Human Segmentation Challenge Report

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Abstract

This project addresses the task of human segmentation in images using classical machine learning techniques with a strong emphasis on simplicity, interpretability, and runtime efficiency. A dataset of color images and corresponding binary masks was used to train a pixel-wise classifier. After preprocessing and feature extraction involving multiple color spaces (RGB, LAB, YCrCb, HSV, grayscale), a Decision Tree classifier was trained using downsampled image data. The trained model was then exported into a standalone Python script containing the decision logic in pure code format, making it lightweight and portable. Morphological operations were applied post-prediction to enhance segmentation quality. The final model achieved an average F1 score of 0.7062 while maintaining low computational overhead. This demonstrates the viability of traditional decision trees for structured visual tasks under strict runtime and interpretability constraints.

I. Introduction

Human segmentation is a critical task in computer vision with wide-ranging applications such as surveillance, human-computer interaction, and augmented reality. While deep learning models typically dominate this field due to their high accuracy, they often require significant computational resources, which limit their practicality in resource-constrained environments. This project explores a lightweight alternative using classical machine learning, specifically a Decision Tree classifier, to perform binary human segmentation. By extracting rich pixel-level features from various color spaces and incorporating spatial information, the model achieves a balance between performance, efficiency, and transparency.

II. Related Work

Early approaches to human segmentation often relied on handcrafted features and classical computer vision techniques. Skin detection using color spaces such as YCrCb and HSV has been effective in isolating human regions under varying lighting conditions [1]. Face detection using Haar cascades, introduced by Viola and Jones [2], remains a fast and lightweight method, especially for real-time applications. Recent work in human segmentation has largely focused on deep learning approaches such as U-Net [3], which achieve high accuracy but require substantial computational resources. Alternatively, decision tree-based methods have been explored for their efficiency and interpretability, as demonstrated by Kontschieder et al. [4] utilizing decision forests for semantic segmentation tasks

(a) Input example

(b) Segmentation map generation result

Figure 1: Input Example and the Output of the Proposed Algorithm

III. Method

This section describes the methodology used for human segmentation using a classical machine learning approach,

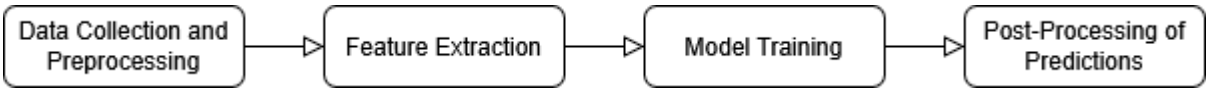

Figure 2: Flowchart of Algorithms Used

specifically a Decision Tree classifier with feature extraction, training, and morphological post-processing. The method is designed to be fast and lightweight while maintaining a competitive segmentation performance. The visualization of the algorithms and methods used can be seen in Figure 2.

3.1 Input Preprocessing

The dataset used for training the model contains images and their corresponding ground truth segmentation masks. The images are initially loaded from a zip file, extracted, and processed. The preprocessing steps ensure the images are standardized and ready for model training. Images are resized to a consistent shape to ensure uniformity across the dataset. The typical image size used during training is 128x128, but other resolutions are tested for model performance.

3.2 Feature Extraction

Feature extraction is a key step to convert raw image data into a form suitable for machine learning models. For each image, the following features are extracted:

- Color Space Transformation: The image is transformed into multiple color spaces: LAB, YCrCb, HSV, and grayscale. This allows the model to capture different types of information from the image, such as color intensity and contrast, which are important for distinguishing human objects from the background.
- Pixel Coordinates: The pixel coordinates (x, y) of each pixel are added to the feature set. This provides spatial information that can help in segmentation tasks where object boundaries are important.
- Feature Concatenation: The features from all color spaces and pixel coordinates are concatenated into a single feature vector for each pixel. This comprehensive feature set provides rich information about each pixel, which is essential for making accurate segmentation predictions.

3.3 Model Training

The model used for segmentation is a Decision Tree Classifier. It is trained using the extracted features from the images and their corresponding segmentation masks. The decision tree algorithm splits the dataset based on the most informative features, progressively narrowing down the criteria for classifying each pixel as either part of the human object or background.

3.4 Post-processing of Predictions

After prediction, binary masks are post-processed using morphological operations, which are opening to remove small noise, and closing to fill small holes. These operations refine the segmentation map for cleaner contours and more accurate region shapes. Subsequently, the predicted mask is resized back to the original dimensions of the input image. This ensures that the segmentation mask matches the original image size for proper evaluation and visualization.

