Title: Automatically Masking Cartridge Case Image Problems

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Introduction

The forensic analysis of fired ammunition components, particularly cartridge cases, is a critical aspect in criminal investigations. Currently, the process of examining these components involves a manual and task of masking specific features on cartridge case images, such as the breech-face impression and firing pin impression. This manual approach, while effective, is time-consuming and prone to human errors, leading to potential delays and inaccuracies in forensic investigations. Addressing this challenge, the objective of this project is to develop an automated algorithm capable of accurately identifying and masking these distinct features on cartridge cases. The development of such an algorithm not only promises to enhance the efficiency and reliability of forensic analyses but also significantly reduces the time and effort involved in the process.

Methodology

1. **Initial approach:** Different methodologies were tested to come up with the best solution respecting the deadline for the answer submission. Given the lack of a labeled dataset at the outset, methods such as shape growing and unsupervised machine learning algorithms like K-Means clustering (KNN) were explored. The shape growing technique based on a priori knowledge about the general characteristics of cartridge case features, attempted to segment the images by progressively growing regions of interest [1]. However, these classical methods did not result in satisfactory results.

2. **Dataset Acquisition**: To overcome the limitations encountered with classical and unsupervised techniques, the project shifted focus to a supervised learning approach. A dataset specifically containing images of cartridge cases was sourced from Kaggle [2]. This dataset provided a diverse range of cartridge case images, which were crucial for training a more robust model. Only one folder containing the cartridge case images belonging to one type of pistol was used for training, evaluating and testing.

3. **Manual Annotation Using VGG Image Annotator:** To prepare the dataset for supervised learning, each image was manually annotated using the VGG Image Annotator tool. This process involved marking the specific features on the cartridge cases, such as breech-face impressions, aperture shears, firing pin impressions, and firing pin drags. The annotations were saved and used to create a labeled dataset, which was essential for using supervised methods.

4. **Data Pre-Processing:** This step is necessary to ensure consistency and optimal performance. This step involved resizing the images to a uniform scale, normalizing the pixel values, and data augmentation (after splitting the images in 3 different folders for training testing and evaluation to prevent data leakage). The manually annotated data from the VGG Image Annotator were saved in JSON format. These JSON files contained precise coordinates for the regions of interest (ROI) corresponding to different features on the cartridge cases. Each generated mask was processed so that individual pixels

corresponded to different feature classes: 0 for the background, 1 for the breech-face impression, 2 for the aperture shear, 3 for the firing pin impression, and 4 for the firing pin drag. This encoding transformed the annotated images into a format suitable for training the model on multi-class segmentation. Finally, 3 different Tensorflow dataset was generated for training, evaluating and testing.

5. **Model Selection and Transfer Learning:** UNet, a convolutional neural network architecture, was chosen for this task due to its efficacy in multi-label image segmentation tasks. The idea behind using this type of neural network originated from a recent publication developing a UNet model for automatic detection of firing pin impression and breech-face impression [3]. The architecture's ability to perform precise localization makes it ideal for segmenting specific features in images, such as those found on cartridge cases. To enhance the model's performance, transfer learning was employed using MobileNet as a feature extractor. MobileNet is a lightweight, efficient convolutional neural network developed primarily for mobile and embedded vision applications. By using a pretrained MobileNet as the encoder in the UNet model, the algorithm benefits from learned features on a diverse set of images, improving its ability to recognize features on cartridge cases.

6. **Model Architecture and Implementation:** The encoder part of the UNet model was built using a pretrained MobileNet, obtained from [4]. The decoder part of the UNet consisted of sequences of Conv2DTranspose, concatenate, and conv2d_block operations, supplemented with Dropout to prevent overfitting. The Conv2DTranspose layers upsample the feature map, and the skip connections from the encoder provide additional contextual information, aiding in more precise segmentation.

