**Report Submission**

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**Eyeglass Segmentation**

**Model Selection**

The U-Net architecture was chosen as the segmentation model for the purpose of segmenting eyeglasses. U-Net's ability to capture small details and spatial correlations in images makes it a popular choice for image segmentation tasks. U-Net's primary characteristics that make it appropriate for this purpose are as follows:  
Symmetric Encoder-Decoder Structure: U-Net's architecture entails an enlarging path (decoder) that follows a contracting path (encoder), which enables the model to extract high-level contextual information as well as low-level features. Skip Connections: In order to facilitate the merging of multi-scale features and preserve spatial information while upsampling, U-Net contains skip connections between appropriate encoder and decoder layers. Quick and Effective Training: U-Net has demonstrated a tendency to converge rapidly during training, which qualifies it for tasks requiring a small amount of processing power.

**Model Retraining Details**

The selected U-Net model was fine-tuned on the eyeglass segmentation dataset to adapt it to the specific characteristics of the task. The training process involved the following steps:

* **Dataset Collection and Preparation**: The training dataset consisted of images of eyeglasses along with corresponding segmentation masks. These images were split into training and validation sets to evaluate the model's performance during training.
* **Data Pre-processing:** To increase the robustness of the model and prevent overfitting, data augmentation techniques such as random rotation, flipping, and scaling were applied to the training images and masks.
* **Building Model and Training:** The U-Net model was trained using the Adam optimizer with a binary cross-entropy loss function. The training process involved iterating over the training set for multiple epochs, adjusting the model parameters to minimize the loss function.
* **Hyperparameter Tuning:** Hyperparameters such as learning rate, batch size, and number of epochs were fine-tuned to optimize the model's performance.

**Performance Evaluation**

The performance of the trained U-Net model was evaluated using the following metrics:

* **Accuracy:** The proportion of correctly classified pixels in the segmentation mask.
* **Precision:** The ratio of true positive pixels to the total number of pixels classified as positive.
* **Recall:** The ratio of true positive pixels to the total number of actual positive pixels.
* **F1-score:** The harmonic mean of precision and recall, providing a balanced measure of the model's performance.

**Tools Used**

The following tools, libraries, and research papers were used in the development of the eyeglass segmentation solution:

* **OpenCV**
* **TensorFlow**
* **U-Net**

**Segmentation on Test Data**

The segmentation results on the test dataset demonstrate the effectiveness of the trained U-Net model in accurately segmenting eyeglasses from input images. Visual demonstrations of the segmentation performance are provided in the attached document.