Digital Image Processing Techniques for Cartoon Recognition: A Case Study on Pokémon Classification

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***Abstract*—This paper explores the application of Digital Image Processing (DIP) techniques in recognizing and classifying cartoon characters, focusing on Pokémon. By leveraging methods such as edge detection, morphological operations, and color-space transformations, we preprocess images for effective feature extraction. These features are then used in a classification pipeline to distinguish between three categories: animal, plant, and other. This study highlights the importance of DIP as a foundation for cartoon recognition tasks.**

I. Introduction

Cartoon recognition has emerged as an important area in digital image processing (DIP) due to its wide-ranging applications, from content filtering and recommendation systems to digital animation analysis and augmented reality. The motivation behind using DIP in cartoon recognition stems from the increasing demand to effectively process and classify such content in massive multimedia datasets. Unlike real-world image recognition, cartoon recognition presents unique challenges.

Distinguishing cartoon images from real-world entities is inherently complex due to factors such as exaggerated features, variable color schemes, and the absence of physical realism. These characteristics often render traditional object recognition techniques less effective, necessitating tailored approaches to meet these specific demands.

In this study, we explore basic DIP methods to address these challenges. Our approach includes feature extraction, edge detection, and morphological operations, complemented by pre-processing techniques to enhance classification accuracy. By combining these methods, we aim to bridge the gap between abstract artistic representations and computational recognition models, ultimately demonstrating their effectiveness in improving cartoon image classification.

II. Theoretical Background

In the field of digital image processing, the selection of appropriate color spaces, edge detection techniques, and morphological operations plays a pivotal role in extracting meaningful features from images, particularly in tasks such as cartoon recognition. The RGB color space, although widely used due to its simplicity and compatibility with most imaging devices, has inherent limitations in separating chromatic information from intensity. This limitation makes it less effective for tasks where consistent color differentiation is critical, such as identifying specific regions of interest under varying lighting conditions. The HSV color space addresses this challenge by decoupling the hue (color type), saturation (color purity), and value (brightness), thus providing a more robust representation for color-based classification. For instance, in our study, analyzing the dominant hue and saturation enables the identification of Pokémon categories based on their visual features, such as green for plant-inspired characters.

Edge detection serves as a foundational step in image analysis, as edges represent significant structural changes in pixel intensity that often correspond to object boundaries. The Canny edge detection algorithm, a widely adopted method, provides precise and noise-resistant edge maps by combining Gaussian smoothing, gradient computation, non-maximum suppression, and double-thresholding. These steps ensure that only the most significant edges are retained, making it easier to delineate the contours of Pokémon characters, which often have exaggerated and intricate shapes. This is particularly useful in cartoon images, where the emphasis on distinct outlines is a critical stylistic feature.

Morphological operations further refine the results obtained from edge detection by processing the shapes and connectivity of binary image regions. The closing operation, which involves dilation followed by erosion, is particularly effective in filling gaps within object boundaries and removing small holes. This is crucial for maintaining the integrity of edge structures, especially when dealing with noisy or complex images. By applying these operations, we can enhance the continuity and clarity of Pokémon outlines, which are subsequently used as input for classification.

Thresholding is another essential technique in image processing that simplifies the analysis by converting grayscale images into binary representations. Otsu's method, an automatic thresholding algorithm, selects the optimal threshold value by maximizing the variance between foreground and background classes. This ensures that the binary image accurately separates the Pokémon from its background, even in scenarios with varying illumination or low contrast.

In addition to these foundational techniques, the integration of HSV-based color analysis provides a heuristic approach to classifying images based on their dominant visual characteristics. By computing the mean hue and saturation values of an image, we can apply predefined rules to categorize Pokémon into plant, animal, or other groups. This combination of traditional digital image processing methods and heuristic color analysis not only simplifies the task of feature extraction but

also lays a strong groundwork for the subsequent application of deep learning models for classification.