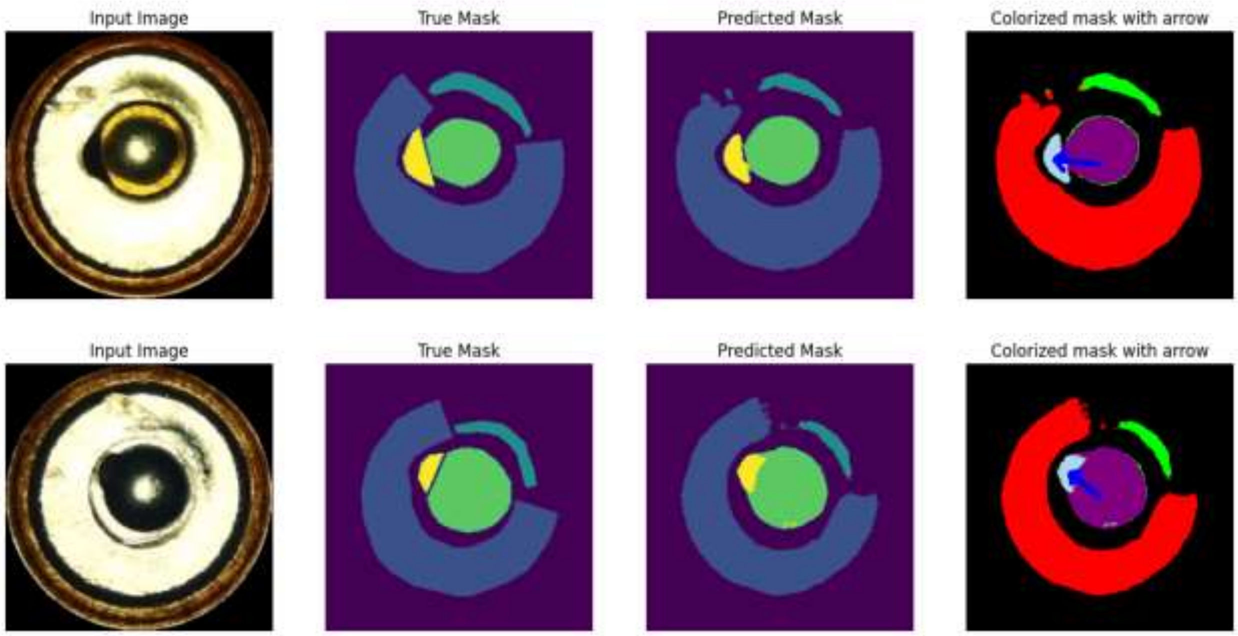
7. **Loss Function and Hyperparameter Tuning:** The model was trained using a sparse categorical cross-entropy loss function. This choice is appropriate for multi-label classification tasks with exclusive classes, as it efficiently manages the computation over multiple class probabilities. In order to improve the performance of the model in detection of smaller regions such as aperture shear class weighting method is used during the training. The purpose of class weighting in this context is to address class imbalance in the training dataset by assigning different importance to each class, ensuring the model does not become biased towards more frequent classes. To further enhance the model's performance, various hyperparameters were carefully tuned. Adjustments were made to parameters like learning rate, batch size, and the number of epochs to find the optimal balance for training efficiency and model accuracy.

Results

The trained model achieved the best validation accuracy of 93.48% which indicates the great performance of the model in segmenting the images.

After predicting the mask, the centroid of firing pin drag is identified and an arrow is drawn from the centroid of the predicted masked image to the centroid of firing pin drag for pinpointing its direction.

The images below present the predicted mask along with the true mask and the original input image.



If it is desired to apply the predicted mask to the input image and replace the background with the original image this can also be achieved as it is implemented below:

References

[1] Borovec, J., Kybic, J., & Sugimoto, A. (2017). Region growing using superpixels with learned shape prior. Journal of Electronic Imaging, 26(6), 061611-061611.

[2] Dnnpy1. (n.d.). Tracks on Bullet Cartridges [Data set]. Kaggle. Retrieved January 22, 2024, from https://www.kaggle.com/datasets/dnnpy1/tracks-on-bullet-cartridges?resource=download\

[3] Le Bouthillier, M. E., Hrynkiw, L., Beauchamp, A., Duong, L., & Ratté, S. (2023). Automated detection of regions of interest in cartridge case images using deep learning. Journal of Forensic Sciences, 68(6), 1958-1971.

[4] Chollet, F. (n.d.). Deep Learning Models [Code and release notes]. GitHub. Retrieved January 22, 2024, from https://github.com/fchollet/deep-learning-models/releases