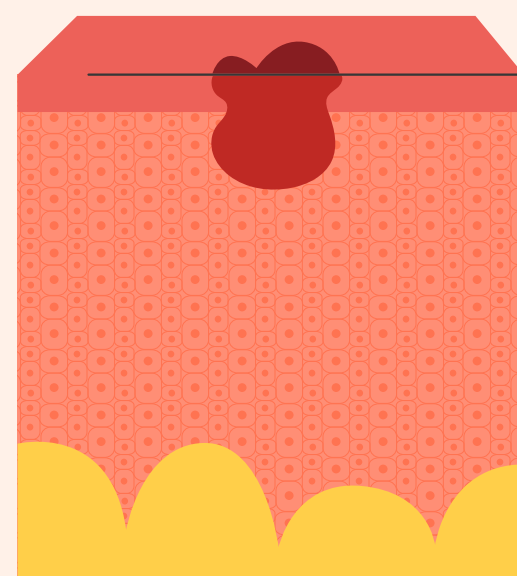
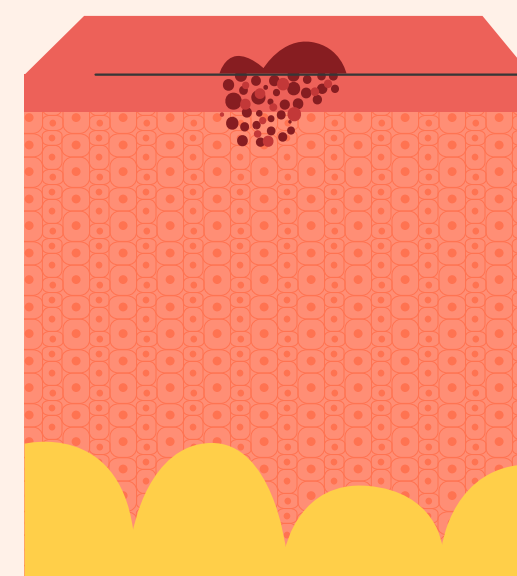


