Melanoma Detection:

Enhancing Precision in Skin Cancer Detection using Deep Learning

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01 Problem Statement

- Rising incidence of melanoma, leading to a significant health challenge.
- Importance of early detection for effective treatment and improved survival rates.
- Challenges faced by dermatologists in accurately diagnosing melanoma, particularly in advanced stages.

02 Related Work

Study	Main Findings
Esteva et al. [1]	Demonstrated the potential of deep neural networks in dermatologist-level classification of skin cancer, achieving performance on par with expert dermatologists.
Haenssle et al. [2]	Conducted a comparative study between a deep learning convolutional neural network and dermatologists in diagnosing melanoma, showing comparable performance.
Yadav and Jadhav [3]	Investigated the application of deep convolutional neural networks for disease diagnosis using medical images, showcasing the effectiveness of CNN-based algorithms.
Dildar et al. [4]	Provided a comprehensive review of various deep learning techniques for skin cancer detection, highlighting the superiority of CNNs.
Perez and Wang [5]	Explored the effectiveness of data augmentation in image classification using deep learning, suggesting the potential of neural augmentation for optimizing classifier performance.

03 Approach and Solution Overview

1. **Initial Approach:**
   - Created a CNN model with existing imbalanced data (class 1: class 0 = 1:50).
   - Low performance due to class imbalance.

2. **Addressing Class Imbalance:**
   - Sourced external images to upsample class 1 (malignant), achieving a ratio of 1:6.
   - Performed data augmentation on class 1 to further balance the classes to 1:2.

04 Approach and Solution Overview

3. Model Iterations:

- First Model: Basic CNN with three CNNs and one dense layer: Better performance than the initial model but unsatisfactory.
- Second Model: Deep CNN network with numerous convolutional and max-pooling layers. Excluded augmented images to reduce training time. Used class weights to address class imbalance. Performed well on validation and test sets.
- Third Model: Transfer learning model using the ImageNet framework. Achieved good performance on both validation and test sets.

4. Key Points:

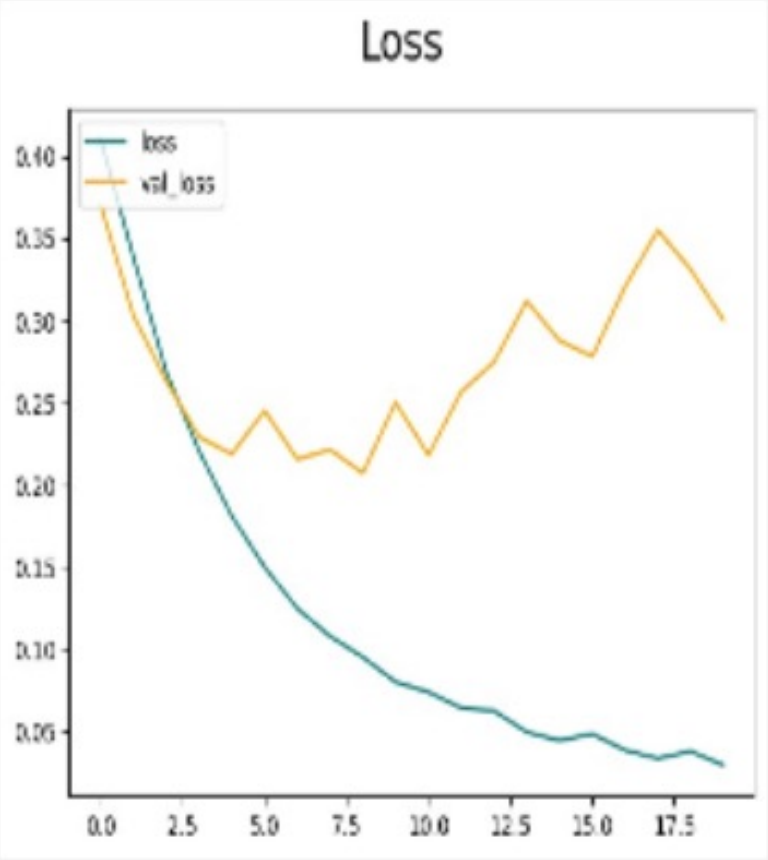
- Initial CNN model had low performance due to class imbalance.
- External images and data augmentation were used to balance classes.
- Deep CNN model without data augmentation used class weights to address imbalance.
- Transfer learning model also performed well on validation and test sets.

