



SkinLink

Bridging Melanoma Detection and Care Between Doctors and Patients

Project #3

TEAM #9

Date

TUE AUG 27 2024

Meet the Team



GIRISH
HOSALLI

Dr. Girish GANs



SEBASTIAN
FAJARDO

Dr. Sebastian
Segmentation



MICHAEL
COX

Dr. Michael Machine



ALISHA
OUTRIDGE

Dr. Alisha
Augmentation



ELPHYS
ALVAREZ

Dr. Elphys Encoder



EZRA
TIMMONS

Dr. Ezra
Embeddings

Agenda

- Intro
 - Meet Team #9
 - Problem We're Solving
- Building the Model
 - Data & Preprocessing
 - Training & Optimization
- Demo
 - Patient App
 - Doctor App
 - Tech We Used
- Future Research & Improvements

Early Detection is key.



Skin cancer is by far the most common type of cancer. Nearly all skin cancers can be treated effectively if they are found early, so knowing what to look for is important. There are many types of skin cancer, each of which can look different on the skin.

- 1 in 5 Americans will develop skin cancer by the age of 70.
- **More than 2 people die of skin cancer in the U.S. every hour.**
- Having 5 or more sunburns doubles your risk for melanoma.



Why is this important

HOW IS MELANOMA DIAGNOSED?

Diagnosis typically begins with a visual examination by a dermatologist, followed by a biopsy where a sample of the suspicious skin lesion is examined microscopically. Additional imaging tests, such as CT scans or MRIs, may be used to assess the extent of spread (Mayo Clinic, 2024).

BENEFITS TO BOTH PATIENTS & MEDICAL PROFESSIONALS

This is beneficial for patients because faster and more accurate diagnosis can lead to earlier intervention, reducing the risk of advanced disease and improving survival rates. Additionally, automated systems can provide patients with quicker access to diagnostic results.

This is also beneficial for the Medical Field because improved diagnostic tools can reduce the workload on dermatologists, allow for more efficient use of healthcare resources, and help in standardizing diagnosis across different settings. This can lead to overall cost savings and better patient outcomes (Health Informatics Journal, 2023).

Data Collection & Pre-Processing

HOW WE MOVED FROM ACQUISITION TO MODEL READINESS

1

Initial Setup

- **Data Acquisition:** Download from Kaggle
- **Setup Directories:** Paths for benign/malignant images

2

Data Inspection and Labeling

- **Load and Label:** Organize images into categories
- **Visual Inspection:** Display a sample in grids for verification

3

Data Preparation and Augmentation

- **Data Conversion:** Convert to Numpy arrays and normalize
- **Augmentation:** Enhance data with rotation, zoom, etc.

4

Storage and Future Use

- **Data Splitting:** Divide into training, validation, testing sets
- **Efficient Storage:** Save processed data in pickle files for easy future access

Making & Optimizing the Model

THIS IS HOW WE REFINED OUR CNN MODEL TO ENSURE HIGH ACCURACY & EFFECTIVE GENERALIZATION, PREPARING IT FOR REAL-WORLD APPLICATIONS.

CNN Model Architecture

- Defined a Convolutional Neural Network (CNN) with:**
- Input layer of shape (300, 300, 3).
 - Four Convolutional layers with ReLU activation, Batch Normalization, and MaxPooling.
 - Flattened output followed by Dense layers.
 - Output layer with Softmax activation for binary classification.

Callbacks for Training

- Compiled the model using Adam optimizer** with a learning rate of 0.0001.
ModelCheckpoint: Saves the best model based on validation loss.
EarlyStopping: Stops training when validation loss stops improving.
ReduceLROnPlateau: Reduces learning rate when validation loss plateaus.
TensorBoard: Logs training metrics for visualization.