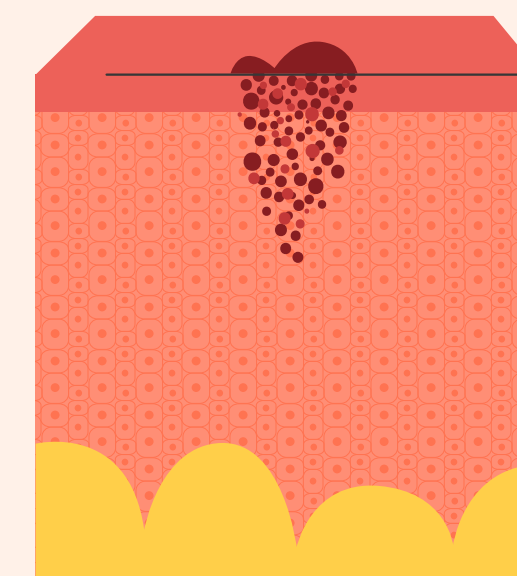
Stage 0



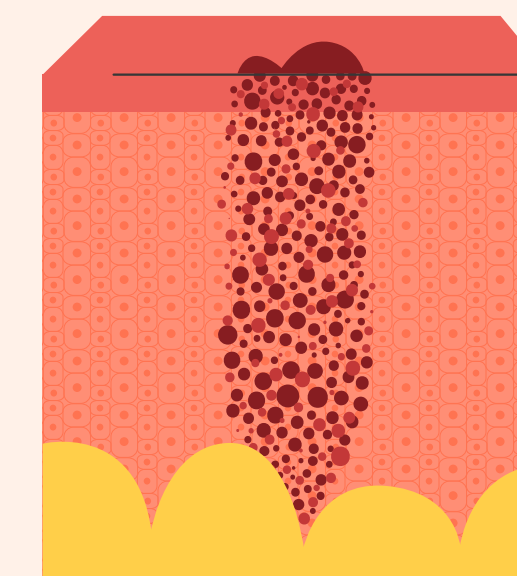
Stage I



Stage II



Stage III



Stage IV

Skin Lesion Classification Project

Team Name: Team Decision Makers

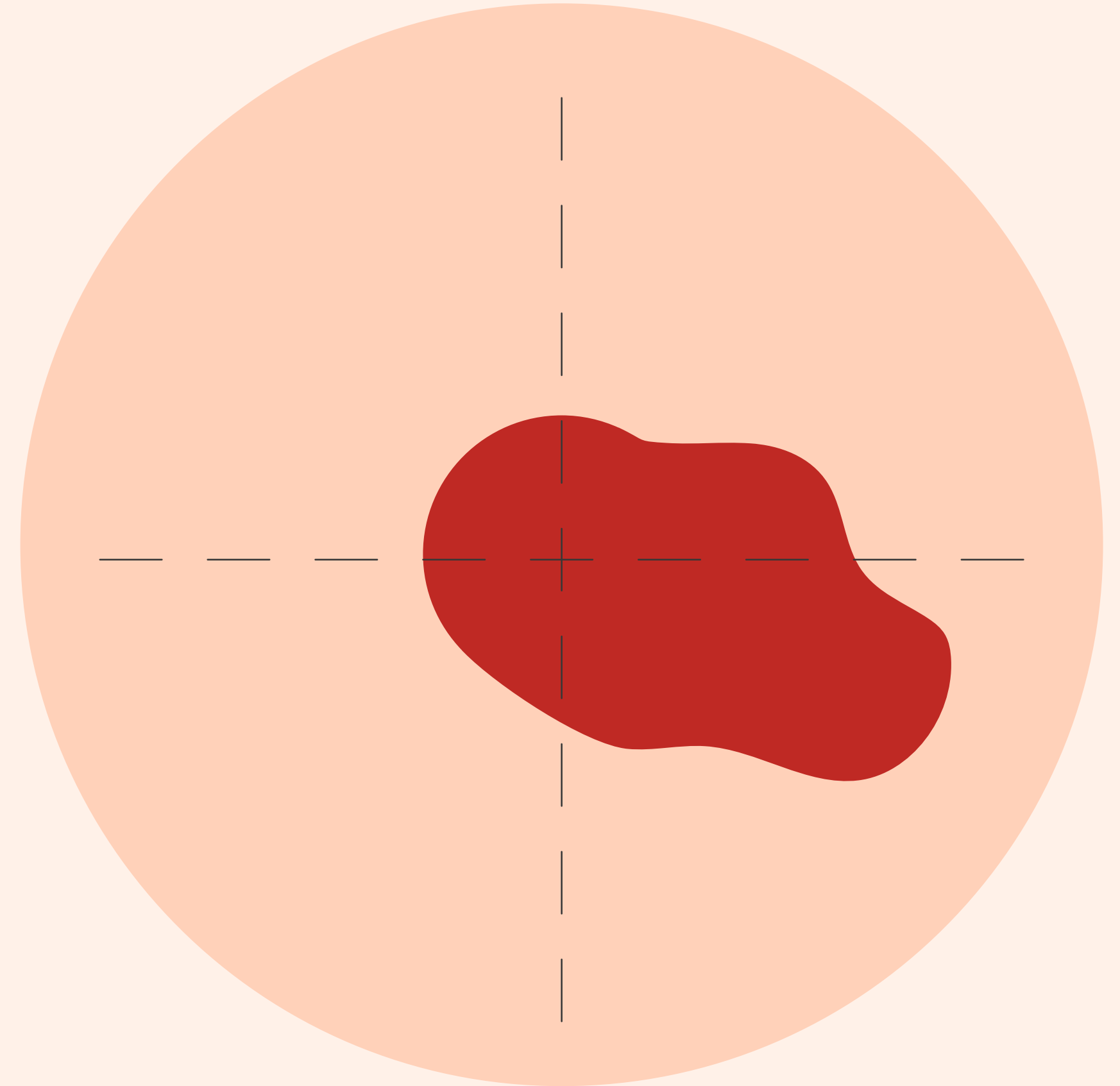
Team Members: Jesse Kranyak, Siriesha Mandava, Mohamed Altoobli, Jeffery Boczkaja

Introduction

- ▶ **Introduce the problem:** Skin lesions are often indicative of various dermatological conditions, and accurate classification is crucial for timely treatment and management.
- ▶ **Importance:** Early detection of skin diseases can significantly improve patient outcomes, reducing morbidity and mortality rates.
- ▶ **Brief overview of the project goals and objectives:** Develop a deep learning model to classify skin lesions using image data and patient metadata.

