Hair Types Classification

Developed by Team Visionaries

Project Overview

About Our Idea !

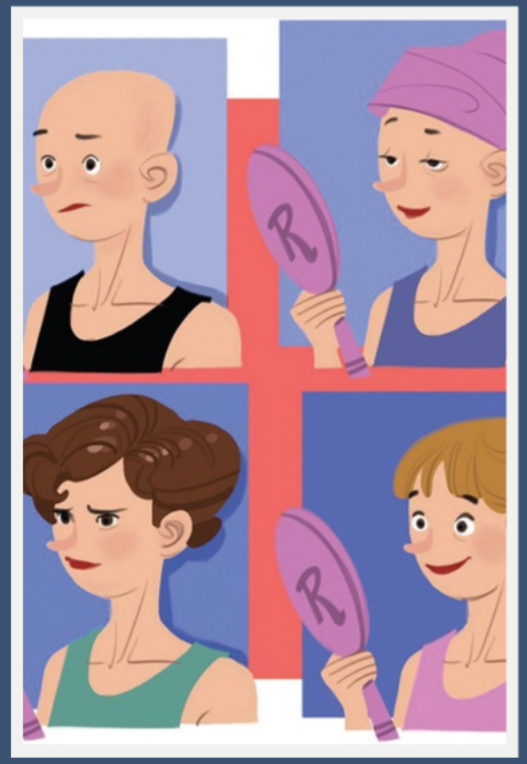
The core idea of this project is to build a computer vision model powered by deep learning to classify hair types with precision. Picture this: a tool that analyzes an image of your hair and instantly identifies whether it's straight, wavy, curly, kinky, or styled in dreadlocks. But it doesn't stop there for each prediction, we provide tailored hair routine tips, like the best shampoos, conditioners, or styling tricks suited to that specific hair type. By leveraging advanced image analysis, this project aims to make hair care simpler and more informed, helping users understand and embrace their unique hair texture.

Dataset Description

Hair Type Dataset (Kaggle)

A high-quality image dataset for classifying four hair types Straight, Wavy, Curly, Kinky plus Dreadlocks as a hairstyle. Useful for training ML models on hair texture recognition.

Straight: 488 | Wavy: 330 | Curly: 514 | Kinky: 217 | Dreadlocks: 443



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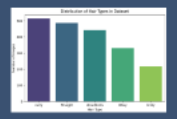
Dataset Pre-Processing

Our Approach!

- Exploratory Data Analysis(EDA)
- Data Preprocessing
- CNN Architecture and Training Pipeline

Exploratory Data Analysis(EDA)

- Imbalanced Dataset



Data Preprocessing

- Organize the dataset **into a DataFrame** and **split it** into **80% training** and **20% testing.**
- Apply **data augmentation** on images to address the issue of limited data.
- Handle the **class imbalance problem** effectively.

Data Preprocessing

- Show few of the dataframe after split

Data Preprocessing

- Offline Augmentation (Preprocessing Stage) – **Using ImageDataGenerator.**

Data Preprocessing

- Compute class weights based on class distribution using compute_class_weight to address the imbalance problem.