Training & Model Evaluation

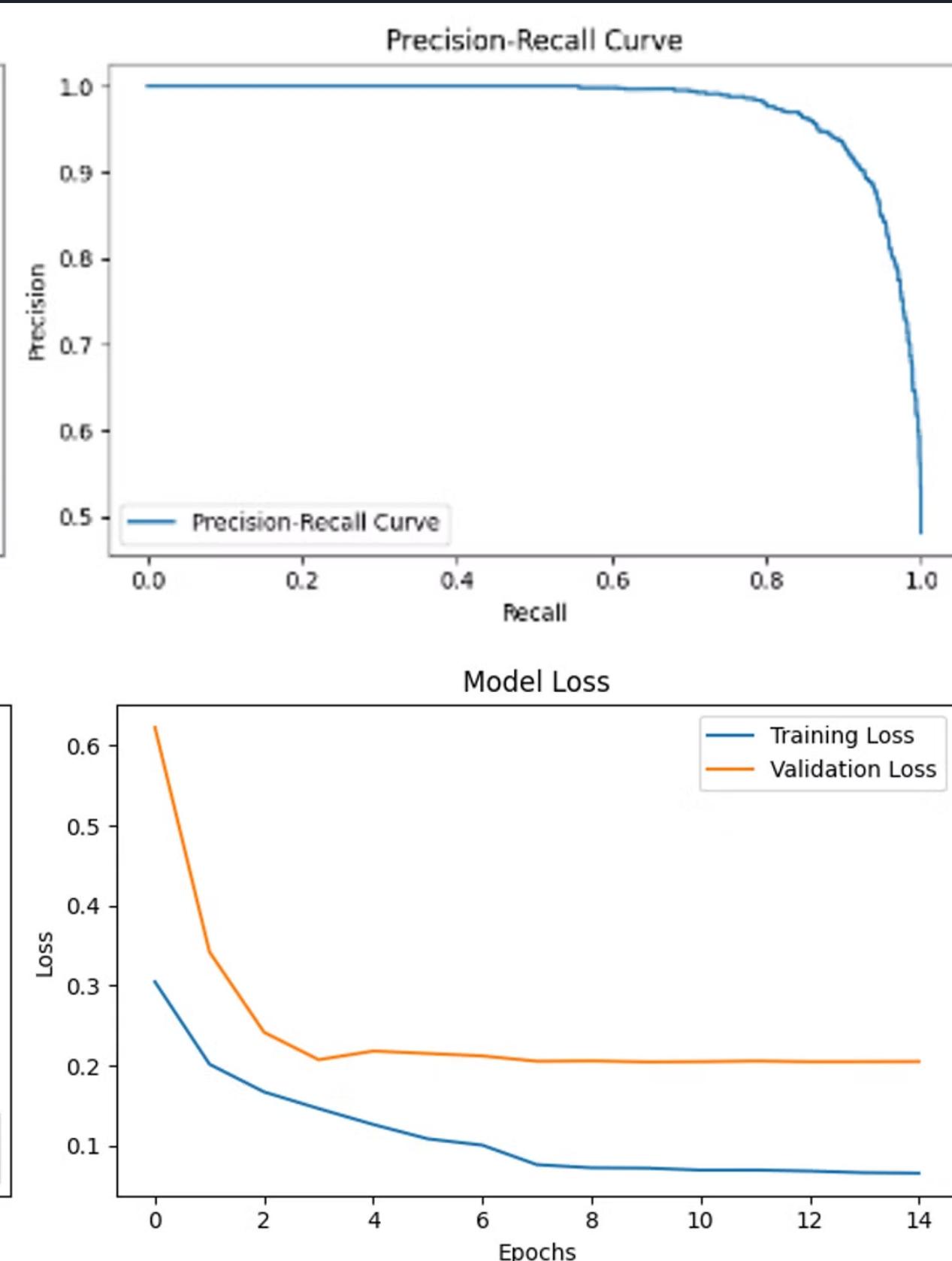
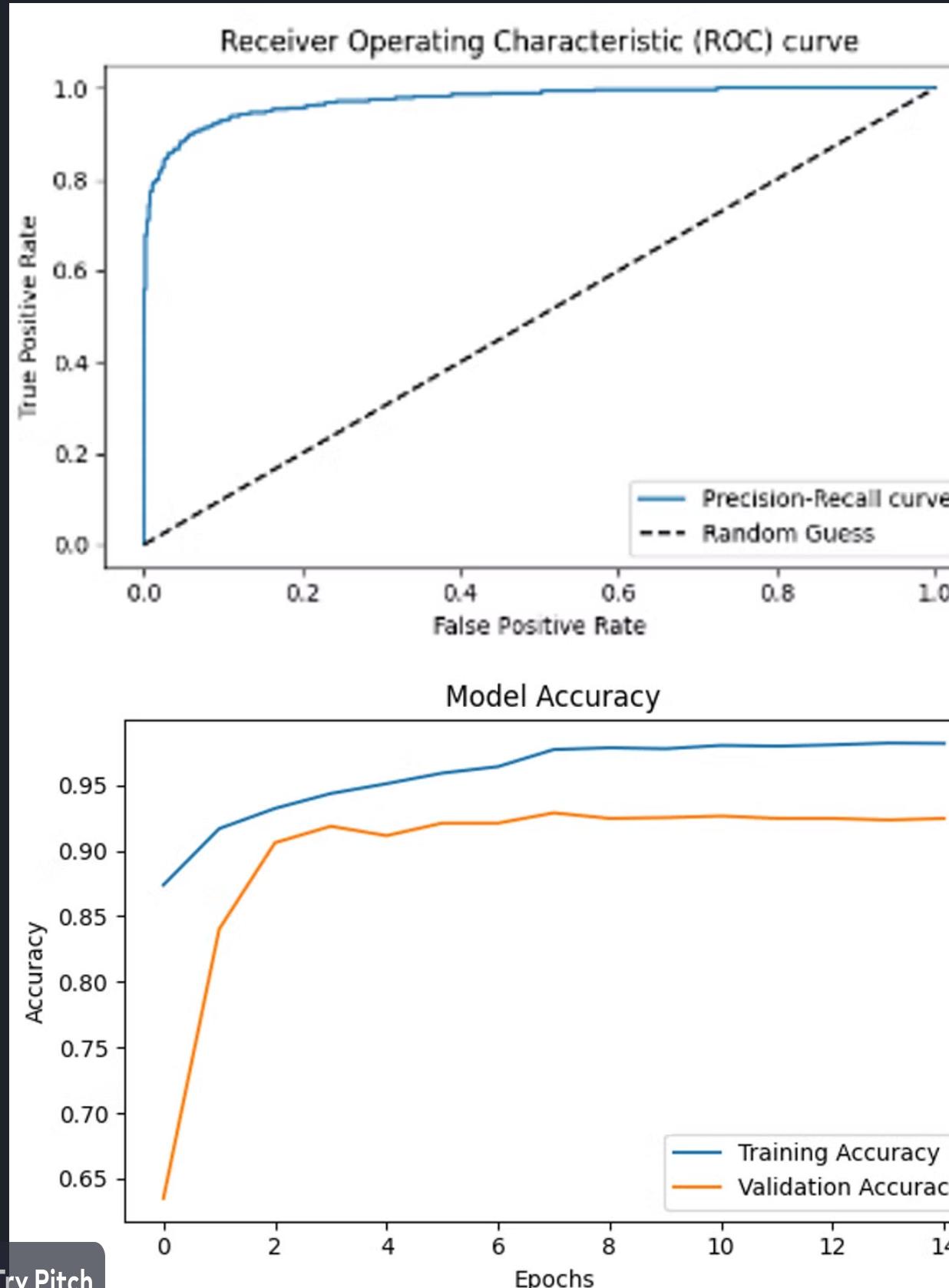
- Trained the model for 50 epochs with batch size of 32.
- Used validation data for model evaluation during training.
- Evaluated the model on the test set.
- Computed accuracy, precision, recall, F1 score, and AUC-ROC.
- Displayed confusion matrix and classification report.

