**Introduction**

The following report summarizes 2 major efforts. The first is an image processing task in which OpenCV is used to mask out an image of a motherboard and separate it from its background. The second involves training a YOLOv8 model to detect and classify various hardware components from a PCB. These techniques have the potential to greatly enhance the manufacturing efficiency of these components, as they can replace time-consuming manual inspections.

**Object Masking**

A black and white photo of a computer motherboard

Description automatically generatedIn order to generate the image mask, OpenCV tools were extensively utilized. After loading the image and converting it to grayscale, the first major step was to apply a gaussian blur to the image. This has the effect of reducing sharp details in the image, ensuring only the large “structural” features remain. The next step was to threshold the image, creating distinct regions based on pixel intensity. For this step, OTSU thresholding was used, meaning the threshold pixel value was automatically generated. Presented below is the thresholded image.

Figure 1: Thresholded image

From this, it can be seen that certain regions of the mother board, like the heatsinks on the left-hand side, are not sufficiently distinct from the background and as such appear as white. This adversely affects the edge detection. Additionally, as the image was taken at a slight angle, there is a shadow casted on the lower left-hand side. This creates a region that is interpreted as part of the motherboard. It is recommended that future images be taken on a distinct background, from an overhead angle, and with sufficient lighting. This would ensure that a cleaner mask can be created, to better extract the motherboard.

After thresholding the image, Canny edge detection was used, generating the following.

A black and white drawing of a computer motherboard

Description automatically generatedFigure 2: Detected Edges

Once the edges were detected, a morphological operation was applied to close edges. A large kernel size was used, as it had the effect of connecting the jagged edges around the motherboard, leading to a more complete mask.

A black rectangular frame with a white background

Description automatically generatedAfter closing the edges, contour detection was performed, and the largest contour was filtered out in order to draw the mask presented next.

Figure 3: Mask Image

A close-up of a computer motherboard

Description automatically generatedLastly, the mask was used to extract the final image of the motherboard.

Figure 4: Final extracted image

As seen in figure 4, the mask obviously isn’t exact. The two main areas of improve as mentioned above would be using a distinct background to better detect components at the edges and using lighting and angles to eliminate shadows.

**Model Training – Setup**

For this portion of the project, a YOLOv8 nano model was trained on a dataset of labelled PCBs to be able to detect components on the PCBs. An image size of 700 was used, as any size above this would lead to the runtime crashing due running out of memory. In an attempt to remedy this, the auto-batch argument was used. This would calculate the optimal batch size given the memory available for training. Although it delayed the memory error, it still occurred after a few epochs of training. As a final attempt, a batch size smaller than the calculated auto-batch was used. Despite not crashing, training was extremely slow and would time out due to inactivity. As recommended, 200 training epochs were used.

**Model Training – Results**

A screenshot of a computer

Description automatically generated Presented first is the normalized confusion matrix of the trained model.

Figure 5: Normalized confusion matrix of trained model

The normalized confusion matrix presents the prediction accuracy of the classifier. The main diagonal represents the correct class predictions, and the other values are miss predictions. The results of this classifier vary greatly. Certain components like buttons and connectors have very high accuracy, meaning the classifier has no problem identifying them and doesn’t confuse them for other components. On the other hand, certain components like pads and resistors have really low accuracy. The most predicted class for these cases is background. This implies that the model isn’t confusing components for each other, but rather struggling to distinguish them from the background. This makes sense, as the misclassified components tend to be the smaller ones. To remedy this, a higher image resolution would be necessary. This would ensure that these small components are recognized as structural features and not background artifacts.

**A graph of different colored lines

Description automatically generated** Presented next is the precision-confidence curve of the model.

Figure 6: Precision-confidence curve

A graph of different colored lines

Description automatically generatedLastly, the precision-recall curve is presented.

Figure 7: Precision-recall curve

**Model Evaluation**

**Conclusion**