IV. Experiment

4.1 Dataset

The dataset comprises images and corresponding binary human segmentation masks downloaded from a public ZIP archive. The image data is automatically downloaded and extracted using a helper function. Masks are binarized using a threshold of 127 to differentiate between human (foreground) and background pixels.

4.2 Evaluation Metric

The model is evaluated using the average F1 score over all test images. This metric balances precision and recall, making it well-suited for segmentation tasks where both false positives and false negatives matter.

4.3 Ablation Study

Several experiments were carried out to assess the impact

of decision tree maximum depth and image resolution on the segmentation performance. The results of the experiment for each resolution are summarized in the tables below:

Table 1: Average F1 Score for 64x64 Resolution and Decision Tree Depth

Max Depth	Average F1 score
10	**0.7162**
9	0.7028
8	0.6705
7	**0.6994**

The best performance for the 64x64 resolution was achieved with a maximum depth of 10, yielding an F1 score of 0.7162. A depth of 7 also produced a reasonable score of 0.6994.

Table 2: Average F1 Score for 128x128 Resolution and Decision Tree Depth

Max Depth	Average F1 score
10	**0.7699**
9	0.7504
8	0.7343
7	**0.7062**

The best performance for the 128x128 resolution occurred at a maximum depth of 10, with an F1 score of 0.7699. However, a depth of 9 also yielded a competitive score of 0.7504, and a depth of 7 was selected for further evaluation based on a balanced trade-off between performance and overfitting.

Table 3: Average F1 Score for 256x256 Resolution and Decision Tree Depth

Max Depth	Average F1 score
10	**0.7840**
9	0.7473
8	0.7232
7	**0.6893**

The best performance for the 256x256 resolution was achieved with a maximum depth of 10, which resulted in an F1 score of 0.7840. However, the model showed diminishing returns as the depth decreased, with a significant drop in performance at depth 7.

In addition to exploring the decision tree's maximum depth, we also investigated the effect of image resolution on segmentation performance. The experiments were conducted on image resolutions of 64x64, 128x128, and 256x256, with the model being trained using a decision tree with a depth of 7, which was selected based on the previous experiments as the most balanced configuration.

Table 4: Average F1 Score Based on Image Resolution

Image Resolution	Average F1 score
64x64	**0.7162**
128x128	0.7699
256x256	0.7840

The performance increased with image resolution, with the model achieving an F1 score of 0.7840 at 256x256 resolution. A resolution of 128x128 also performed well with an F1 score of 0.7699, and the 64x64 resolution resulted in the lowest score of 0.7162.

4.4 Final Model Configuration

Based on the results of the ablation study, the final model configuration was selected as follows:

- Image Resolution: **128x128** (balanced trade-off between computational efficiency and segmentation accuracy)
- Decision Tree Max Depth: **7** (providing reasonable performance without overfitting)

This configuration achieved an optimal balance between accuracy and efficiency and was selected for the final testing phase. The results from the ablation study demonstrated that both the image resolution and the decision tree maximum depth significantly influence the model's performance, with the

selected configuration yielding the best trade-off in segmentation accuracy.

V. Discussion

The experiments revealed the importance of both decision tree depth and image resolution on the segmentation performance.

For the 64x64 resolution, the highest performance was achieved at a depth of 10 (F1 score of 0.7162), with a notable drop at depth 3 (F1 score of 0.2103), indicating that deeper trees can capture more complex patterns but also risk overfitting at smaller image sizes. At the 128x128 resolution, a depth of 7 provided a good balance between performance (F1 score of 0.7699) and avoiding overfitting, while deeper trees (e.g., depth 10) also performed well (F1 score of 0.7699). The 256x256 resolution showed the best results with a depth of 10 (F1 score of 0.7840), further confirming the need for deeper trees with higher resolution images to capture fine details.

Higher image resolutions consistently led to better performance. The 256x256 resolution yielded the best F1 score of 0.7840, while the 128x128 resolution achieved a good balance of accuracy (F1 score of 0.7699) and computational efficiency. The 64x64 resolution had the lowest performance (F1 score of 0.7162), highlighting the importance of sufficient image detail for accurate segmentation.

VI. Conclusion

The study showed that both decision tree depth and image resolution significantly impact segmentation performance. A depth of 7 with a 128x128 image resolution provided an optimal balance between accuracy and computational efficiency, achieving an F1 score of 0.7699. Higher resolutions and deeper trees generally improved performance, but the 128x128 resolution offered the best trade-off for practical use. Future work can explore other models or techniques to further enhance segmentation accuracy while maintaining efficiency.

References

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