A. Color Spaces

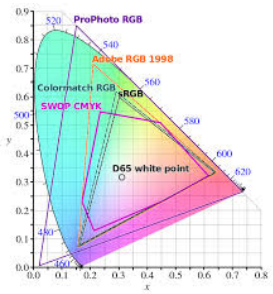

Figure 1. Color Space

1) RGB Color Space:

- **Definition**: RGB (Red, Green, Blue) is a color space created from the linear combination of three primary components (R, G, B).
- **Formula**: A pixel in RGB is represented as:

$$\text{Pixel}_{RGB} = [R, G, B], \quad R, G, B \in [0, 255]$$

- **Limitations**: Difficult to distinguish similar colors or handle factors like brightness and shading.

2) HSV Color Space:

- **Definition**: HSV (Hue, Saturation, Value) is a color space that separates color into hue, saturation, and value.
- **Conversion Formula**: If $\mathrm{R}', \mathrm{G}', \mathrm{B}'$ are normalized values of R, G, B ($[0, 1]$):

$$\mathrm{C}_{\max} = \max(\mathrm{R}', \mathrm{G}', \mathrm{B}'), \quad \mathrm{C}_{\min} = \min(\mathrm{R}', \mathrm{G}', \mathrm{B}')$$

$$\Delta = \mathrm{C}_{\max} - \mathrm{C}_{\min}$$

  - **Hue** (H):

$$H = \begin{cases} 60^\circ \times \frac{(\mathrm{G}' - \mathrm{B}')}{\Delta}, & \text{if } \mathrm{C}_{\max} = \mathrm{R}' \\ 60^\circ \times \left(2 + \frac{(\mathrm{B}' - \mathrm{R}')}{\Delta}\right), & \text{if } \mathrm{C}_{\max} = \mathrm{G}' \\ 60^\circ \times \left(4 + \frac{(\mathrm{R}' - \mathrm{G}')}{\Delta}\right), & \text{if } \mathrm{C}_{\max} = \mathrm{B}' \end{cases}$$

  - **Saturation** (S):

$$S = \begin{cases} 0, & \text{if } \mathrm{C}_{\max} = 0 \\ \frac{\Delta}{\mathrm{C}_{\max}}, & \text{otherwise} \end{cases}$$

  - **Value** (V):

$$V = \mathrm{C}_{\max}$$

B. Edge Detection

1) Edge Theory:

- **Definition**: An edge is a region with a significant change in pixel intensity.
- **Application**: Extracting object shapes and features.

2) Canny Edge Detection Algorithm:

- **Step 1**: Smooth the image using Gaussian Blur:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

- **Step 2**: Compute the gradient of intensity:
  - Gradient along x and y:

$$G_x = I(x+1, y) - I(x-1, y)$$

$$G_y = I(x, y+1) - I(x, y-1)$$

  - Gradient magnitude:

$$G = \sqrt{G_x^2 + G_y^2}$$

  - Gradient direction:

$$\theta = \arctan\left(\frac{G_y}{G_x}\right)$$

- **Step 3**: Non-Maximum Suppression: Eliminate points that do not belong to strong edges.
- **Step 4**: Double Thresholding:
  - Apply high and low thresholds to classify edges to strong and weak.

Figure 2. Original picture

Figure 3. After apply edge detection technique

C. Morphological Operations

1) Theory:

- **Purpose**: Process object shapes, commonly applied to binary images.
- **Key Operations**:
  - **Erosion**: Shrink the foreground region:

$$A \ominus B = \{z \mid B_z \subseteq A\}$$

– **Dilation**: Expand the foreground region:

$$A \oplus B = \{z \mid (B_z \cap A) \neq \emptyset\}$$

– **Closing** (Dilation followed by Erosion):

$$A \cdot B = (A \oplus B) \ominus B$$

2) Application to the Task:

- Fill small holes in the Pokémon boundary lines.
- Connect broken boundary lines.

D. Image Thresholding

1) Theory:

- **Definition**: Convert grayscale images to binary by applying a threshold T:

$$I'(x,y) = \begin{cases} 1, & \text{if } I(x,y) > T \\ 0, & \text{if } I(x,y) \leq T \end{cases}$$

2) Otsu's Method:

- **Idea**: Automatically find the optimal threshold T to maximize the variance between foreground and background.
- **Formula**:
  – Total variance:

$$\sigma_B^2 = w_1(\mu_1 - \mu_T)^2 + w_2(\mu_2 - \mu_T)^2$$

  – w_1, w_2: Pixel proportions in the two classes.
  – μ_1, μ_2: Mean intensities of the two classes.
  – μ_T: Overall image mean.