Fine Tuning

- Optimized the model with TensorFlow Keras Optimizers.
- Received an Accuracy score of 93%

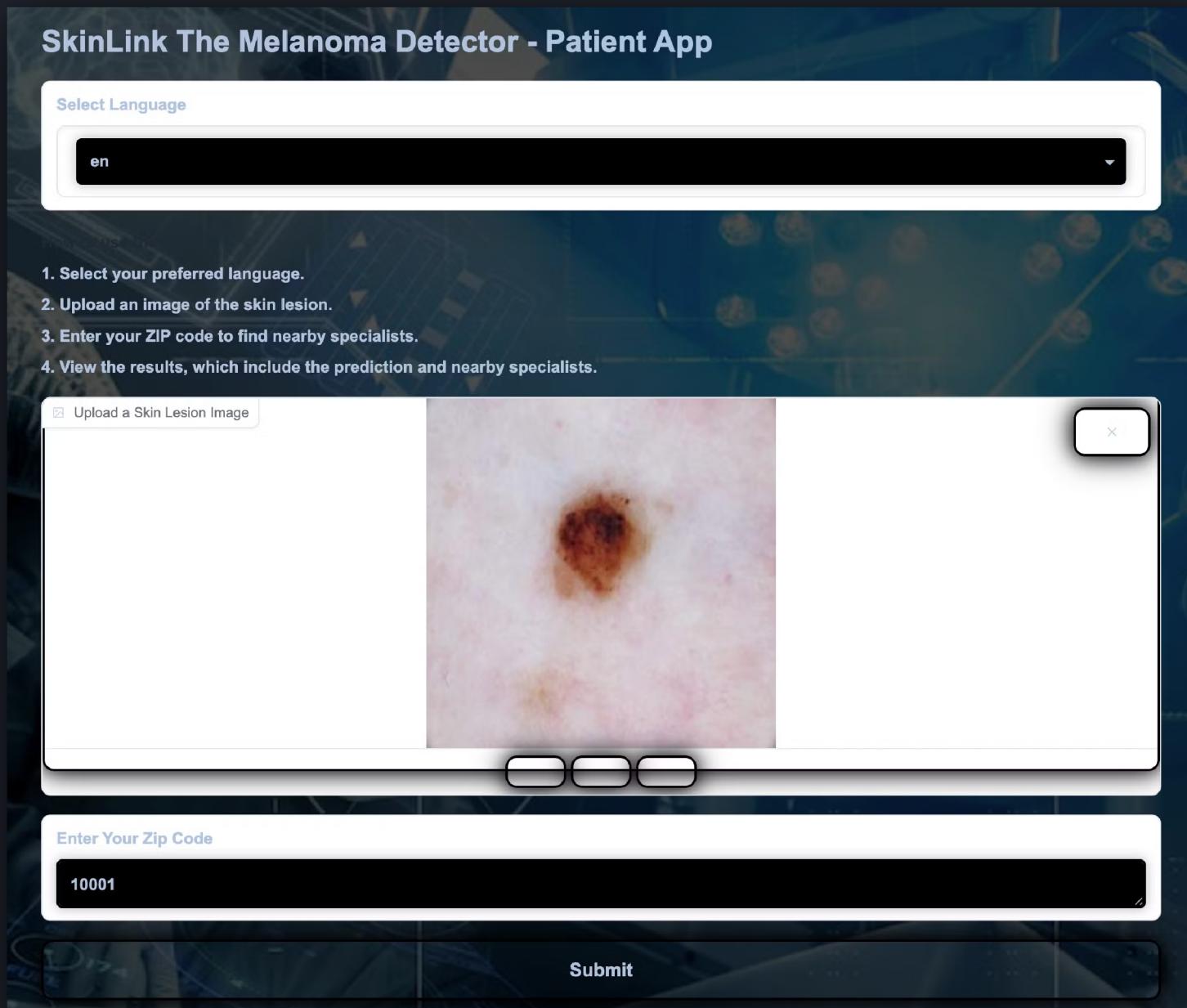
Model Performance Metrics Overview

EVALUATING ACCURACY, PRECISION, LOSS ACROSS TRAINING EPOCHS & PREDICTIONS



Demo: SkinLink, the Melanoma Detector

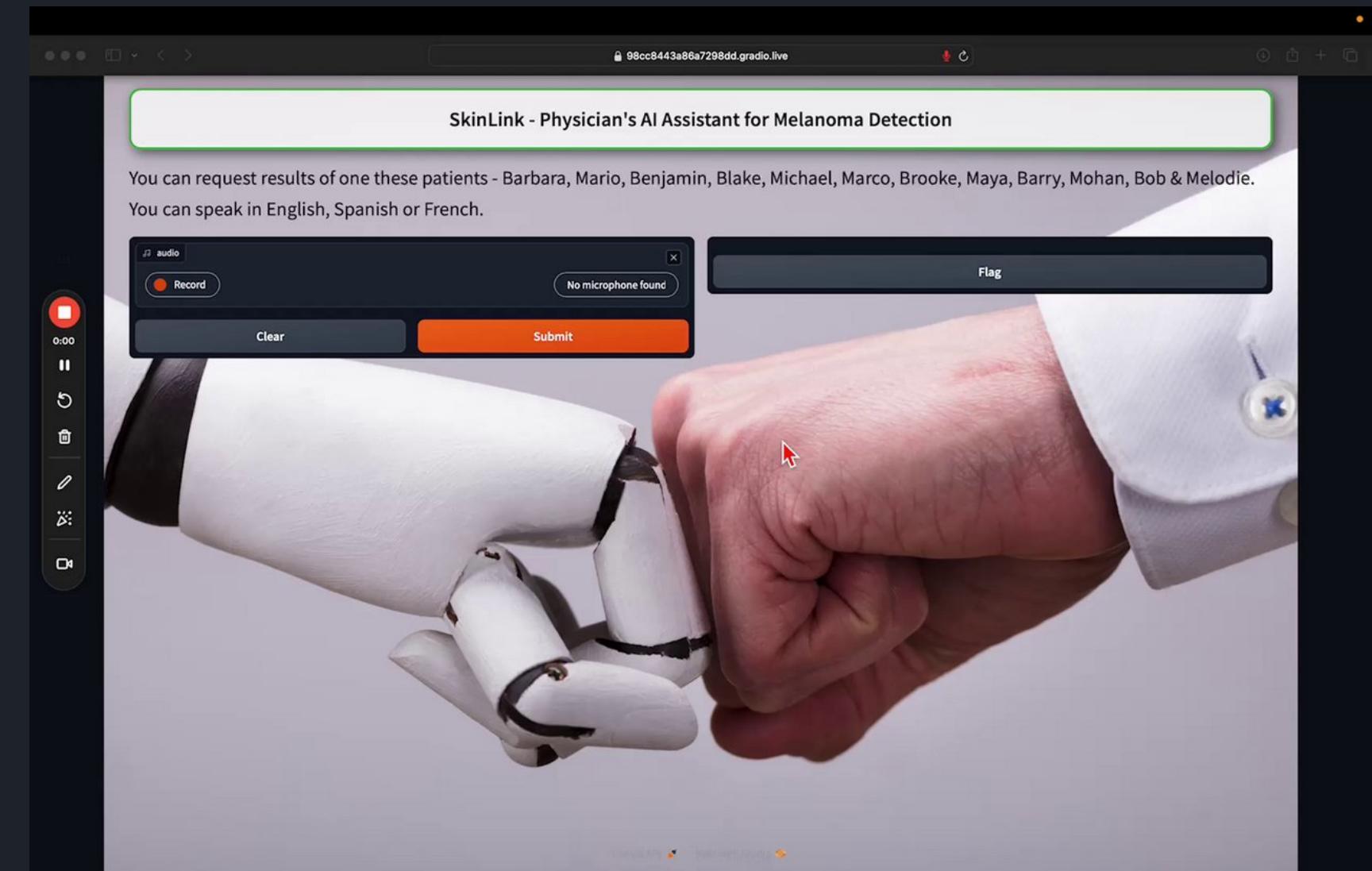
WE BUILT A CNN MODEL TO BRIDGE MELANOMA DETECTION & CARE BETWEEN DOCTORS AND PATIENTS



Patient-side view of the App

Patients can upload pics of changes that they see with their skin & possible melanoma to a doctor to review, analyze and provide feedback.

