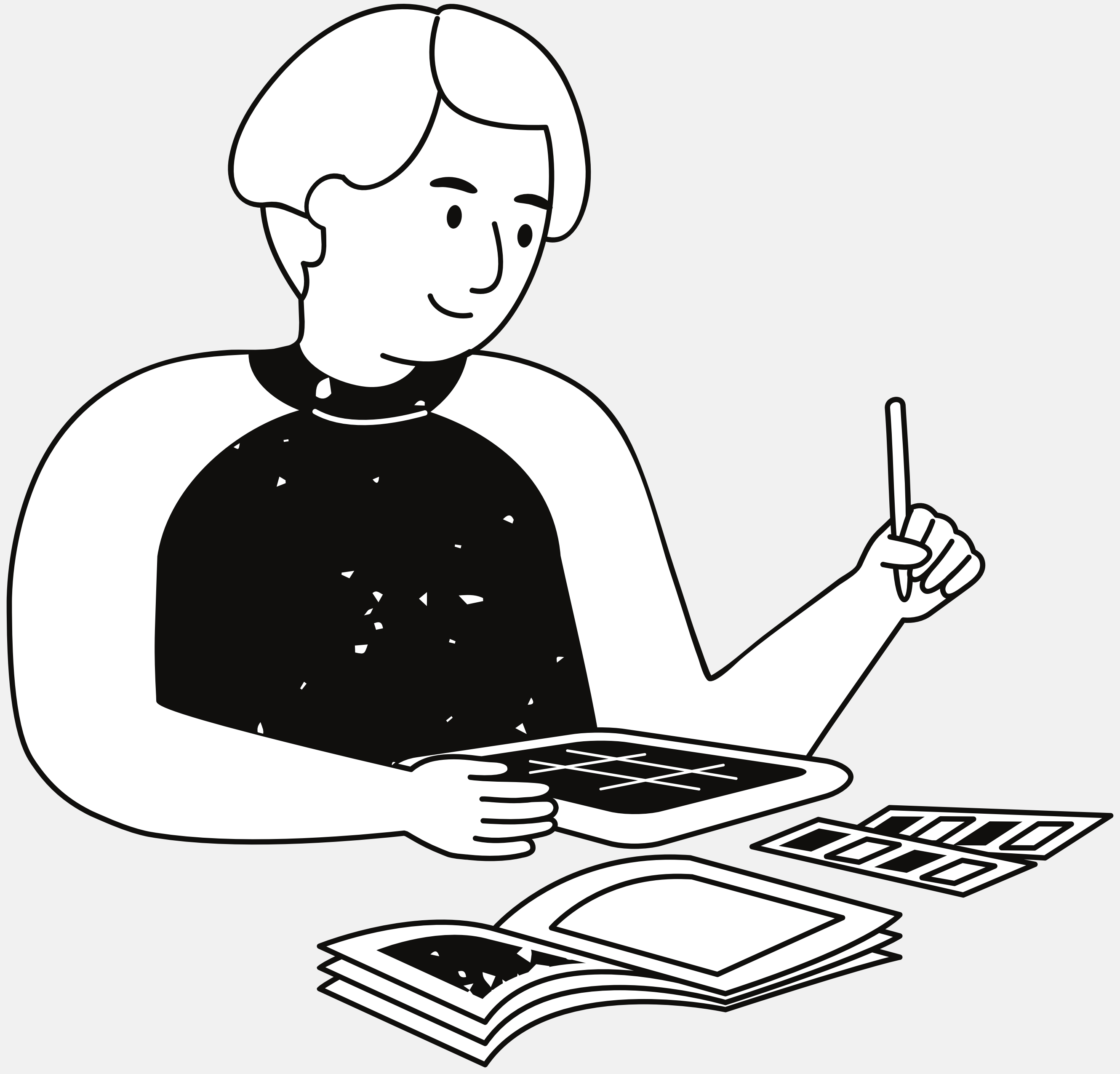
Skin Disease Classification using CNN on HAM10000

By: SAGNIK NANDI

Program: Summer School - Capstone Project

Problem Statement

- Skin cancer and related conditions are among the most common medical cases worldwide.
- Delayed or incorrect diagnosis can be life-threatening.
- Problem: Manual dermatological diagnosis is subjective and resource-intensive.
- Goal: Use a CNN to automatically classify skin lesions from dermoscopy images into 7 disease categories.



Motivation & Relevance

The increasing burden of skin diseases and limited access to dermatologists have made early, AI-assisted diagnosis more crucial than ever. Deep learning offers scalable, cost-effective solutions for timely detection and better patient outcomes.

01.

AI for Early Detection
Skin cancer, especially melanoma, is highly treatable if detected early. Deep learning models can assist doctors with fast, accurate diagnosis.

02.