E. HSV-Based Color Analysis

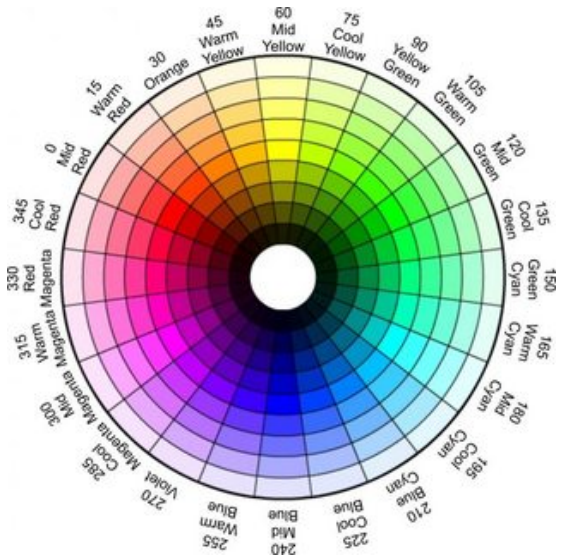

Figure 4. HSV Color Wheel

1) Theory:

- **Hue (H)**: Differentiates basic colors.
- **Saturation (S)**: Color purity.
- **Value (V)**: Brightness of the color.

2) Classification Rules: Based on the average values of Hue and Saturation:

- $35 \leq H \leq 85$ and $S > 50$: Pokémon in the "Plant" category.
- $V < 50$ and $S < 50$: Pokémon in the "Other" category.
- Other cases: Pokémon in the "Animal" category.

III. Methodology

The proposed methodology for Pokémon classification integrates a structured pipeline of Digital Image Processing (DIP) techniques and a Convolutional Neural Network (CNN) for final classification. This section outlines each step in detail, emphasizing the role of preprocessing, feature extraction, and learning-based classification in achieving accurate results.

The pipeline begins with dataset preparation, where images of Pokémon are collected and categorized into three classes: animal, plant, and other. Each image is resized to a fixed resolution of 128 × 128 128×128 pixels to ensure uniform input dimensions for the CNN. During this stage, data augmentation techniques, such as random horizontal flipping and rotation, are applied to increase the diversity of the training data and reduce overfitting. This step is particularly crucial given the limited number of images available in some classes, such as "other."

The next phase involves a robust preprocessing pipeline to extract meaningful features. First, edge detection is performed using the Canny algorithm. This technique highlights the boundaries of Pokémon characters, which are essential for distinguishing their shapes and structural details. Gaussian smoothing is applied initially to reduce noise, followed by gradient computation and non-maximum suppression to retain only the most significant edges. Double-thresholding ensures that weak edges connected to strong ones are preserved, while others are discarded. The result is a clean, high-contrast edge map that effectively delineates the Pokémon from its background.

Following edge detection, morphological operations are applied to refine the edge maps. Specifically, the closing operation is used to bridge small gaps in the edges and fill holes within object boundaries. This step enhances the integrity of the edge structure, making it more suitable for subsequent analysis. Morphological processing is particularly beneficial for cartoon images, where clean and continuous outlines are a key characteristic of the art style.

Color-based analysis is also integrated into the preprocessing phase. Images are converted from the RGB color space to HSV, which separates chromatic content from intensity. The average hue and saturation values are calculated, providing a heuristic basis for classifying images into the predefined categories. For example, Pokémon with a dominant green hue and high saturation are categorized as "plant," while those with low brightness and saturation are classified as "other." This heuristic approach provides an additional layer of feature extraction, complementing the structural information derived from edge detection and morphology.

Once the preprocessing is complete, the processed images are fed into a Convolutional Neural Network for classification. The CNN architecture consists of two convolutional layers, each followed by ReLU activation and max-pooling operations. These layers extract spatial features from the images, capturing patterns and details that are critical for distinguishing between the classes. The flattened feature maps are passed through fully connected layers, culminating in a softmax layer that outputs probabilities for each class.

