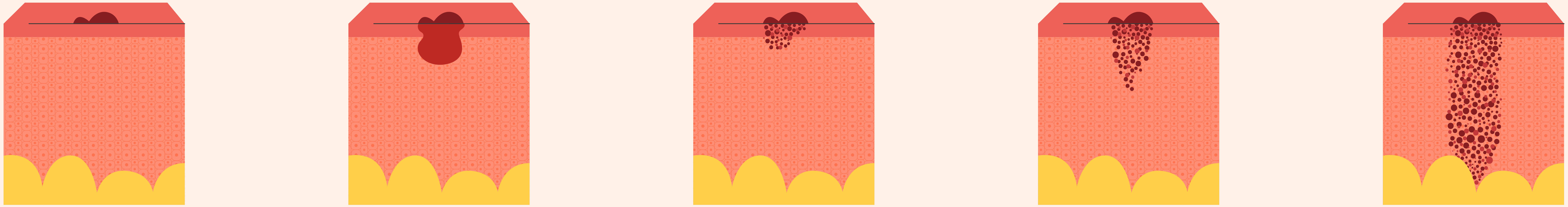


Stage 0 | Stage I | Stage II | Stage III | Stage IV

Skin Lesion Classification Project

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

Introduction

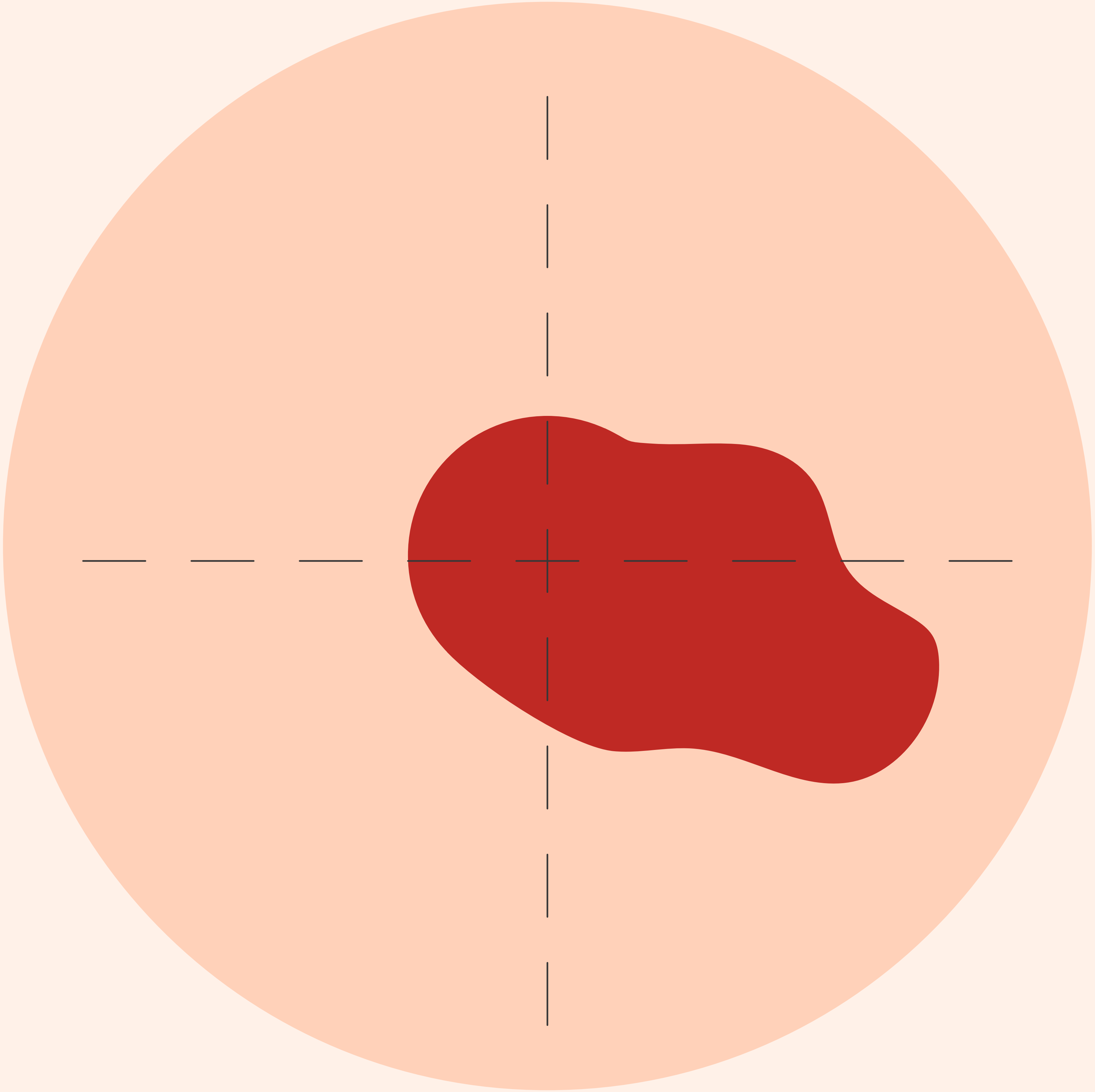
- **Introduce the problem:** Skin lesions are often indicative of various dermatological conditions, and accurate classification is crucial for timely treatment and management.
- **Importance:** Early detection of skin diseases can significantly improve patient outcomes, reducing morbidity and mortality 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.