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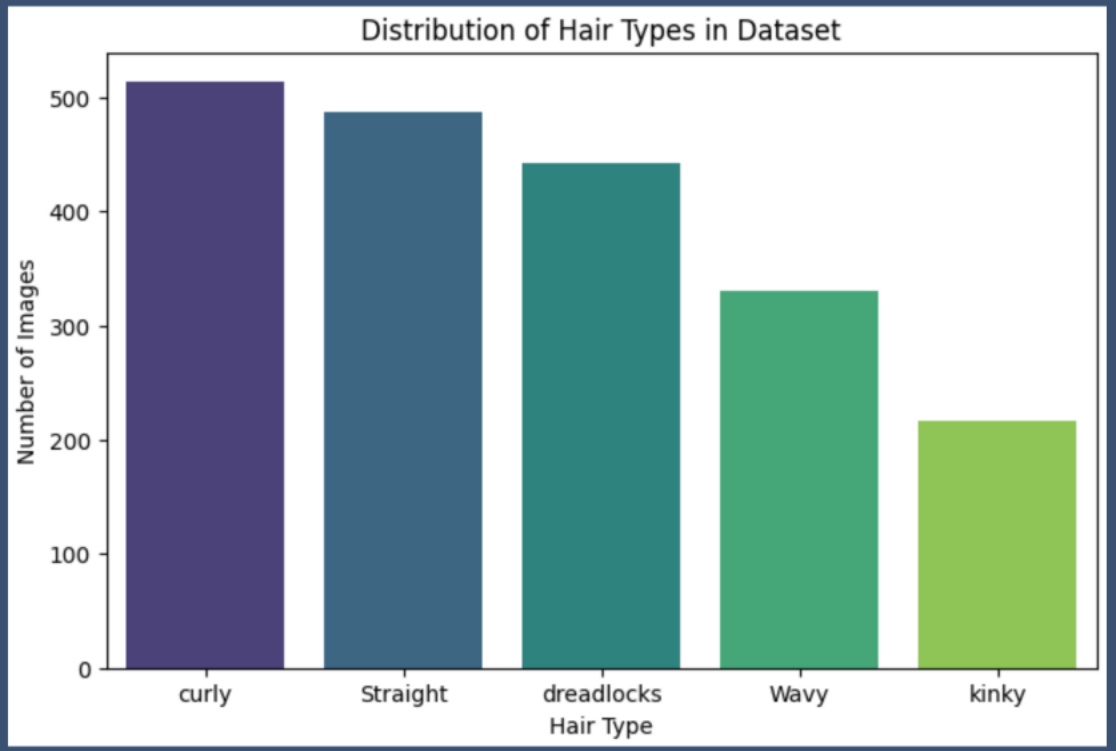
Exploratory Data Analysis(EDA)

- Imbalanced Dataset



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- Handle the **class imbalance problem** effectively.

Data Preprocessing

- Show few of the dataframe after split

	filename	Class
187	curly/image16.jpg	curly
115	curly/curl-tips-styling-1561743013.jpg	curly
569	Straight/8-centreparted-layered-cut-for-long-h...	Straight
1176	kinky/image44.jpg	kinky
1858	Wavy/images (3).jpg	Wavy
1917	Wavy/images5.jpg	Wavy
1537	dreadlocks/image49.jpg	dreadlocks
307	curly/image31.jpg	curly
466	curly/images47.jpg	curly
1026	kinky/011b913aca7afbdd7feb6cdd4481b3bf4.jpg	kinky

Data Preprocessing

- Offline Augmentation (Preprocessing Stage) → **Using ImageDataGenerator.**

```
# Creating data generators for image preprocessing and augmentation.
# The training data generator applies rescaling and various augmentations
# (rotation, shifting, zooming, and flipping) to enhance model generalization.
# The testing data generator only rescales images to normalize pixel values.
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=15,
    width_shift_range=0.1,
    height_shift_range=0.1,
    zoom_range=0.2,
    horizontal_flip=True
)
test_datagen = ImageDataGenerator(rescale=1./255)
```

Data Preprocessing

- Compute class weights based on class distribution using compute_class_weight to address the imbalance problem.

```
# Computing class weights to handle class imbalance in the dataset.
# Extracts class labels from the training generator.
# Retrieves class names and calculates weights using the "balanced" strategy.
# The computed weights help the model give appropriate importance to underrepresented classes.

# Extract class labels
y_train = train_generator.classes  # Get labels for training set
class_labels = list(train_generator.class_indices.keys())

# Compute class weights
class_weights = compute_class_weight("balanced", classes=np.unique(y_train), y=y_train)
class_weight_dict = dict(enumerate(class_weights))

print("Class Indices:", train_generator.class_indices)
print("Class Weights:", class_weight_dict)
```

```
Class Indices: {'Straight': 0, 'Wavy': 1, 'curly': 2, 'dreadlocks': 3, 'kinky': 4}
Class Weights: {0: 0.820671834625323, 1: 1.2076045627376426, 2: 0.7746341463414634, 3: 0.8971751412429378, 4: 1.825287356321839}
```

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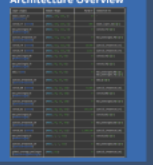
Modeling

Modeling Techniques

Custom CNN models

CNN Model 1

Architecture Overview

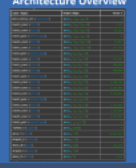


- **Number of Layers:** 4 Conv Blocks + Global Average Pooling + Dense
- **Activation Functions:** ReLU (Conv), Softmax (Output)
- **Optimizer:** Adam (LR = 0.0005)
- **Loss Function:** Sparse Categorical Crossentropy
- **Results:** Accuracy: 91% Best: Dreadlocks (86% recall), Kinky (91% recall) Worst: Wavy (45% recall)

Transfer Learning

VGG16

Architecture Overview



Why VGG16?