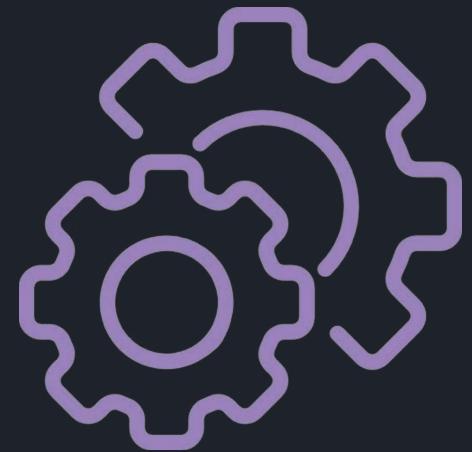
Try Pitch



Doctor-side of the view of the App

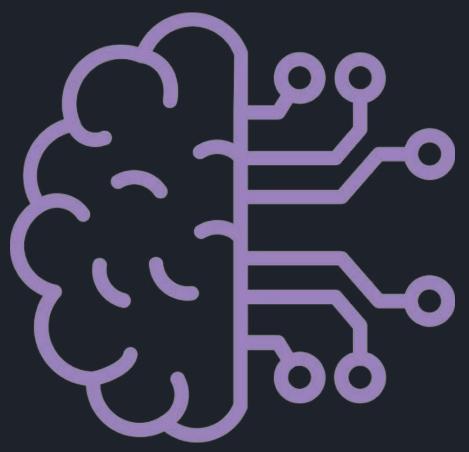
Doctor's can look up patient results to review in detail with patients & send them feedback on the results faster than they might be able to get to the office or while the patient is in their office.

Technology Overview



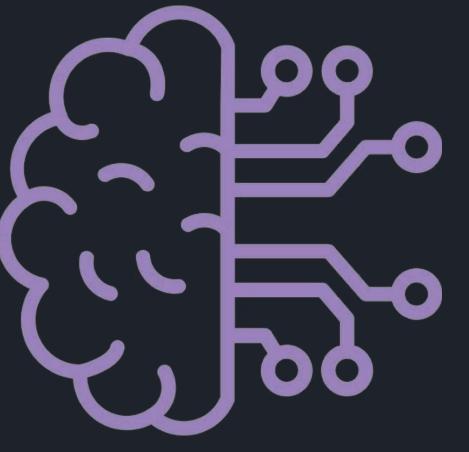
Preparation

- Numpy
- Pandas
- Pickle
- Matplotlib



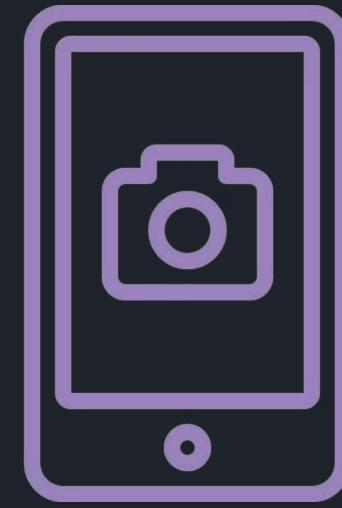
Models Used

- langdetect
- OpenAI whisper
- spacy en_core_web_sm
- Custom CNN Model
- Helsinki-NLP



Train-Test

- Ski-Learn
- TensorFlow

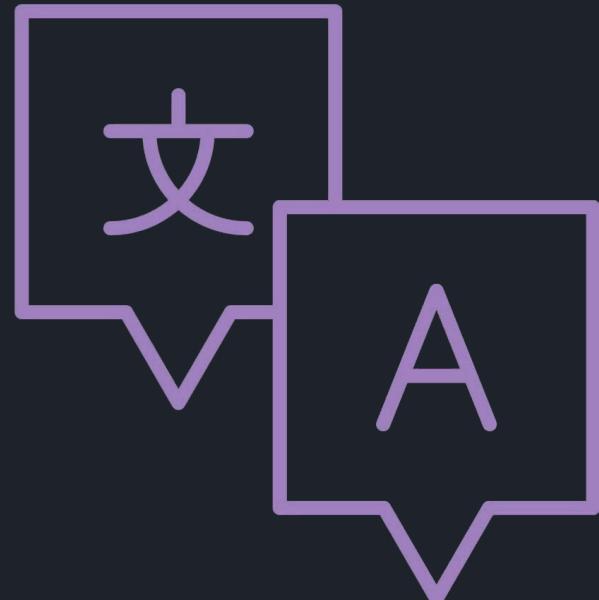


Application

- Gradio
- Google Cloud Storage

Future Research & Improvements

Completed!