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.

```
Found 20517 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 (MaxPooling2     (None, 111, 111, 32)  0           ['conv2d[0][0]']
 D)

 conv2d_1 (Conv2D)              (None, 109, 109, 64)  18496       ['max_pooling2d[0][0]']

 max_pooling2d_1 (MaxPoolin     (None, 54, 54, 64)    0           ['conv2d_1[0][0]']
 g2D)

 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)            1194604     ['concatenate[0][0]']
                                                      8

 batch_normalization (Batch     (None, 64)            256         ['dense_1[0][0]']
 Normalization)
```

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```
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
```

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```
# 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
```

[ ]

[42]
```
!pip install -q -U keras-tuner
```

```
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 129.1/129.1 kB 4.1 MB/s eta 0:00:00
```

[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
```

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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.

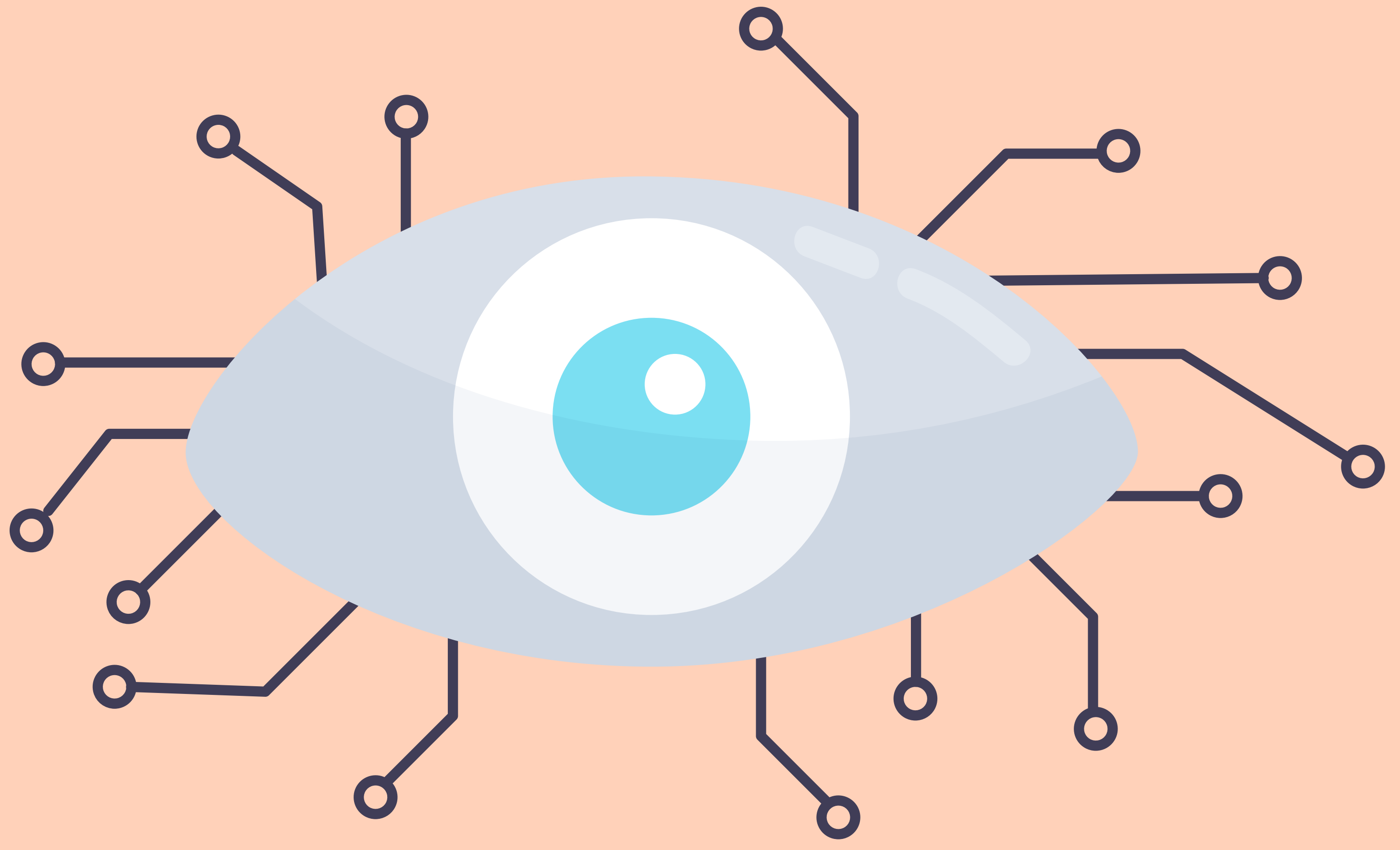
- **Optimization methods like hyperparameter tuning:**