Project Overview

- ▶ **Description of the ISIC 2019 dataset:**
A comprehensive dataset containing images of various skin lesions, along with associated metadata such as age, sex, and anatomical site.
- ▶ **Objective:**
Develop a dual-input neural network model that integrates both image data and patient metadata to improve diagnostic accuracy.
- ▶ **Application:**
The model aims to serve as a diagnostic aid for dermatologists, facilitating more accurate and efficient diagnosis of skin lesions.



Data Acquisition

- ▶ **Querying the ISIC API for dataset access:**
accessing the ISIC 2019 dataset through the API, including authentication and endpoint usage.
- ▶ **Handling metadata for training and testing data:**
providing context for the images and ensuring proper alignment between image data and patient information.
- ▶ **Preprocessing steps to ensure data readiness for analysis:**
data preprocessing steps such as resizing images, normalizing pixel values, and handling missing metadata.

Model Architecture

- ▶ **the dual-input neural network architecture:**
Break down the architecture into its components, including the image input branch, metadata input branch, and combining branches.
- ▶ **Integration of image data and metadata for comprehensive analysis:**
Discuss how the model leverages both image data and patient metadata to improve diagnostic accuracy and provide more contextually informed predictions.
- ▶ **Visualization of the model's design:**
Provide visual representations of the model architecture, including diagrams or flowcharts illustrating the flow of data through the network.



Training Strategies

- ▶ **Initialization of data generators for training, validation, and testing:**
the role of data generators in feeding data batches to the model during training, validation, and testing phases.
- ▶ **Techniques such as early stopping and model checkpointing:**
how early stopping prevents overfitting by halting training when validation loss ceases to improve, and how model checkpointing saves the best model weights based on validation performance.
- ▶ **Optimization methods like hyperparameter tuning:**
the use of hyperparameter tuning techniques such as grid search or random search to optimize model performance.