Multi-Language Support & Resources

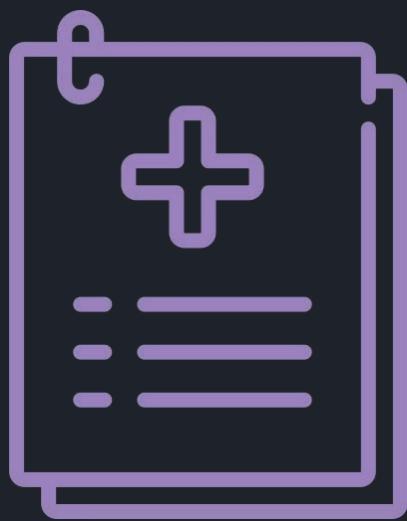
In the future, **additional languages** should be included to help more patients use the application.

In addition, resources on what to do, **nutritional resources and mental health** advice would be included.



Expansion & Inclusive Participation

At the current moment, all sample images were of fair tone skin. Therefore, the model was trained on only fair-tone images. Future Research must include an inclusive sample of participants.



Process Improvement

There should be additional research investigating if the speed of receiving **diagnosis leads to an increase in survival rate.**

In Progress!



Integrated Patient & Doctor App (progressive web app)

Build a mobile web interface so that patients and doctors can login to access our product from a single app accessible on the web & their phone.

Multiple Language Support & Resources Integration

Completed!

SkinLink - Physician's AI Assistant for Melanoma Detection

You can request results of one these patients - Barbara, Mario, Benjamin, Blake, Michael, Marco, Brooke, Maya, Barry, Mohan, Bob & Melodie.
You can speak in English, Spanish or French.

La prédition de notre modèle pour Benjamin est **benign** avec 99,98% de confiance.

La predicción de nuestro modelo para Benjamin es **benign** con una confianza del 99,98%.

Analyzed Image

Flag

Analyzed Image

Flag

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Thank You

Q&A?