Strong feature extraction with pre-trained ImageNet weights, proven for image classification.

- **Layers Added:** Flatten, Dense (ReLU) + Dropout (0.5) + Dense (ReLU) + Dropout (0.5) + Output Layer (Softmax)
- **Optimizer:** Adam (LR = 0.0001 (initial) and 5e-6 (for fine-tuning))
- **Loss Function:** Sparse Categorical Crossentropy
- **Results:** Accuracy: 86% Best: Dreadlocks (95% recall), Kinky (91% recall) Worst: Curly (81% recall)

Custom CNN models

CNN Model 2

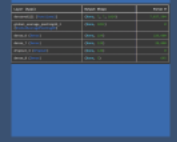
Architecture Overview

- **Number of Layers:** 4 Conv Blocks + Flatten + 2 Dense Layers
- **Activation Functions:** ReLU (Conv & Dense), Softmax (Output)
- **Optimizer:** Adam (LR = 0.0005)
- **Loss Function:** Sparse Categorical Crossentropy
- **Results:** Accuracy: 91.1% Best: Dreadlocks (91% recall), Straight (97% recall) Challenges: Wavy Hair (45% recall, misclassified often as Curly)

Transfer Learning

DenceNet121

Architecture Overview



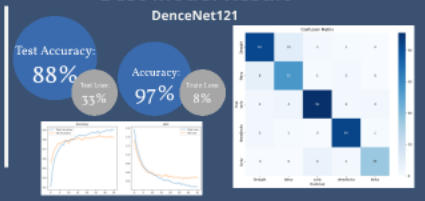
Why DenseNet?

Pretrained on ImageNet, great for small datasets like hair type classification.

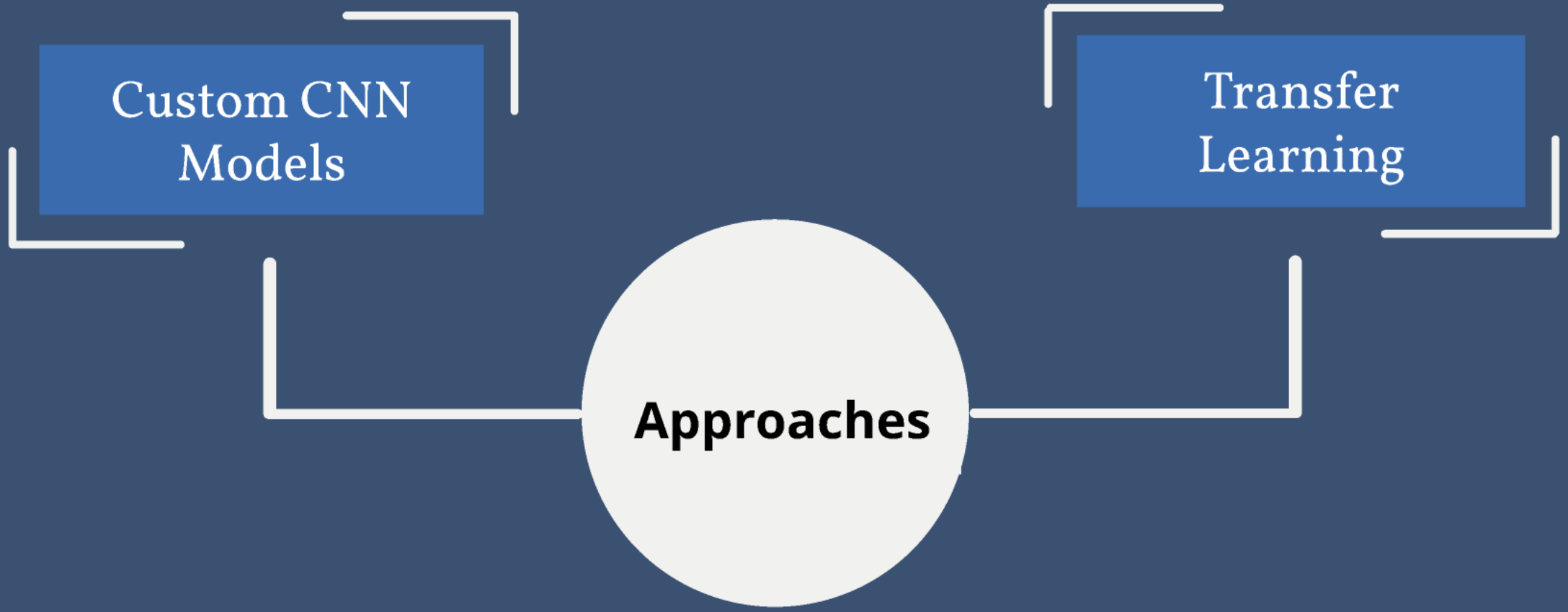
- **Layers Added:** Global Average Pooling, Dense (ReLU) + Dense (ReLU) + Dropout (0.5) Output Layer (Softmax)
- **Optimizer:** Adam (LR 0.0001)
- **Loss Function:** Sparse Categorical Crossentropy
- **Results:** 88% Best: Dreadlocks (94% recall), Curly (91% precision)