Model Evaluation

▶ **Evaluation metrics including accuracy, precision, recall, and F1-score:**

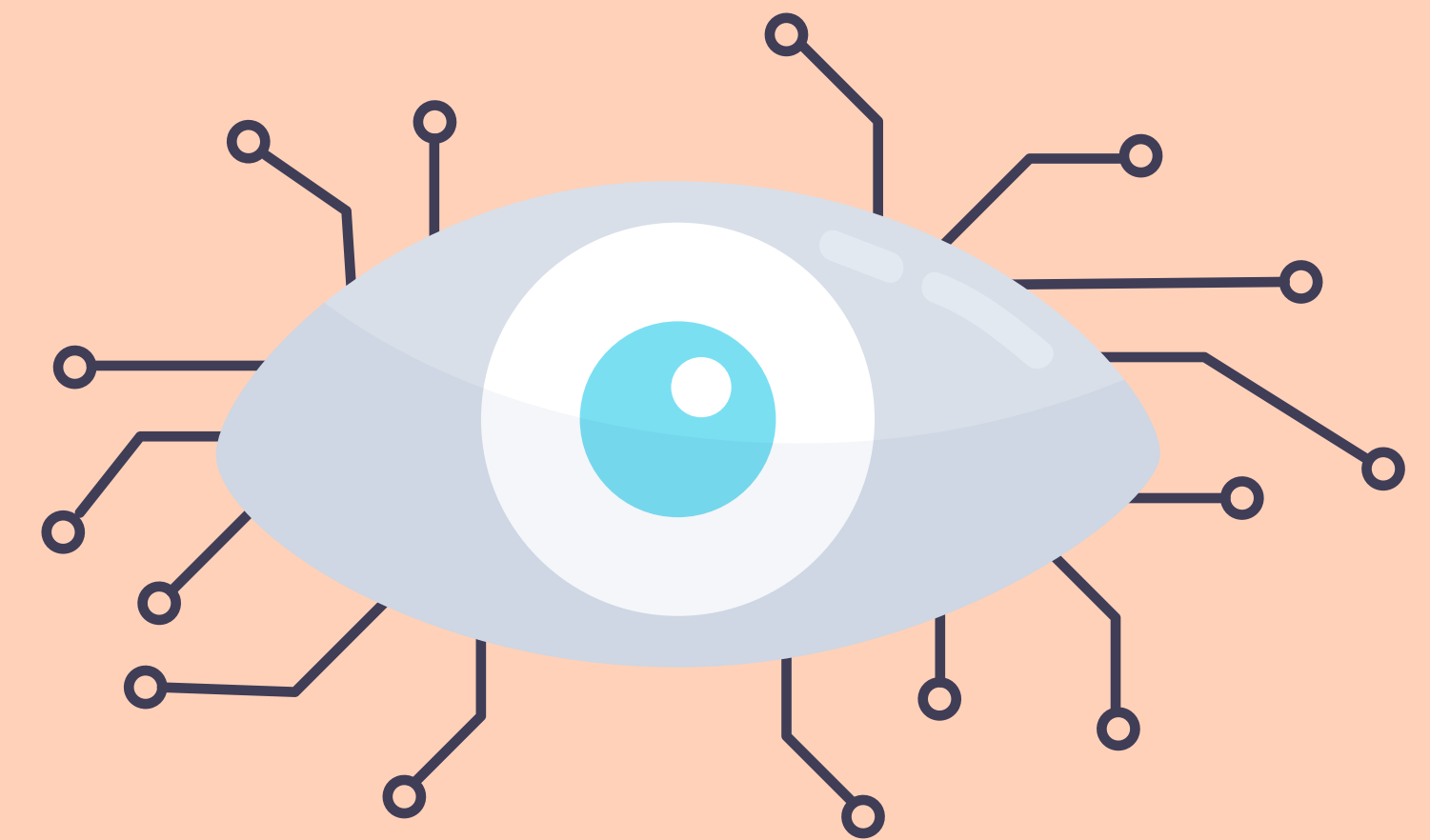
Define each evaluation metric and explain their importance in assessing model performance.

▶ **Confusion matrix analysis to identify model performance across different classes:**

examples of confusion matrices and explain how they help identify misclassifications and model weaknesses.

▶ **ROC curves and AUC values for per-class evaluation:**

Explain the use of ROC curves and AUC values to assess the model's ability to discriminate between classes and visualize its performance.



User Interface Development

- ▶ **Development of a web-based user interface using Gradio:**
the process of developing a user-friendly interface for the model using the Gradio library.
- ▶ **Upload functionality for skin lesion images:**
users can upload skin lesion images through the interface for prediction.
- ▶ **Integration of metadata input for enhanced predictions:**
the inclusion of metadata input fields in the interface to provide additional context for predictions.