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Extra Appendix Slides

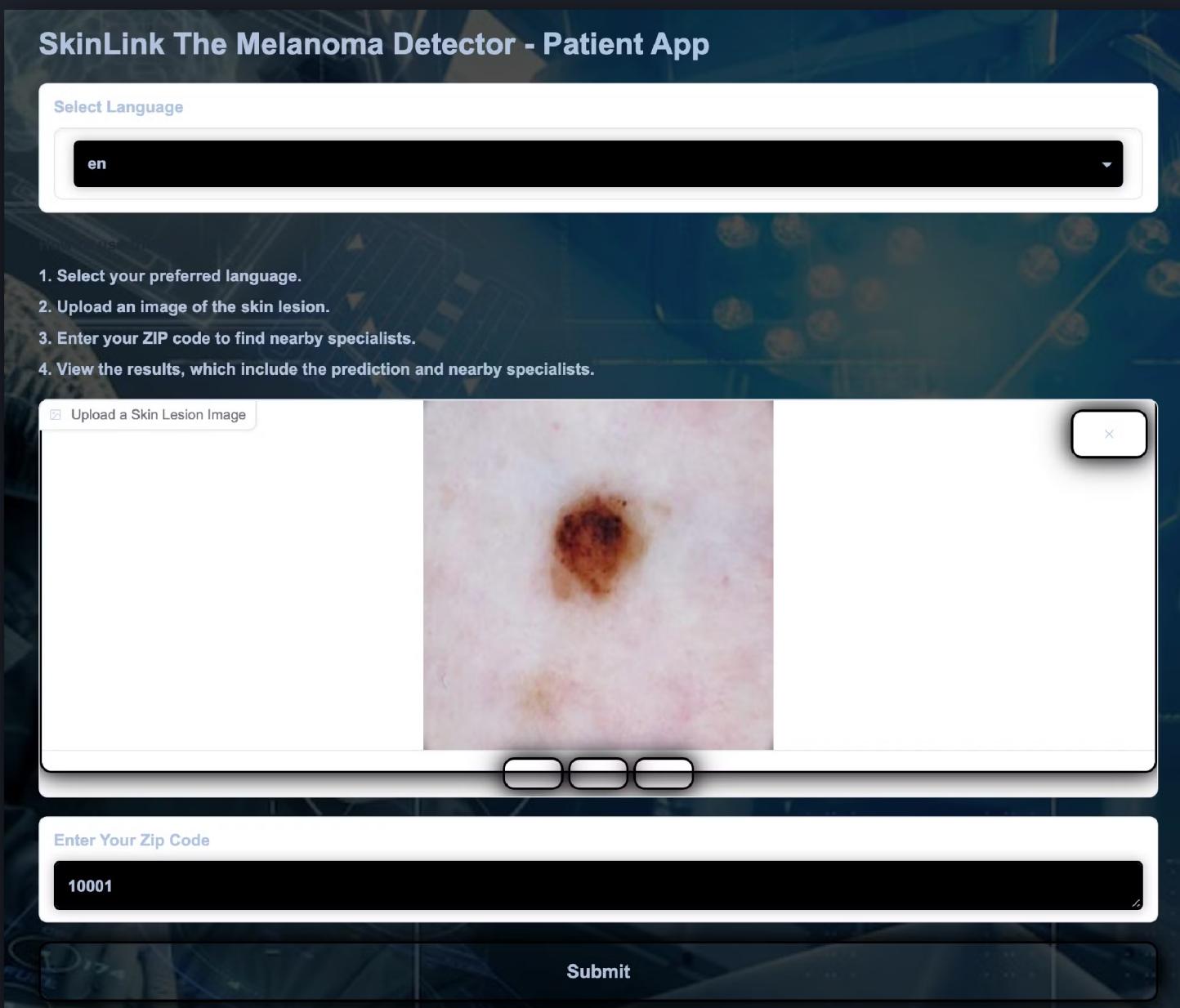
NOT FOR PRESENTATION

Agenda

- Intro 30-60 Secs
 - Meet Team #9 (Alisha) 15-30 Secs
 - Problem We're Solving (Elphys) 15-30 Secs
- Building the Model (Girish) 1.5-2 min
 - Data & Preprocessing
 - Training & Optimization
- Demo 3-4.5 min