Best Model Result

DenceNet121



Modeling Techniques



Custom CNN models

Number of Layers: 6 Conv Blocks + Global Average Pooling + Dense

Activation Functions: ReLU (Conv), Softmax (Output)

Optimizer: Adam (LR = 0.0003)

Loss Function: Sparse Categorical Crossentropy

Results: Accuracy: 70%
Best: Dreadlocks (86% recall), Kinky (91% recall)
Worst: Wavy (45% recall)

CNN Model 1

Architecture Overview

Layer (type)	Output Shape	Param #	Connected to
input_layer_22 (InputLayer)	(None, 224, 224, 3)	0	-
conv2d_77 (Conv2D)	(None, 224, 224, 32)	896	input_layer_22[0][0]
max_pooling2d_78 (MaxPooling2D)	(None, 112, 112, 32)	0	conv2d_77[0][0]
spatial_dropout2d_15 (SpatialDropout2D)	(None, 112, 112, 32)	0	max_pooling2d_78[0][0]
conv2d_79 (Conv2D)	(None, 112, 112, 64)	18,496	spatial_dropout2d_15[…
conv2d_78 (Conv2D)	(None, 112, 112, 64)	2,112	spatial_dropout2d_15[…
max_pooling2d_80 (MaxPooling2D)	(None, 56, 56, 64)	0	conv2d_79[0][0]
max_pooling2d_79 (MaxPooling2D)	(None, 56, 56, 64)	0	conv2d_78[0][0]
add_1 (Add)	(None, 56, 56, 64)	0	max_pooling2d_80[0][0… max_pooling2d_79[0][0]
spatial_dropout2d_16 (SpatialDropout2D)	(None, 56, 56, 64)	0	add_1[0][0]
conv2d_80 (Conv2D)	(None, 56, 56, 128)	73,856	spatial_dropout2d_16[…
max_pooling2d_81 (MaxPooling2D)	(None, 28, 28, 128)	0	conv2d_80[0][0]
spatial_dropout2d_17 (SpatialDropout2D)	(None, 28, 28, 128)	0	max_pooling2d_81[0][0]
conv2d_81 (Conv2D)	(None, 28, 28, 256)	295,168	spatial_dropout2d_17[…
max_pooling2d_82 (MaxPooling2D)	(None, 14, 14, 256)	0	conv2d_81[0][0]
spatial_dropout2d_18 (SpatialDropout2D)	(None, 14, 14, 256)	0	max_pooling2d_82[0][0]
conv2d_82 (Conv2D)	(None, 14, 14, 512)	1,180,160	spatial_dropout2d_18[…
max_pooling2d_83 (MaxPooling2D)	(None, 7, 7, 512)	0	conv2d_82[0][0]
spatial_dropout2d_19 (SpatialDropout2D)	(None, 7, 7, 512)	0	max_pooling2d_83[0][0]
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0	spatial_dropout2d_19[…

Custom CNN models

Number of Layers:4 Conv Blocks + Flatten + 2 Dense Layers

Activation Functions: ReLU (Conv & Dense), Softmax (Output)

Optimizer: Adam (LR = 0.0005)

Loss Function: Sparse Categorical Crossentropy

Results: Accuracy: 76.1%
Best: Dreadlocks (81% recall), Straight (77% recall)
Challenges: Wavy Hair (45% recall, misclassified often as Curly)

CNN Model 2

Architecture Overview

Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 222, 222, 32)	896
max_pooling2d_8 (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_9 (Conv2D)	(None, 109, 109, 64)	18,496
max_pooling2d_9 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_10 (Conv2D)	(None, 52, 52, 128)	73,856
max_pooling2d_10 (MaxPooling2D)	(None, 26, 26, 128)	0
conv2d_11 (Conv2D)	(None, 24, 24, 256)	295,168
max_pooling2d_11 (MaxPooling2D)	(None, 12, 12, 256)	0
flatten_2 (Flatten)	(None, 36864)	0
dense_4 (Dense)	(None, 256)	9,437,440
dropout_2 (Dropout)	(None, 256)	0
dense_5 (Dense)	(None, 5)	1,285

Transfer Learning

Why VGG16?

