- Convolutional Neural Networks (CNNs) have shown remarkable performance in image classification tasks.
- We propose a CNN-based approach for melanoma detection using dermoscopic images.
- Our model leverages transfer learning from pre-trained CNNs to improve accuracy and efficiency.

Problem Statement

- Melanoma is the deadliest form of skin cancer, responsible for the majority of skin cancer deaths.
- Early detection is key to improving survival rates for melanoma patients.
- We aim to build a CNN model capable of accurately detecting melanoma.
- This model will automate image evaluation, aiding dermatologists and reducing manual effort.

Dataset Overview

- Dataset: HAM10000 (ISIC)
- Images: 2,357 (malignant and benign)
- Skin Cancer Types: 9 classes (e.g., Melanoma, Nevus)
- Image Size: Resized to 180x180 pixels
- Split: Training and validation sets

CNN Architecture

- Input Layer: Rescales images to (180, 180, 3)
- Convolutional Layers: Extract spatial features
- MaxPooling Layers: Downsample feature maps
- Fully Connected Layer: Flattened output for classification
- Output Layer: Softmax function for 9-class classification

CNN Model Performance

- Data Augmentation: Random flips, rotations, and crops to increase diversity.
- Regularization: L1/L2 regularization and dropout to prevent overfitting.
- Optimizer: Adam optimizer for efficient gradient descent.
- Performance Metrics: Accuracy, sensitivity, specificity, and AUC-ROC curve.

IT Solutions for Melanoma Detection

- High accuracy in classifying melanoma images, outperforming traditional methods.
- Efficient and automated image evaluation, aiding dermatologists in diagnosis.
- Potential for early detection, leading to improved patient outcomes and survival rates.
- Scalable solution for widespread use in clinical settings.
- Further research can explore model interpretability and generalization to other skin lesions.

Model Performance

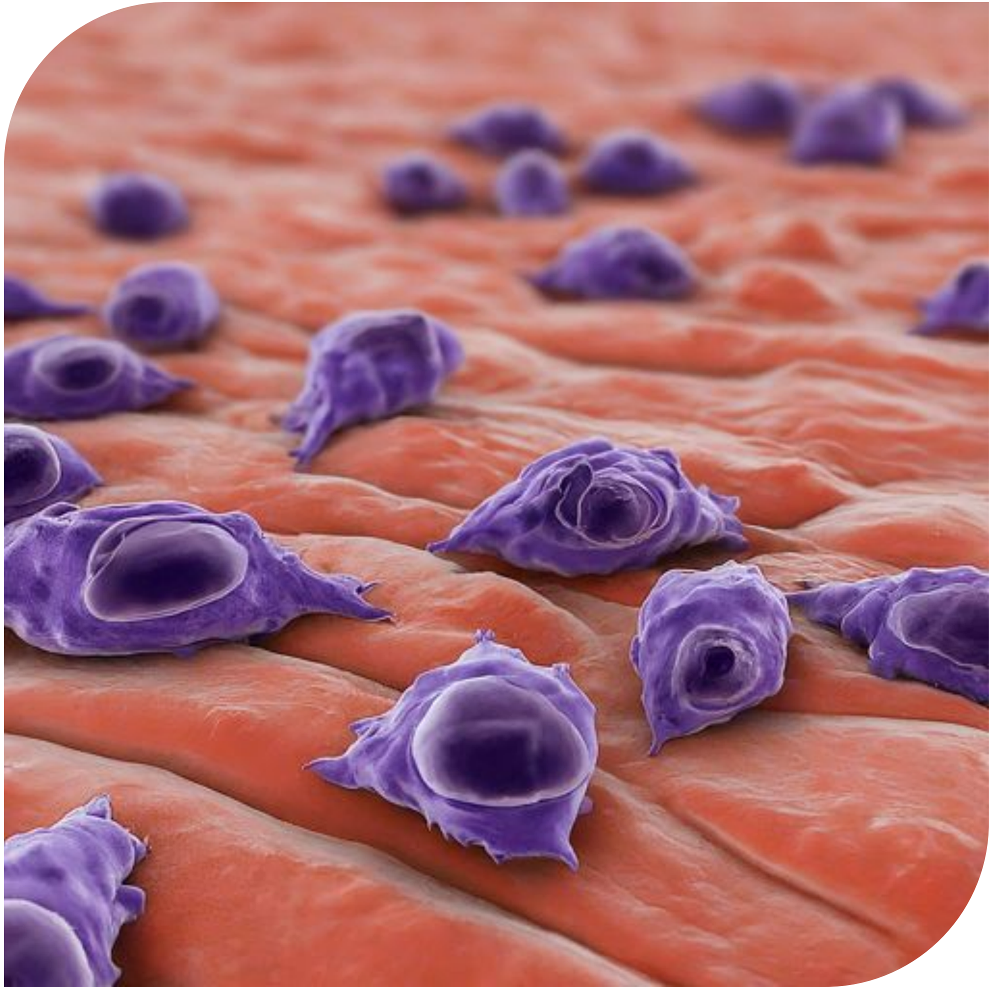
- Training accuracy steadily increased while validation accuracy plateaued.
- Training loss decreased consistently but validation loss increased.
- These trends indicate overfitting, where the model performs well on training data but poorly on unseen data.
- Class imbalance and small dataset size likely contributed to overfitting.