  the use of hyperparameter tuning techniques such as grid search or random search to optimize model performance.

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.

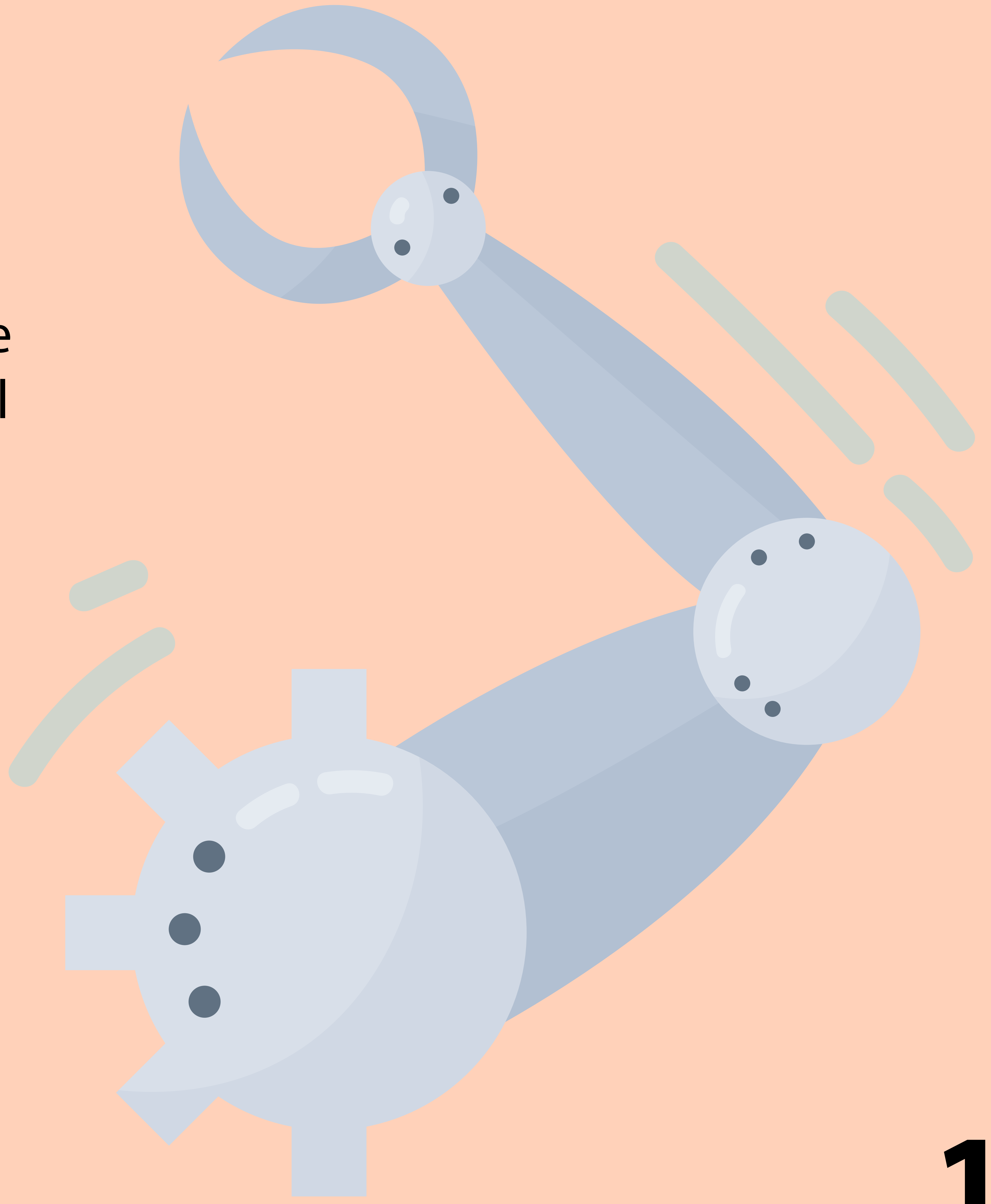
- **Upload functionality for skin lesion images:**
  users can upload skin lesion images through the interface for prediction.

- **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

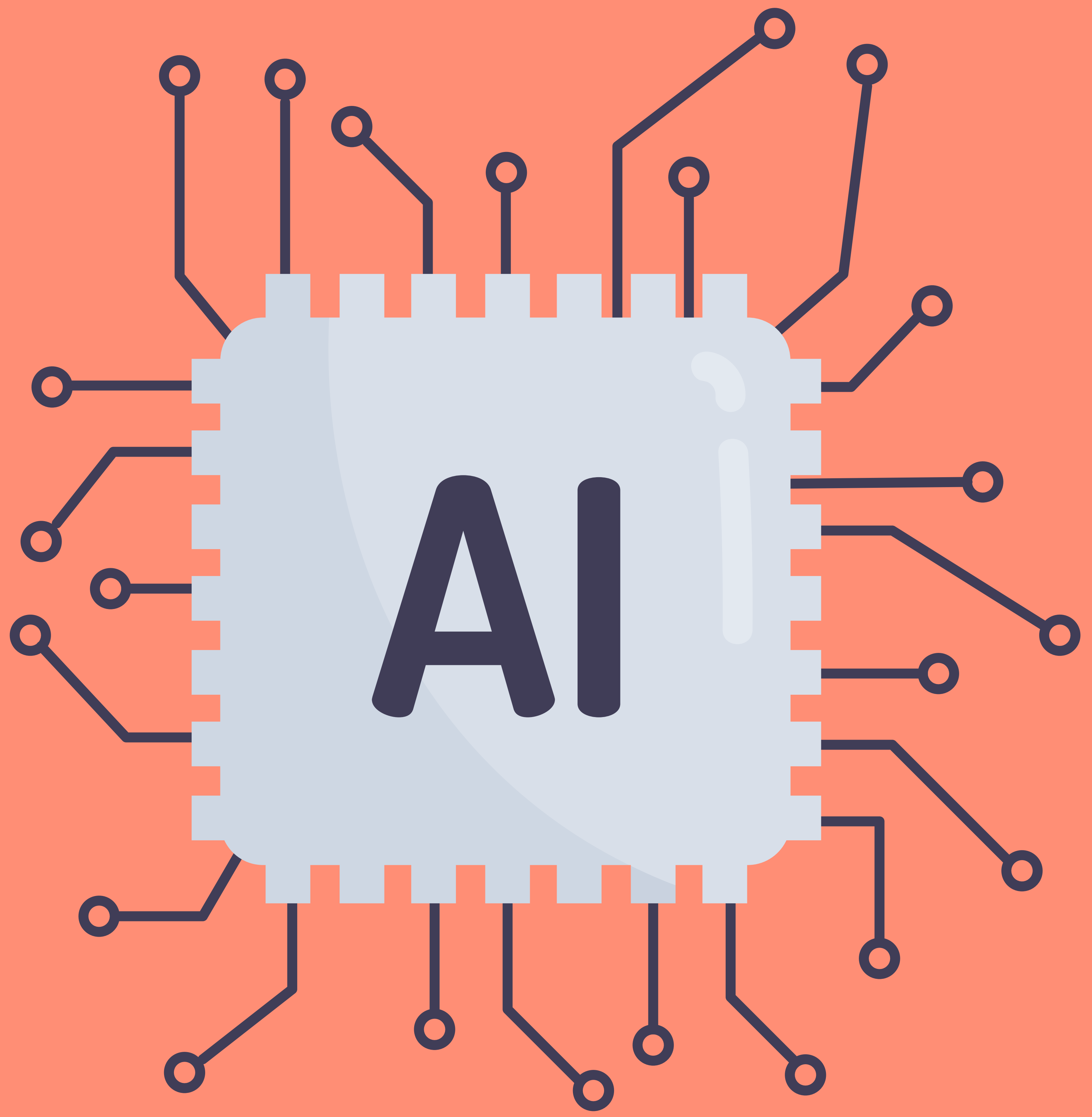
Techniques for model refinement and improvement:
knowledge distillation transfers knowledge from a larger, more complex "teacher" model to a smaller, simpler "student" model to improve generalization.

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