 - Patient App (Sebastian 2.5 min)
 - Doctor App (Girish 2min)
 - Tech We Used
- Future Research & Improvements (Michael) 15 Secs

Demo: SkinLink, the Melanoma Detector

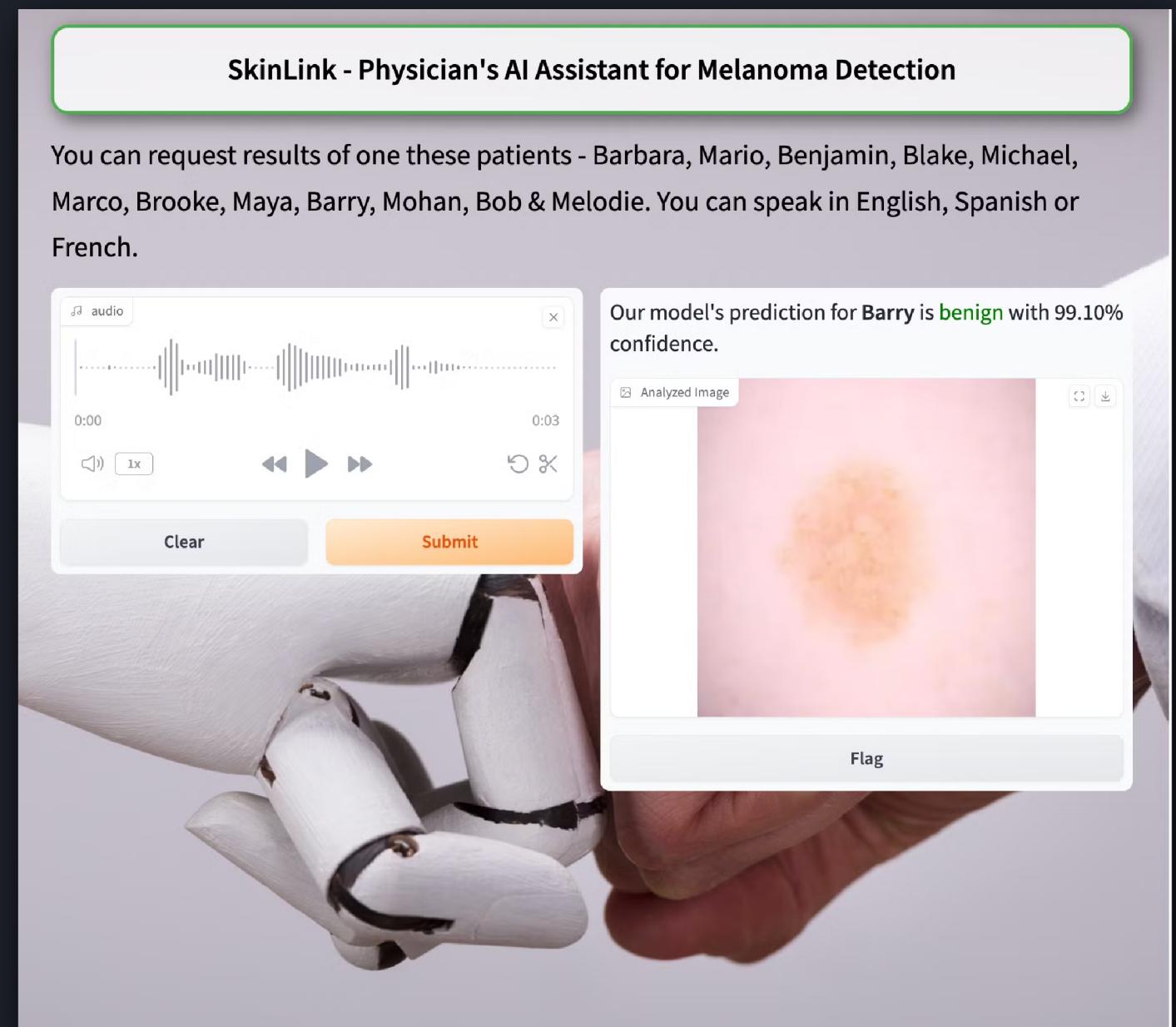
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Data Collection & Pre-Processing

The package with the labeled skin cancer images was downloaded from **Kaggle**.