Addressing Overfitting

- Overfitting due to small dataset and class imbalance.
- Applied Augmentor library to balance class distribution.
- Added dropout layers to regularize model.
- Reduced model complexity to prevent overfitting.

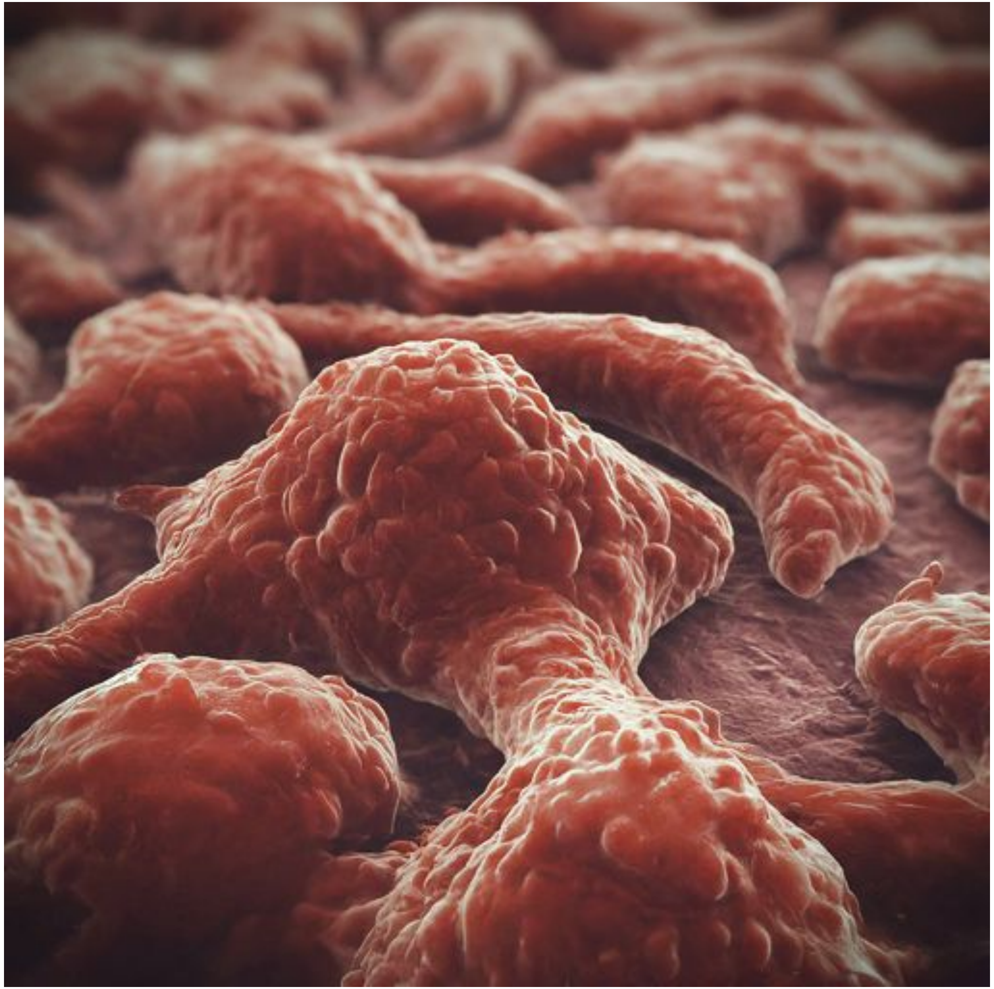
Class Imbalance Handling

- Class Distribution: Imbalanced classes (e.g., Melanoma had fewer images).
- Solution: Used Augmentor to increase the sample size for underrepresented classes.
- Result: Achieved a more balanced dataset, improving model's ability to learn from all classes.



Final Model Results

- Improved validation accuracy after applying data augmentation and regularization.
- Model generalized better on unseen validation data.
- Further improvements possible with transfer learning and advanced augmentation techniques.



Conclusion

- CNNs are effective for melanoma detection.
- Overfitting is a challenge due to small datasets and class imbalance.
- Data augmentation and regularization are crucial to combat overfitting.
- Future work: explore deeper architectures or transfer learning for further improvement.