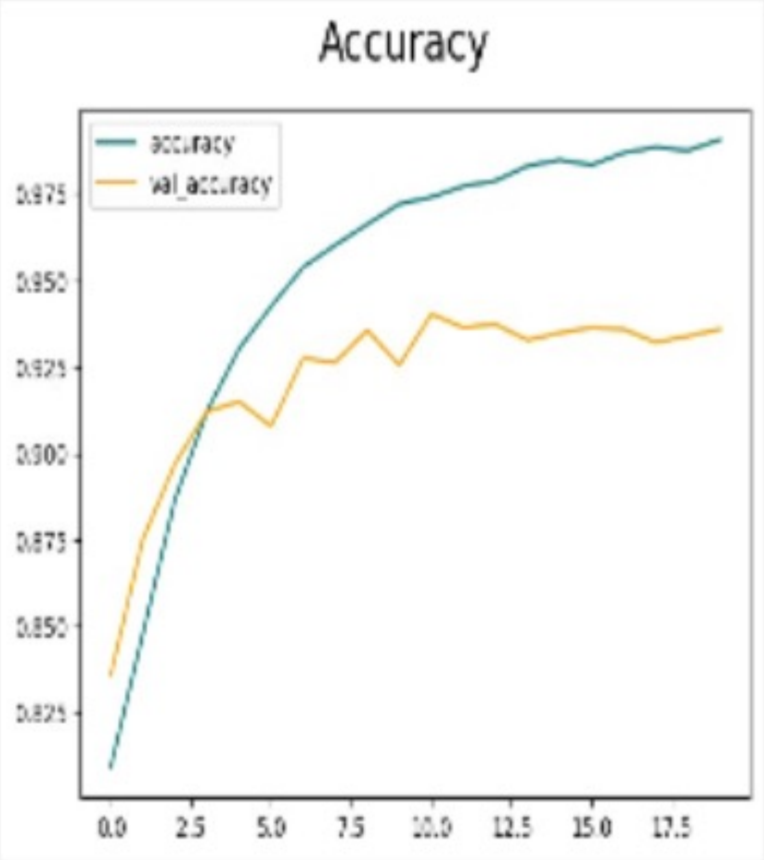
05 Dataset Information

- SIIM-ISIC Melanoma Classification Challenge dataset:
  33,126 dermoscopic images. Includes patient demographics, lesion characteristics, clinical history.
- External dataset:
  Only malignant images, integrated for class balance. Original: 581 malignant, 32,079 benign; after integration: 5,025 malignant, 32,079 benign.