Strong feature extraction with pre-trained ImageNet weights, proven for image classification.

Layers Added: Flatten, Dense (ReLU) + Dropout (0.5) + Dense (ReLU) + Dropout (0.5) + Output Layer (Softmax)

Optimizer: Adam (LR = 0.0001 (initial) and 3e-6 (for fine-tuning)).

Loss Function: Sparse Categorical Crossentropy

Results: Accuracy: 86%
Best: Dreadlocks (93% recall), Kinky (91% recall)
Worst: Curly (81% recall)

VGG16

Architecture Overview

Layer (type)	Output Shape	Param #
keras_tensor_145 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1,792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36,928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73,856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147,584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295,168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590,080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590,080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten_4 (Flatten)	(None, 25088)	0
dense_9 (Dense)	(None, 512)	12,845,568
dropout_8 (Dropout)	(None, 512)	0
dense_10 (Dense)	(None, 256)	131,328
dropout_9 (Dropout)	(None, 256)	0
dense_11 (Dense)	(None, 5)	1,285

Transfer Learning

Why DenseNet?

Pretrained on ImageNet, great for small datasets like hair type classification.

- **Layers Added**: Global Average Pooling, Dense (ReLU) + Dense (ReLU) + Dropout (0.3) Output Layer (Softmax)
- **Optimizer**: Adam (LR 0.0001)
- **Loss Function**: Sparse Categorical Crossentropy
- **Results**: 88%
  Best: Dreadlocks (94% recall), Curly (91% precision)

DenceNet121

Architecture Overview

Layer (type)	Output Shape	Param #
densenet121 (Functional)	(None, 7, 7, 1024)	7,037,504
global_average_pooling2d_3 (GlobalAveragePooling2D)	(None, 1024)	0
dense_6 (Dense)	(None, 224)	229,600
dense_7 (Dense)	(None, 128)	28,800
dropout_3 (Dropout)	(None, 128)	0
dense_8 (Dense)	(None, 5)	645

Best Model Result

DenceNet121

Test Accuracy:

88%

Test Loss:

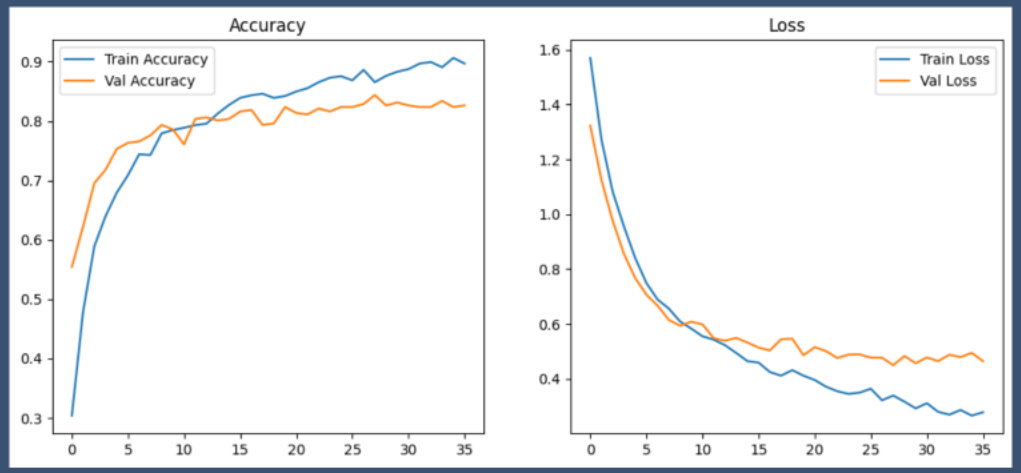
33%

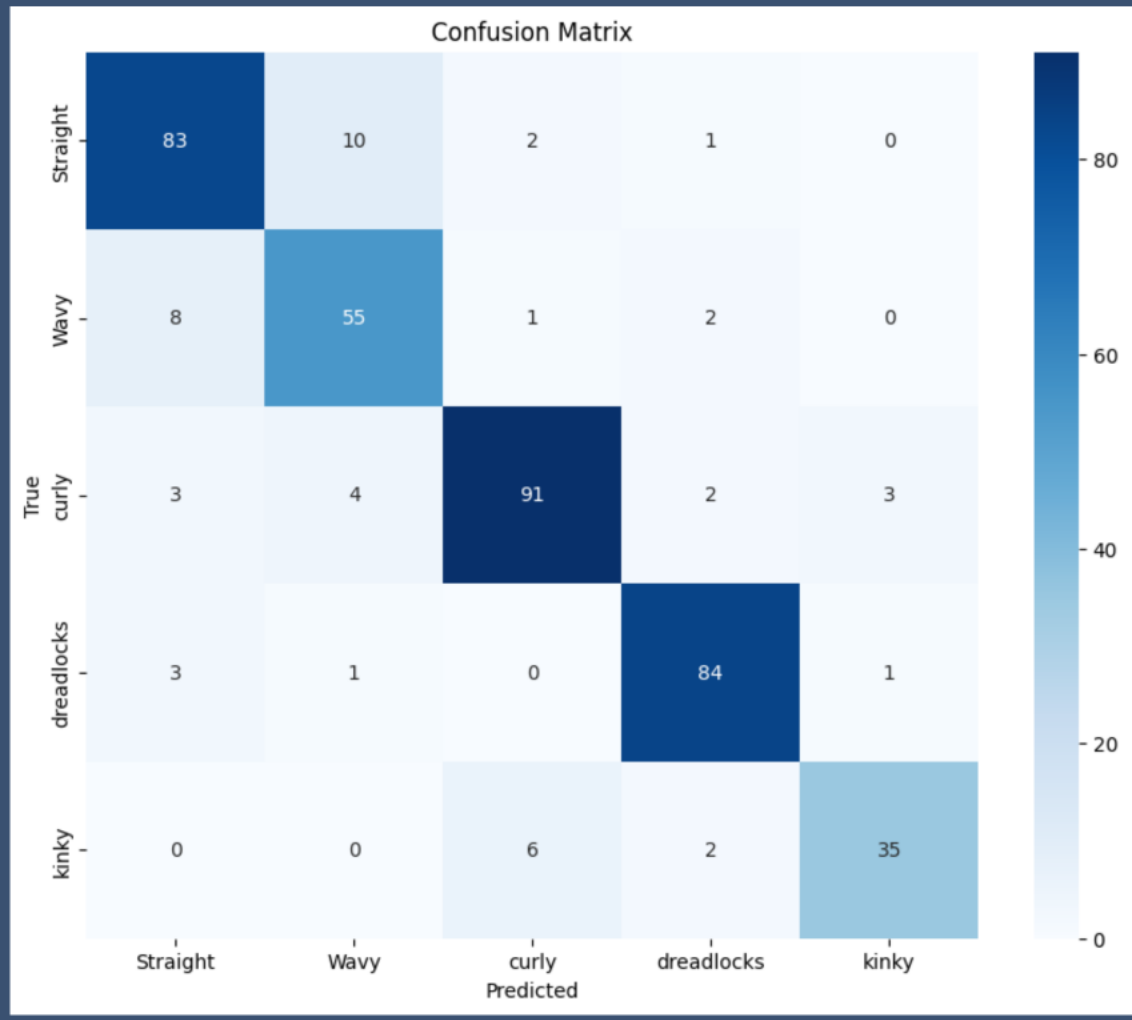
Accuracy:

97%

Train Loss:

8%





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Conclusion and Streamlit develpment

Streamlit

This Streamlit app classifies hair types from uploaded images using a TensorFlow model (advanced_densenet_model.h5). Users can upload images in JPG, JPEG, or PNG formats,

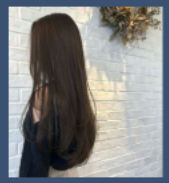
and the app preprocesses these images before making predictions. The predicted hair type and confidence level are displayed, along with fun facts and care tips related to the hair type.

The layout features a sidebar for uploads and a main area for results, enhanced with custom CSS for better visuals.

Conclusion

In conclusion, our hair type classification project effectively combines deep learning and user-friendly design to empower users with insights about their hair.
By using a Streamlit application, we provide real-time predictions.

This innovative approach not only enhances users' understanding of their unique hair types but also promotes better hair care practices, ultimately contributing to healthier hair.



Visionaries Group
Thank you!

Group Names:
- Mayar Fawaz althebati
- Shatha Saleh Alqubaisi
- Raghad Khaled Almutairi
- Wareef Yousef Alqurashi

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