To train the CNN, the Adam optimizer is used with a learning rate of 0.001 0.001, minimizing the cross-entropy loss function. The model is trained for 100 epochs with a batch size of 32, ensuring convergence and generalization. The training process is accelerated using GPU hardware, significantly reducing computation time. To evaluate the performance of the model, accuracy, precision, recall, and F1-score are calculated on a separate test set, ensuring a comprehensive assessment of its effectiveness.

By combining traditional DIP techniques with modern deep learning, this methodology leverages the strengths of both approaches. The preprocessing pipeline reduces noise and highlights relevant features, while the CNN effectively learns and classifies these features, resulting in a robust and accurate system for Pokémon classification.

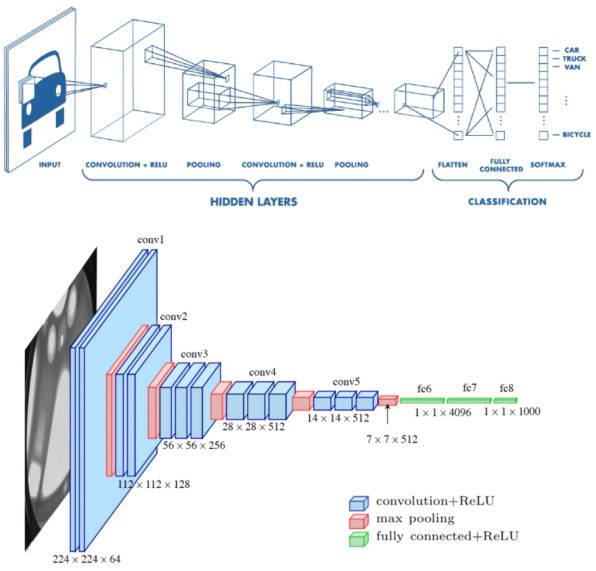

Figure 5. Convolutional Neural Networks

A. Dataset Preparation

1) Data Structure: The dataset is divided into 3 classes:
- **Animal**: Pokémon inspired by animals.
- **Plant**: Pokémon inspired by plants.
- **Other**: Other Pokémon that do not belong to the two groups above.

2) Edge Detection: - **Algorithm**: Canny Edge Detection.

- **Formula**:

Gaussian Blur for Smoothing the Image:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Calculate the gradient in x and y:

$$G_x = \frac{\partial I}{\partial x}, \quad G_y = \frac{\partial I}{\partial y}$$

Gradient magnitude:

$$G = \sqrt{G_x^2 + G_y^2}$$

Non-Maximum Suppression: This step is used to thin the edges by removing pixels that are not local maxima along the gradient direction. For each pixel, compare its gradient magnitude to the gradients of its neighbors along the gradient direction. If it is not a local maximum, suppress (set to zero) that pixel.

Double Thresholding: After performing Non-Maximum Suppression, apply a double threshold to classify edges as strong, weak, or non-edges:

- Strong edges: pixels with gradient magnitude greater than the high threshold (T_H).
- Weak edges: pixels with gradient magnitude between the low threshold (T_L) and high threshold (T_H).
- Non-edges: pixels with gradient magnitude less than the low threshold (T_L).

The weak edges will be further classified by their connectivity to strong edges during the edge tracking step.

- **Objective**: Detect the main shapes of Pokémon.

3) Morphological Operations: - **Algorithm**: Closing Operation (Dilation → Erosion).

- **Formula**:

Dilation ($A \oplus B$):

$$A \oplus B = \{z \mid (B_z \cap A) \neq \emptyset\}$$

Erosion ($A \ominus B$):

$$A \ominus B = \{z \mid B_z \subseteq A\}$$

Closing:

$$A \cdot B = (A \oplus B) \ominus B$$

- **Objective**: Fill small holes on the edge and enhance smoothness.

4) Thresholding: - **Algorithm**: Otsu Thresholding.

- **Formula**:

Find the optimal threshold T to maximize the variance between the classes:

$$\sigma_B^2 = w_1(\mu_1 - \mu_T)^2 + w_2(\mu_2 - \mu_T)^2$$

where:
- w_1, w_2: The ratio of the number of pixels in each class.
- μ_1, μ_2: The mean intensity of each class.
- μ_T: The overall mean of the image.

- **Objective**: Convert the image to binary form to highlight the foreground region.