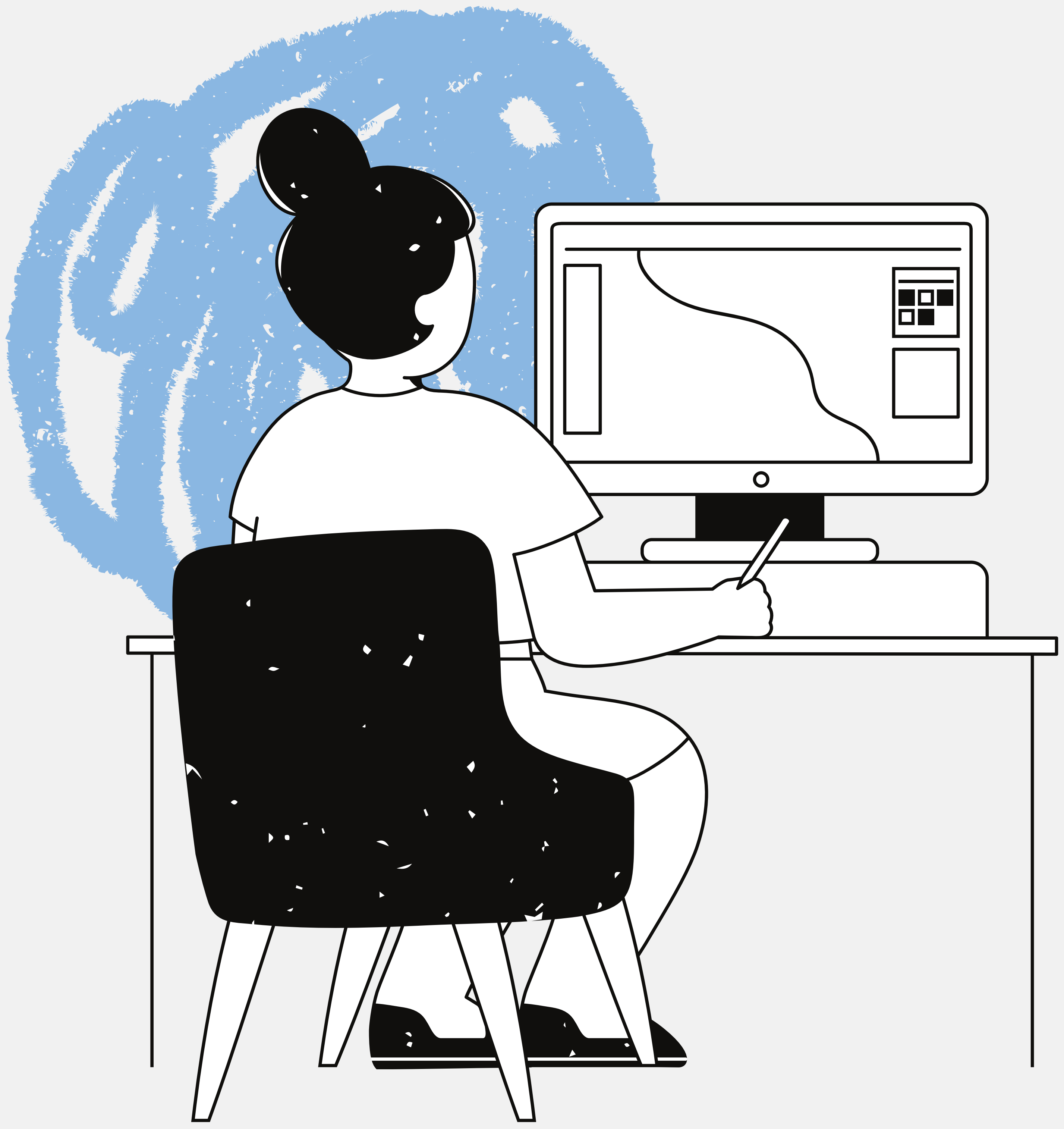
Bridging Specialist Gaps
Many regions lack enough trained dermatologists. AI tools can help democratize healthcare access globally.

03.

Real-World Application
The project showcases the practical use of CNNs in the medical field, aligning well with global trends in AI-assisted healthcare.

Literature Review

- Studies show CNNs outperform dermatologists on specific image classification tasks.
- Most use large models like ResNet, InceptionV3 with fine-tuning.
- In this project:
  - Simpler CNN built from scratch, suitable for beginners.
  - Validated approach on real-world medical dataset (HAM10000).