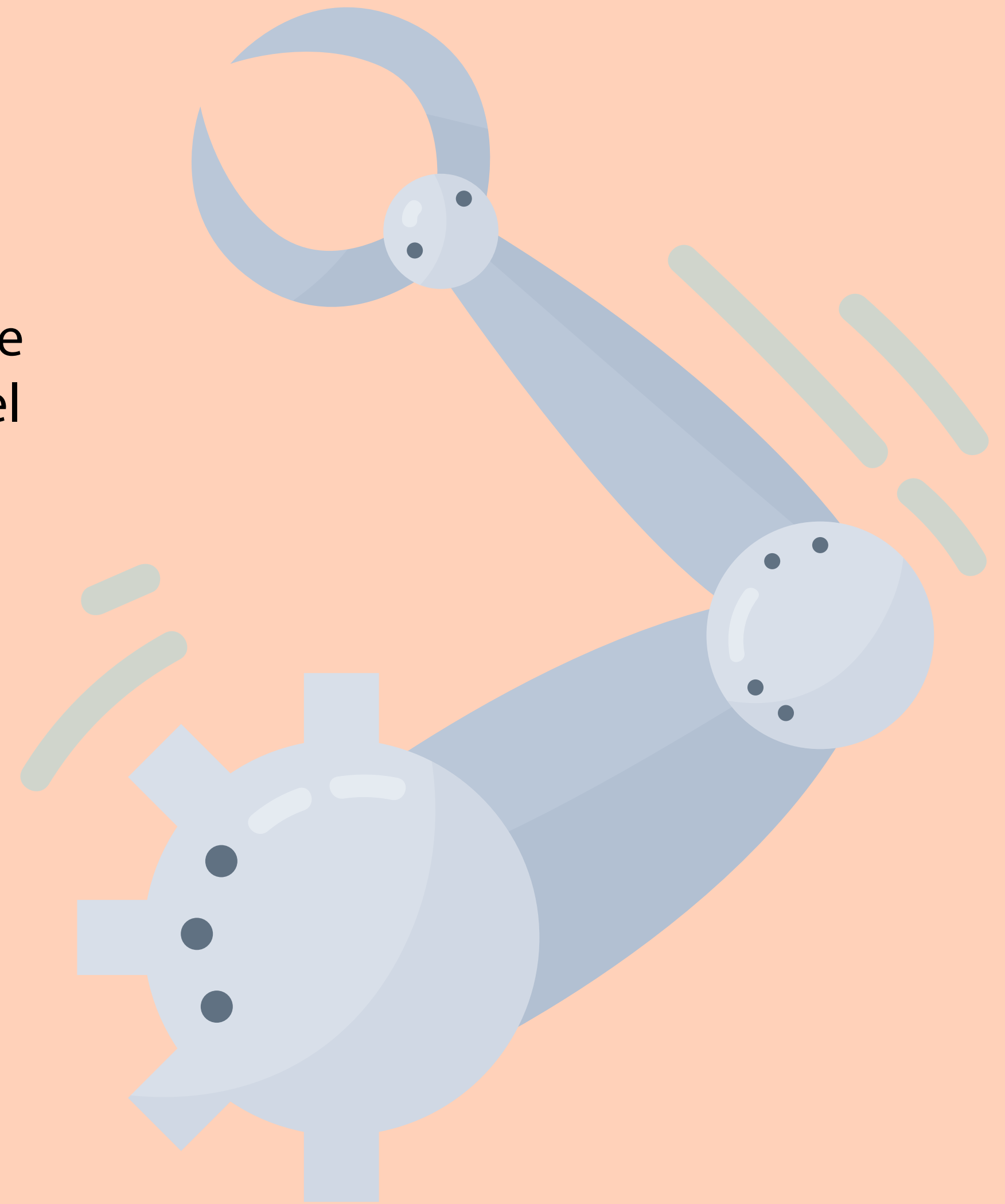
Knowledge Distillation and Fine-tuning

▶ **Techniques for model refinement and improvement:**

knowledge distillation transfers knowledge from a larger, more complex "teacher" model to a smaller, simpler "student" model to improve generalization.