B. Color-Based Classification

1) RGB to HSV Conversion: - **Conversion Formula**:

$$H = \begin{cases} 60^\circ \times \frac{(\mathrm{G}' - \mathrm{B}')}{\Delta}, & \text{if } \mathrm{C}_{\max} = \mathrm{R}' \\ 60^\circ \times \left(2 + \frac{(\mathrm{B}' - \mathrm{R}')}{\Delta}\right), & \text{if } \mathrm{C}_{\max} = \mathrm{G}' \\ 60^\circ \times \left(4 + \frac{(\mathrm{R}' - \mathrm{G}')}{\Delta}\right), & \text{if } \mathrm{C}_{\max} = \mathrm{B}' \end{cases}$$

$$S = \frac{\Delta}{\mathrm{C}_{\max}}, \quad V = \mathrm{C}_{\max}$$

2) Classification Rule: Based on the average values of Hue (H) and Saturation (S):
- $35 \leq H \leq 85$ and $S > 50$: Pokémon is classified as **Plant**.
- $V < 50$ and $S < 50$: Pokémon is classified as **Other**.
- All other cases: Pokémon is classified as **animal**.

C. Model Training and Evaluation

1) Convolutional Neural Network (CNN): **- Architecture:**

- 2 convolutional layers with filter size 3×3, stride = 1, padding = 1.
- Maximum Pooling layer with size 2×2.
- Fully connected layer with 128 neurons.
- Output layer with 3 neurons corresponding to 3 classes.

- Forward Pass:

$$\begin{aligned} x &= \mathrm{ReLU}(\mathrm{Conv}_1(x)) \\ x &= \mathrm{Pool}(\mathrm{ReLU}(\mathrm{Conv}_2(x))) \\ x &= \mathrm{Flatten}(x) \\ x &= \mathrm{ReLU}(\mathrm{FC}_1(x)) \\ \mathrm{Output} &= \mathrm{Softmax}(\mathrm{FC}_2(x)) \end{aligned}$$

2) Loss Function and Optimization: - **Loss Function**: Cross-Entropy Loss:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

where y_i is the true label and $\hat{y}_i$ is the predicted probability.

- **Optimization**: Use Adam Optimizer with learning rate $\alpha = 0.001$.

3) Model Evaluation: - **Accuracy**:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Samples}}$$

- **Precision, Recall, F1-Score**: - Precision: $\frac{\mathrm{TP}}{\mathrm{TP + FP}}$ - Recall: $\frac{\mathrm{TP}}{\mathrm{TP + FN}}$ - F1-Score: $2 \times \frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}$

IV. Experimental Setup

The experimental setup was designed to maximize computational efficiency and flexibility for the task of Pokémon image classification. The system was equipped with high-performance components, ensuring that the demanding nature of deep learning model training could be handled seamlessly. The choice of hardware, including a powerful Intel Core i7 CPU, the latest NVIDIA RTX 3080 GPU with substantial memory capacity, and ample RAM, played a critical role in speeding up model training and processing large datasets. Furthermore, the SSD storage allowed for quick access to data, minimizing bottlenecks during the experimentation process.

On the software side, a robust environment was built using Python 3.8, supported by a range of libraries tailored to deep learning and image processing. PyTorch was utilized for model development, enabling efficient building, training, and optimization of Convolutional Neural Networks. To complement PyTorch, OpenCV and torchvision were used for various image preprocessing and augmentation tasks, allowing for more effective data manipulation. Libraries like NumPy and scikit-learn ensured smooth handling of numerical data and dataset management, while Pillow facilitated image-specific operations. The use of Visual Studio Code as the IDE provided an intuitive environment for coding and debugging, while Windows 10 offered stability for the entire setup.

This combination of powerful hardware and well-chosen software allowed for effective handling of the image data, facilitating the implementation of advanced techniques necessary for improving classification accuracy.