Dataset Description

Source:
Harvard Tschandl et al.
(HAM10000 open dataset)

Images resized to 64x64 pixels for model efficiency

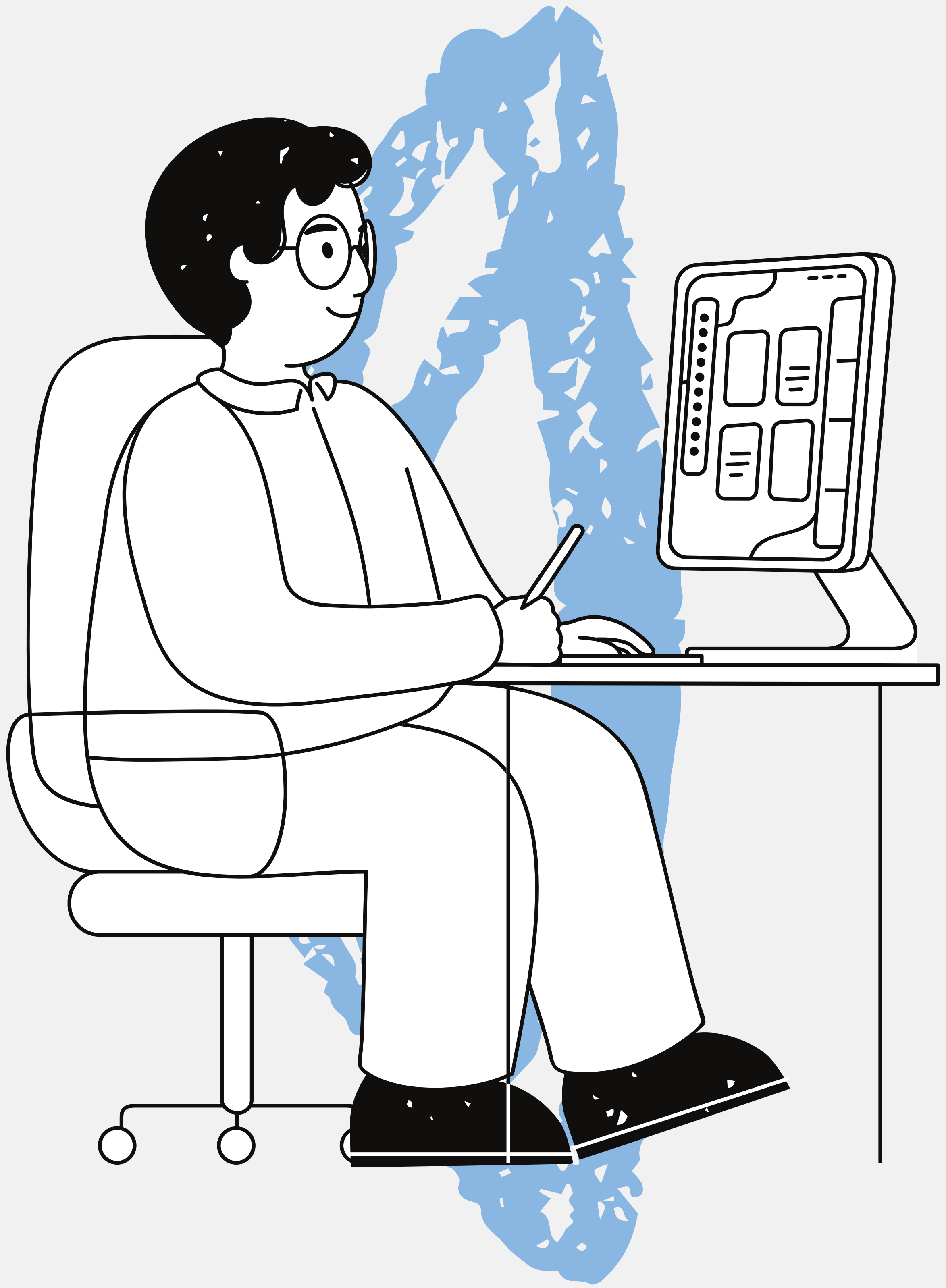
Classes:
7 skin diseases (nv, mel, bkl, bcc, akiec, vasc, df)

Subset Used:
~3000 images (due to Colab limitations)

Metadata includes diagnosis labels

Model Architecture

- Input Layer: 64x64x3 images (normalized)
- Conv2D Layer 1 → ReLU → MaxPooling
- Conv2D Layer 2 → ReLU → MaxPooling
- Flatten → Dense(128) → Dropout
- Output Layer: Dense(7), Softmax
- Total Params: ~100K
- Designed for clarity and efficiency, not just depth



Training Strategy & Hyperparameters

- Split: 80% train / 20% test
- Optimizer: Adam
- Loss Function: Categorical Crossentropy
- Epochs: 10
- Batch Size: 32
- No pretrained weights (pure CNN)
- Training done on Python T4 GPU
- Early stopping considered but not required

Link to Code

Results & Evaluation

- Training Accuracy: ~67.5%
- Validation Accuracy: ~68.2%
- Model shows consistent performance across train and test sets.
- Performance may improve with:
- More data
- Advanced augmentation
- Hyperparameter tuning
- Accuracy is decent for a 7-class classification problem with limited preprocessing.