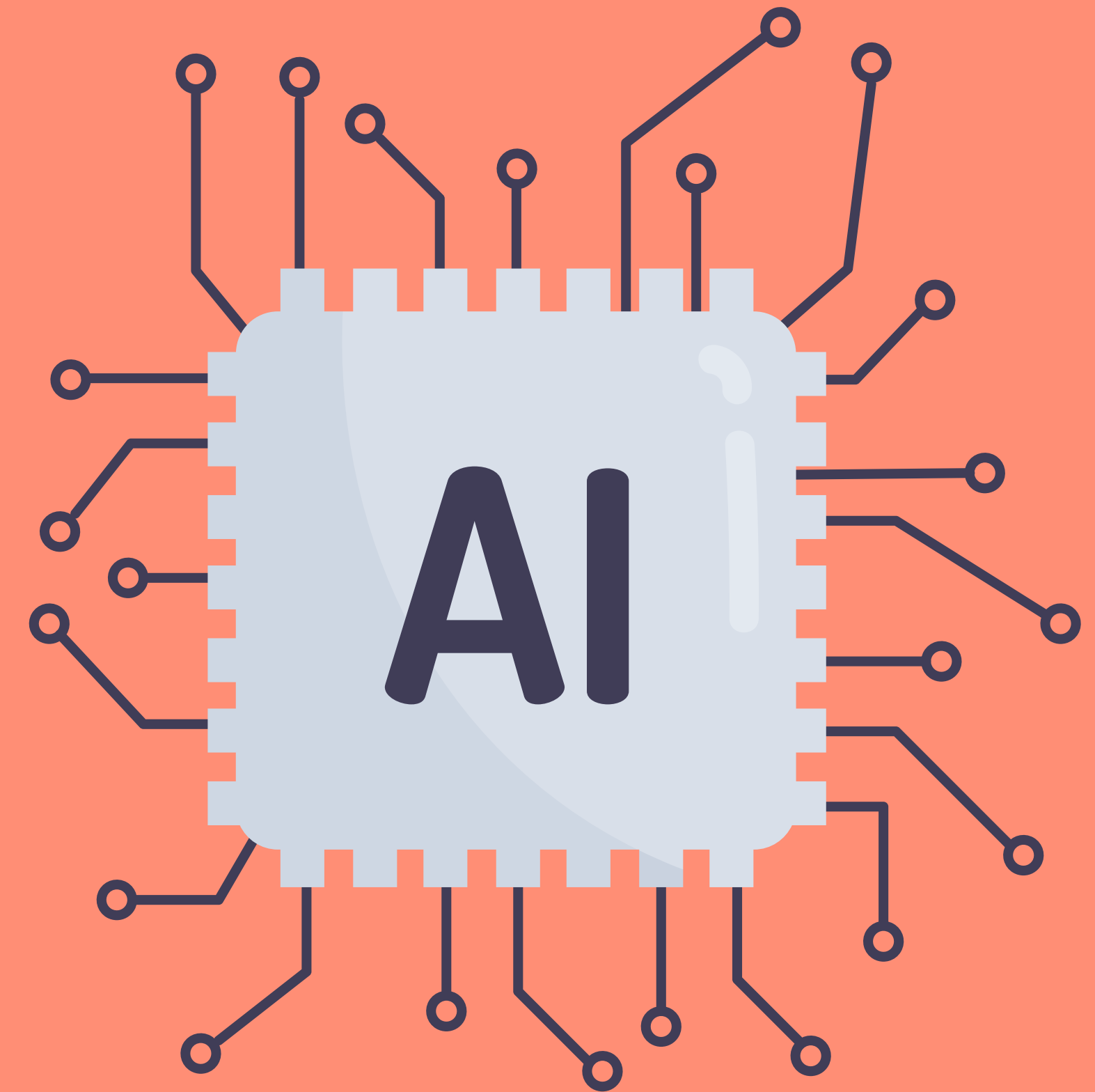
▶ **Fine-tuning with regularization for robust feature learning:**

the process of fine-tuning a pre-trained model with regularization techniques such as L1/L2 regularization to prevent overfitting and improve model robustness.



Further Model Evaluation

- ▶ **Analysis of misclassifications and model weaknesses:**
- ▶ **Exploration of potential enhancements for model performance:**



Future Directions

- ▶ **Potential directions for future development and research:**
possible avenues for expanding the model's capabilities, such as including more diagnostic categories or integrating with electronic medical records systems.
- ▶ **Expansion of the model to include more diagnostic categories:**
the model could be extended to classify a broader range of skin lesions, potentially improving its utility in clinical practice.
- ▶ **Integration with medical systems for real-world application:**
the feasibility of integrating the model into existing medical systems for use by healthcare providers in real-world settings.

Use Case: Diagnostic Aid

Demonstration of the model's application as a diagnostic aid:

the model could be used by dermatologists to assist in diagnosing skin lesions, potentially improving diagnostic accuracy and patient outcomes.

Limitations and Challenges

- ▶ **Discussion of limitations such as dataset biases and model interpretability:**
potential biases in the dataset and challenges related to interpreting model predictions in clinical practice.
- ▶ **Challenges encountered during model development and deployment:**
difficulties encountered during the project, such as data preprocessing issues or technical challenges with model training.

Credits

References

CancerNet-SCa

- ▶ Introduction: CancerNet-SCa is a deep neural network tailored for skin cancer detection from dermoscopy images.
- ▶ Motivation: Skin cancer is prevalent in the U.S., urging for effective early detection methods.
- ▶ Development: Inspired by deep learning advancements, CancerNet-SCa is developed under the Cancer-Net initiative.