Final Model

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Epoch 22/30
113/113 ━━━━━━━━━━━━━━━━━━━━ 126s 1s/step - accuracy: 0.7814 - loss: 0.5446 - val_accuracy: 0.7633 - val_loss: 0.7060 - learning_rate: 1.0000e-04
Epoch 23/30
113/113 ━━━━━━━━━━━━━━━━━━━━ 125s 1s/step - accuracy: 0.7796 - loss: 0.5437 - val_accuracy: 0.7600 - val_loss: 0.7102 - learning_rate: 1.0000e-04
Epoch 24/30
113/113 ━━━━━━━━━━━━━━━━━━━━ 125s 1s/step - accuracy: 0.7891 - loss: 0.5293 - val_accuracy: 0.7656 - val_loss: 0.7012 - learning_rate: 1.0000e-04
Epoch 25/30
113/113 ━━━━━━━━━━━━━━━━━━━━ 125s 1s/step - accuracy: 0.7813 - loss: 0.5200 - val_accuracy: 0.7722 - val_loss: 0.6939 - learning_rate: 1.0000e-04
Epoch 26/30
113/113 ━━━━━━━━━━━━━━━━━━━━ 125s 1s/step - accuracy: 0.8054 - loss: 0.4941 - val_accuracy: 0.7778 - val_loss: 0.7045 - learning_rate: 1.0000e-04
Epoch 27/30
113/113 ━━━━━━━━━━━━━━━━━━━━ 125s 1s/step - accuracy: 0.7963 - loss: 0.4780 - val_accuracy: 0.7722 - val_loss: 0.7149 - learning_rate: 1.0000e-04
Epoch 28/30
113/113 ━━━━━━━━━━━━━━━━━━━━ 125s 1s/step - accuracy: 0.8196 - loss: 0.4485 - val_accuracy: 0.7756 - val_loss: 0.6967 - learning_rate: 1.0000e-04
Epoch 29/30
113/113 ━━━━━━━━━━━━━━━━━━━━ 125s 1s/step - accuracy: 0.8362 - loss: 0.4322 - val_accuracy: 0.7856 - val_loss: 0.6815 - learning_rate: 1.0000e-04
Epoch 30/30
113/113 ━━━━━━━━━━━━━━━━━━━━ 125s 1s/step - accuracy: 0.8348 - loss: 0.4202 - val_accuracy: 0.7900 - val_loss: 0.6878 - learning_rate: 1.0000e-04
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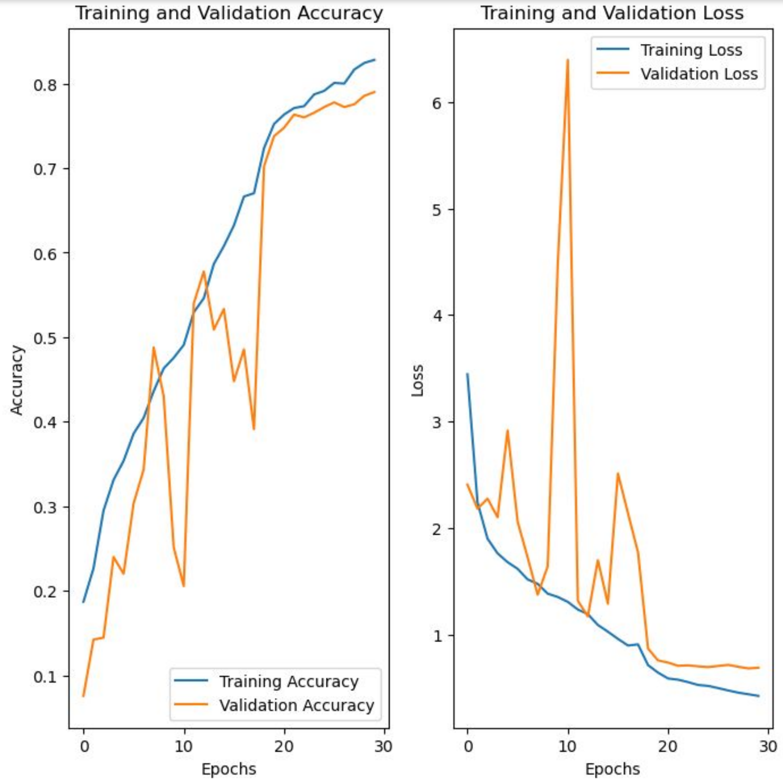
Training and Validation Accuracy
Accuracy
Epochs
Training Accuracy
Validation Accuracy
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0
10
20
30
Training and Validation Loss
Loss
Epochs
Training Loss
Validation Loss
1
2
3
4
5
6
0
10
20
30

```
C:\Users\navee\Downloads\data\Test\actinic keratosis\*
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
Actual Class: actinic keratosis
Predictive Class: actinic keratosis
```