Challenges Faced

01

Uploading large image datasets on Google Colab (time & memory)

02

Image shape/mode mismatches (RGB vs Grayscale)

03

Unbalanced dataset (some diseases had fewer examples)

04

Minor bugs in preprocessing and evaluation fixed via debugging

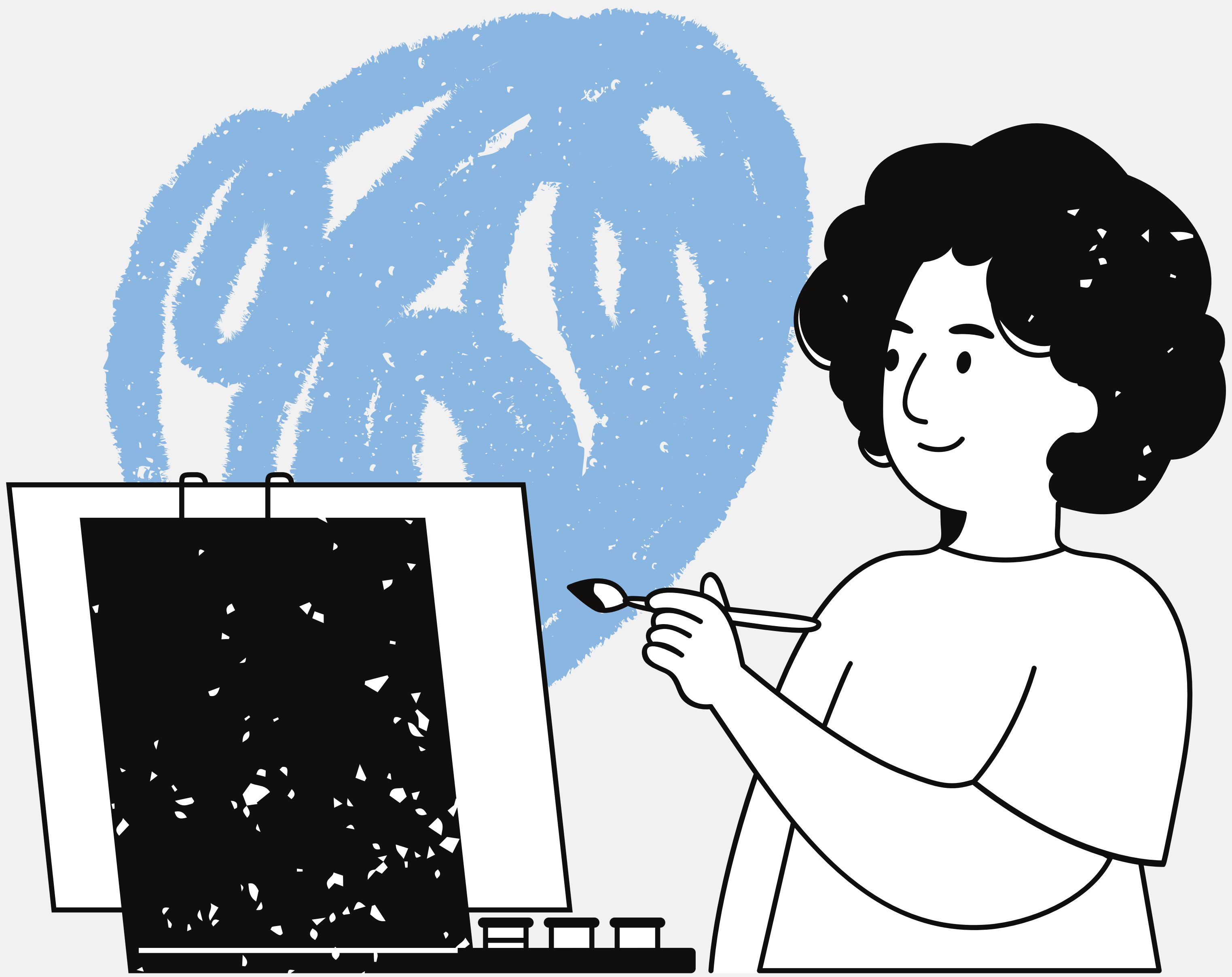
Conclusion & Future work

Conclusion:

- Successfully built an end-to-end AI solution for skin disease classification
- Understood and applied deep learning techniques
- Validated feasibility of AI in healthcare screening

Future Work:

- Use pretrained models (e.g., MobileNetV2, ResNet50)
- Train on full dataset (~10k images)
- Add data augmentation for better generalization
- Deploy as a web app for real-time use



References

- HAM10000: Tschandl et al., Scientific Data (2018)
- TensorFlow / Keras Docs
- scikit-learn (for preprocessing, label encoding)
- OpenAI/StackOverflow (debugging help)