Key Features

▶ **Model Design:**

First machine-designed neural network for skin cancer detection.

▶ **Innovations:**

Incorporates attention condensers for improved accuracy.

▶ **Performance:**

Outperforms ResNet-50 with superior accuracy and reduced complexity.



Open Source & Impact

- ▶ **Open Source:**
Available to researchers and clinicians for further development.
- ▶ **Encouragement:**
Aims to catalyze advancements in skin cancer detection methods.
- ▶ **Future Outlook:**
Promises a new era of precision diagnostics for dermatological conditions.

```
✓ dropout (Dropout)          (None, 64)          0          ['batch_normalization[0][0]']
✓ dense_2 (Dense)            (None, 1)            65          ['dropout[0][0]']

=====
Total params: 11965953 (45.65 MB)
Trainable params: 11965825 (45.65 MB)
Non-trainable params: 128 (512.00 Byte)

Epoch 1/10
642/642 [=====] - ETA: 0s - loss: 0.2005 - accuracy: 0.9240
Epoch 1: val_accuracy improved from -inf to 0.98904, saving model to CancerNet_best_model.keras
642/642 [=====] - 565s 868ms/step - loss: 0.2005 - accuracy: 0.9240 - val_loss: 0.07
Epoch 2/10
642/642 [=====] - ETA: 0s - loss: 0.4416 - accuracy: 0.8318
Epoch 2: val_accuracy did not improve from 0.98904
642/642 [=====] - 542s 844ms/step - loss: 0.4416 - accuracy: 0.8318 - val_loss: 0.44
Epoch 3/10
642/642 [=====] - ETA: 0s - loss: 0.4197 - accuracy: 0.8374
Epoch 3: val_accuracy did not improve from 0.98904
642/642 [=====] - 530s 826ms/step - loss: 0.4197 - accuracy: 0.8374 - val_loss: 0.42
Epoch 4/10
642/642 [=====] - ETA: 0s - loss: 0.4239 - accuracy: 0.8357
Epoch 4: val_accuracy did not improve from 0.98904

[41] # !cp CancerNet_best_model.keras /content/drive/MyDrive/

[39] from google.colab import files

✓ 4s completed at 6:47 PM
```

```
✓ 40s # Evaluate the model on the test data
test_loss, test_accuracy = model.evaluate(test_metadata_gen, verbose=1)

print("Test Loss:", test_loss)
print("Test Accuracy:", test_accuracy)

➔ Found 2534 validated image filenames belonging to 2 classes.
80/80 [=====] - 37s 459ms/step - loss: 0.4270 - accuracy: 0.8299
Test Loss: 0.42697906494140625
Test Accuracy: 0.8299131989479065

[ ]

✓ 6s [42] !pip install -q -U keras-tuner

----- 129.1/129.1 kB 4.1 MB/s eta 0:00:00

✓ 2m [43] # Hyperparameter Tuning
import kerastuner as kt
from tensorflow import keras
from kerastuner import Hyperband
from kerastuner import HyperParameters
from tensorflow.keras import layers
from tensorflow.keras.optimizers import Adam

✓ 4s completed at 6:47 PM
```



```
Found 2051/ validated image filenames belonging to 2 classes.
Found 2280 validated image filenames belonging to 2 classes.
Model: "model"
```

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 224, 224, 3)]	0	[]
conv2d (Conv2D)	(None, 222, 222, 32)	896	['input_1[0][0]']
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0	['conv2d[0][0]']
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18496	['max_pooling2d[0][0]']
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0	['conv2d_1[0][0]']
input_2 (InputLayer)	[(None, 5)]	0	[]
flatten (Flatten)	(None, 186624)	0	['max_pooling2d_1[0][0]']
dense (Dense)	(None, 32)	192	['input_2[0][0]']
concatenate (Concatenate)	(None, 186656)	0	['flatten[0][0]', 'dense[0][0]']
dense_1 (Dense)	(None, 64)	11946048	['concatenate[0][0]']
batch_normalization (Batch Normalization)	(None, 64)	256	['dense_1[0][0]']

✓ 4s completed at 6:47 PM