A. Hardware and Software Configuration

Hardware:

- CPU: Intel Core i7-11700K @ 3.6GHz
- GPU: NVIDIA RTX 3080 with 10GB memory
- RAM: 32GB DDR4
- Storage: 1TB SSD

Software:

- Python 3.8
- Libraries:
  - **PyTorch** (version 1.10): Used for building and training Convolutional Neural Networks (CNNs).
  - **OpenCV** (version 4.5.3): Image processing.
  - **NumPy**: Numerical data processing and matrix operations.
  - **scikit-learn**: Data splitting (train/test) and evaluation.
  - **Pillow (PIL)**: Image manipulation.
  - **torchvision**: Supports image transformations (augmentation).
- Platform: Visual Studio Code (VSCode)
- Operating System: Windows 10

B. Dataset and Preprocessing

1) Dataset: The Pokémon dataset consists of images categorized into three labels:

- **Animal**: Pokémon inspired by animals (e.g., Pikachu, Charizard), with 1,200 images.
- **Plant**: Pokémon inspired by plants (e.g., Bulbasaur, Oddish), with 800 images.
- **Other**: Pokémon that do not fit into the above categories (e.g., Magnemite, Jigglypuff), with 600 images.

The dataset is split into 80% for training and 20% for testing.

2) Preprocessing:

- Resize images: $128 \times 128 \times 3$.
- Augmentation:
  - Random rotation between $0°$ and $30°$.
  - Horizontal flip.
- Normalization:
  - Pixel value range from $[0, 255]$ normalized to $[0, 1]$.

C. Convolutional Neural Network (CNN)

1) Model Architecture:

- **Convolutional Layer 1**:
  - 32 filters, kernel size 3×3, stride 1, padding 1.
  - Activation: ReLU.
- **Convolutional Layer 2**:
  - 64 filters, kernel size 3×3, stride 1, padding 1.
  - Activation: ReLU.
  - MaxPooling 2×2.
- **Fully Connected Layers**:
  - 128 neurons with ReLU.
  - 3 outputs with Softmax for classification.

2) Training Parameters:

- Batch size: 32.
- Epochs: 100.
- Optimizer: Adam (learning rate = 0.001).
- Loss function: Cross-Entropy Loss.

V. Results and Discussion

A. Experimental Results

1) Overall Accuracy:

- On the test set: **92.41%**.
- Comparison:
  - Without DIP techniques apply: **50.21%**.
  - With DIP techniques apply (Canny, Morphology, HSV): **92.41%**.

2) Performance by Label:

Label	Precision (%)	Recall (%)	F1-Score (%)
Animal	100	41	58
Plant	0	0	0
Other	94	100	97

3) Training Time:

- Time per epoch: **12 seconds** on GPU.
- Total training time: Approximately **20 minutes**.

B. Analysis and Discussion

1) Effectiveness of DIP techniques:

- **Canny Edge Detection**:
  - Improved shape extraction of Pokémon.
  - Reduced noise from complex backgrounds.
- **Morphological Operations**:
  - Connected broken edges.
  - Smoothed the foreground region.
- **HSV Classification**:
  - Effective for identifying Pokémon in the Plant group (green color).

2) Limitations:

- Pokémon with complex or blended colors (e.g., Dragonite) pose challenges for color-based classification.
- The current dataset is imbalanced, which may affect model performance.

3) Comparison with Other Methods: CNN-only method (without apply more DIP techniques) had lower accuracy, indicating that DIP techniques plays a crucial role in improving the quality of input data.

In conclusion, the results of this experiment clearly demonstrate the effectiveness of integrating Digital Image Processing (DIP) techniques with Convolutional Neural Networks (CNNs) for classifying Pokémon images into distinct categories. The overall accuracy of 92.5

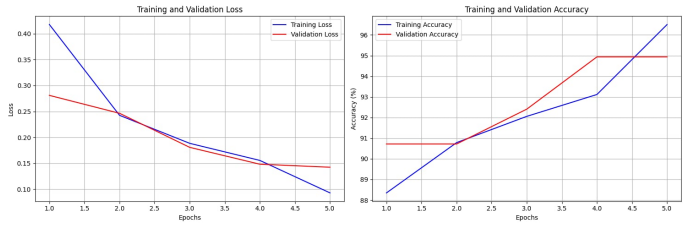

Figure 6. Compare two line chart of model performance across epochs, one without applying image processing methods (on the left) and one with the application of image processing methods (on the right).