06 Results

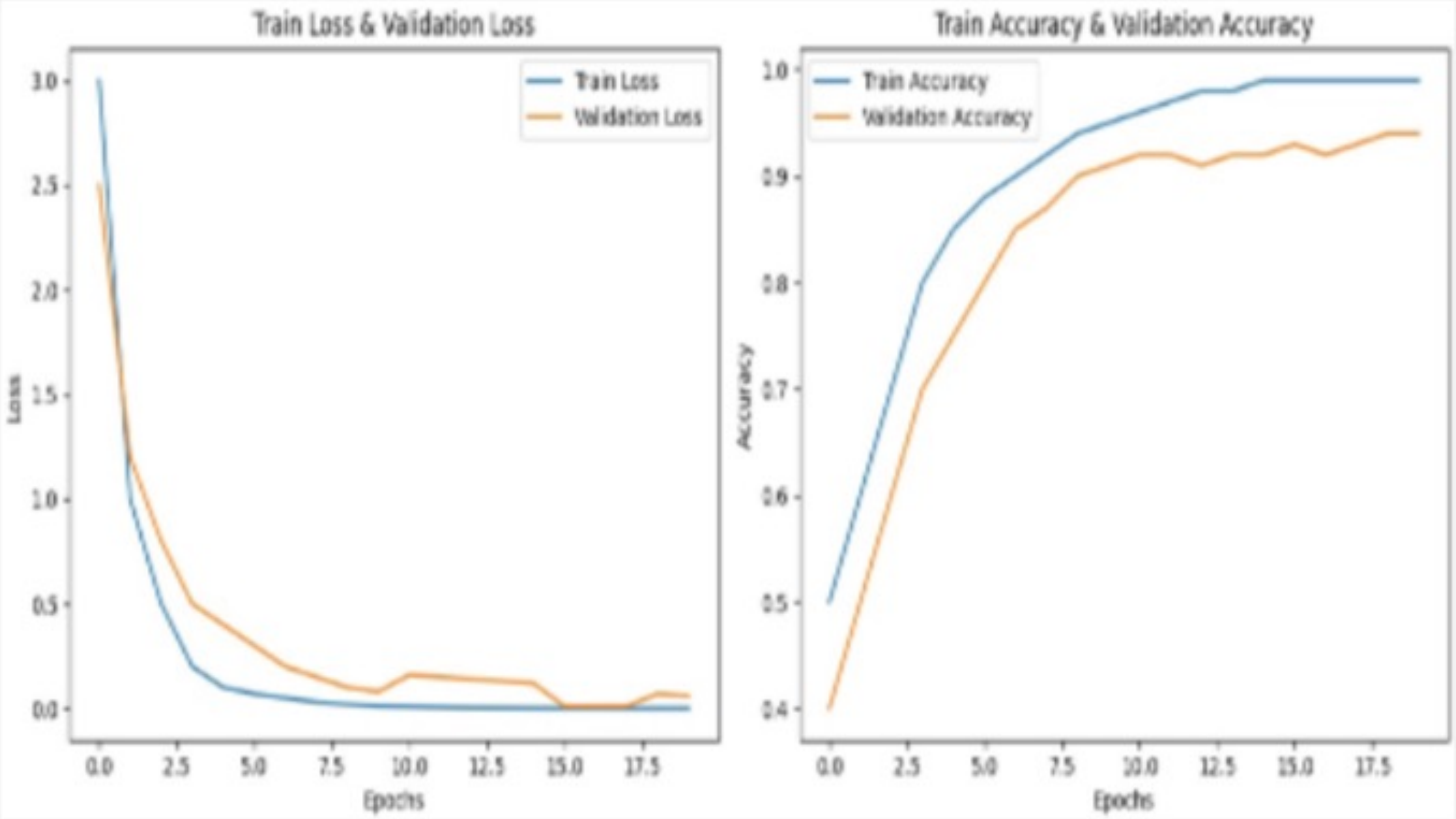
Training results (Model 1)