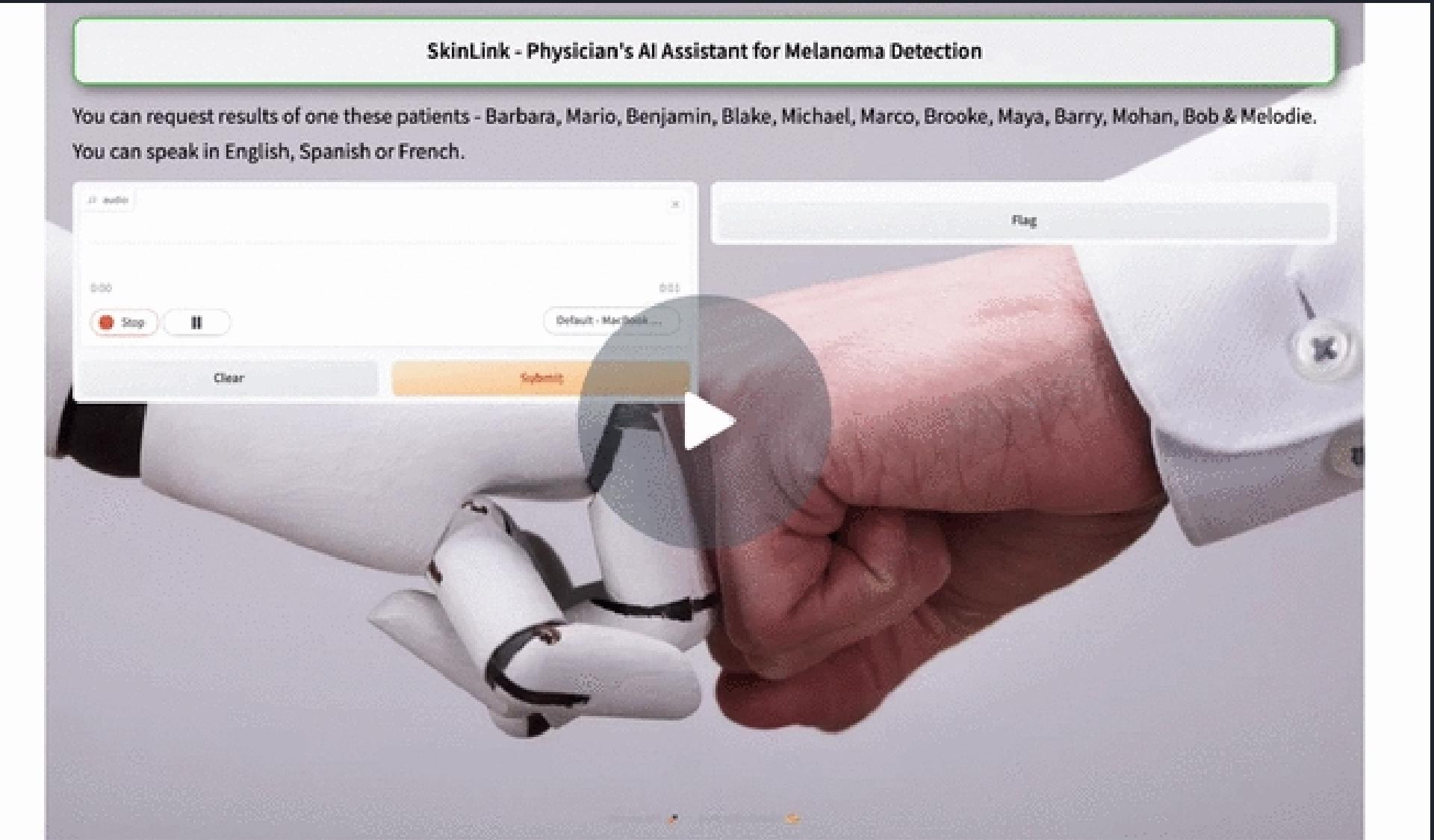
In this project, we organized and processed a dataset of melanoma images to train a machine-learning model.

We began by defining paths for **benign and malignant image directories**, then loaded and labeled the images. A sample of images from the dataset was displayed in a 5x10 subplot grid for visual inspection.

Each image was converted to a floating-point Numpy array and **normalized to the range [0, 1]**. The dataset was split into training and testing sets, and the training data was augmented with techniques such as random rotation, translation, zoom, and flipping to improve model performance.

The augmented images were also displayed in a grid to verify the augmentation process. Subsequently, we stored the processed datasets, including training, validation, and testing sets, in pickle files for future use. This includes saving the images and labels separately.

We also demonstrated how to load these pickle files to ensure the data was correctly saved and could be recalled accurately. **This comprehensive preparation and storage process facilitates effective model training, evaluation, and reuse of the dataset in future experiments.**





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