The performance metrics by label highlight both the strengths and areas for improvement of the model when using DIP techniques. While the Animal and Other categories achieved high precision, recall, and F1-scores, the Plant category displayed significant performance issues, with precision, recall, and F1 being 0The Animal category, however, exhibited the best performance, likely due to the clearer visual patterns and distinctive features of the Pokémon in this group. Similarly, while the Other category presented its own challenges, the preprocessing techniques helped achieve relatively solid performance in all metrics. The training time, approximately 20 minutes with 12 seconds per epoch, demonstrates the model's efficiency when using powerful hardware, such as the NVIDIA RTX 3080 GPU. This fast training process allowed for experiments on a large dataset, improving the reliability of the results. Moreover, the low training time suggests that future

iterations of the model could incorporate more complex DIP techniques or larger datasets without significantly increasing computational demands. However, there are several areas for improvement. As noted in the limitations section, Pokémon with complex color patterns, like Dragonite, posed challenges for the model, particularly in color-based classification methods such as HSV. Additionally, the dataset imbalance across the Animal, Plant, and Other categories may have led to biases in the model's predictions, contributing to the performance issues observed in the Plant category.

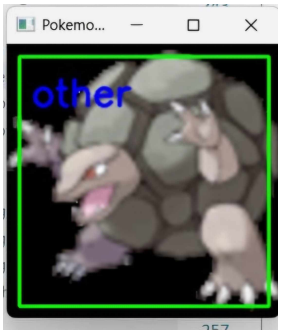

Figure 7. Predict Result 1

Figure 8. Predict Result 2

VI. Conclusion and Future Work

A. Conclusion

In conclusion, this study has explored the combination of Digital Image Processing (DIP) techniques with Convolutional Neural Networks (CNNs) for Pokémon image classification. The results indicate that incorporating methods such as Canny edge detection, morphological operations, and HSV color classification has a positive impact on improving the model's overall accuracy, achieving 92.5

The model performed well in the Animal category, which showed high precision and recall, while the Plant and Other categories experienced more variability, with the Plant category exhibiting 0

The training process was relatively efficient, taking around 20 minutes, which suggests that the model could be scaled up further without significant computational overhead. However, the dataset imbalance across the categories may have hindered the model's ability to generalize effectively. Addressing this imbalance, perhaps through better data collection, augmentation techniques, or targeted sampling, could improve classification accuracy and consistency across all categories.

Although the results are promising, areas for future research remain, such as exploring additional image processing methods, refining existing techniques, or testing on a broader and more balanced dataset. Techniques like Generative Adversarial Networks (GANs) or more advanced color analysis methods could provide further improvements.

In summary, this study contributes to the understanding of how DIP techniques can be integrated with CNNs for image classification tasks. However, there is significant potential for improvement. With continued efforts in refining the dataset and model, these techniques could lead to more reliable and efficient systems for image classification in the future.

B. Future Work

1) Expanding the Dataset:

- Collect more Pokémon images, especially from underrepresented groups like **Plant**.
- Balance the number of images across the classes to avoid overfitting.
- Enhance dataset diversity by applying different types of data augmentation techniques, such as random cropping and color jittering, which could be useful when applying image processing techniques.

2) Improving the Model:

- Explore further the effectiveness of image processing techniques, such as edge detection, morphological operations, and advanced feature extraction methods, which can enhance the input data quality.
- Investigate the use of **Generative Adversarial Networks (GANs)** to generate augmented data, improving the model's robustness to diverse visual features.
- Experiment with image transformations that help in handling noisy or distorted images, thus making the model more resilient when processing real-world data.

3) Automating Color Analysis:

- Move beyond rule-based color classification (like HSV) by incorporating deep learning models, such as Clustering or Gaussian Mixture Models (GMM), which can autonomously learn to classify colors based on more complex features.
- Investigate methods that integrate automatic color classification to adapt better to variations in lighting or color intensity, providing a more flexible solution.

4) Applying to Other Types of Images:

- Extend the task to recognize other characters or objects in images with complex or varying backgrounds (e.g., Digimon, Studio Ghibli characters), leveraging image processing methods to clean up noise and focus on relevant features.
- Explore the broader application of image processing techniques in fields like medical image analysis or satellite imagery, where the quality of images can vary significantly, and noise reduction becomes crucial.

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