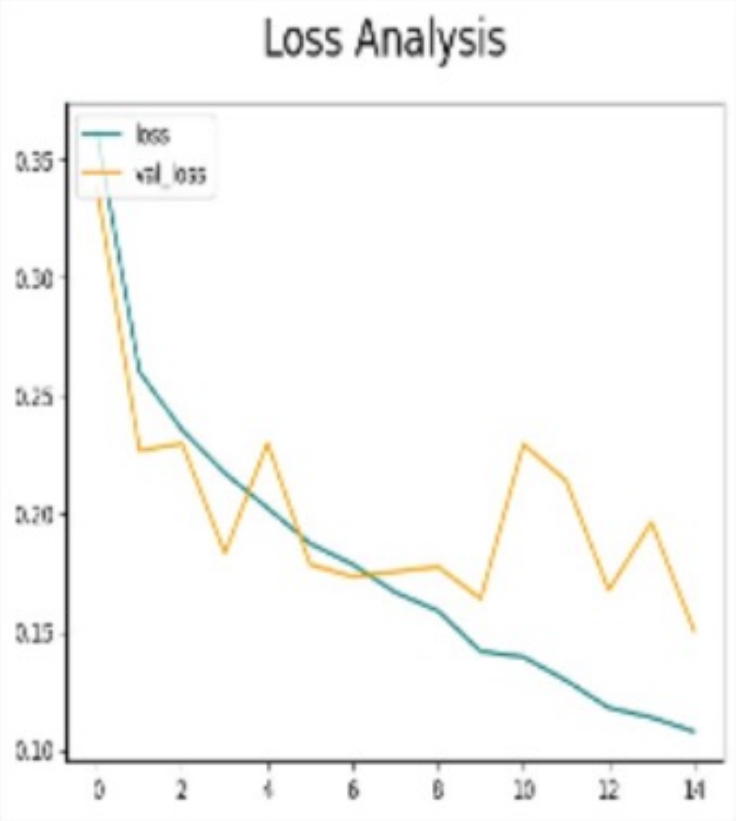
06 Results

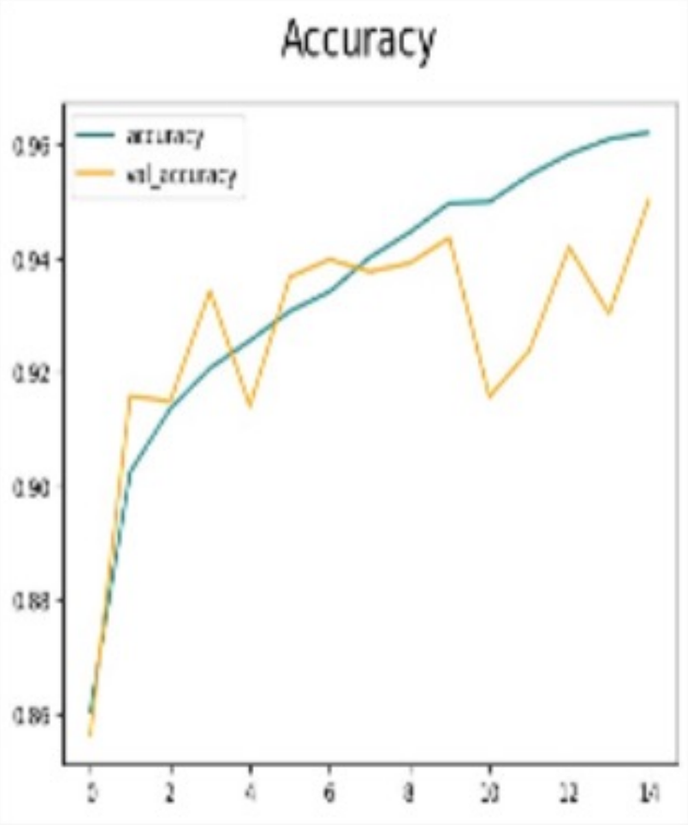
Training results (Model 2)



06 Results

Training results (Model 3)





06 Results and Performance Measures

Testing results

1. **CNN with External Data and Data Augmentation:**
   - Demonstrates strong precision, indicating accurate classification of positive instances.
   - Shows a recall of 0.714, suggesting some positive instances were missed.

2. **DCNN with External Data (No Data Augmentation):**
   - Exhibits higher precision at 0.933 and outstanding recall of 0.966.
   - Shows robustness in correctly identifying positive instances.

3. **Inception Model with External Data (No Data Augmentation):**
   - Showcases a precision of 0.947 and a recall of 0.947, indicating balanced performance.
   - Stands out as a reliable classifier for the given task.

07 Results and Performance Measures

#	Model Name	Accuracy	Precision	Recall
1	CNN	0.950	0.882	0.714
2	DCNN	0.981	0.933	0.966
3	Inception	0.988	0.947	0.947

09 Conclusion

- The Inception model demonstrated the highest precision, recall, and accuracy scores among the CNN, DCNN, and Inception models.
- The Inception architecture shows promise in accurately diagnosing skin lesions, balancing model complexity with superior performance.
- Consideration of both computational efficiency and performance metrics is crucial for model deployment in real-world applications.

10 Future Work

- Further optimization of model architectures to improve performance and efficiency.
- Exploration of advanced regularization techniques to mitigate overfitting.
- Investigation of domain-specific features to enhance model performance and robustness in dermatological image classification tasks.

Thank
you!