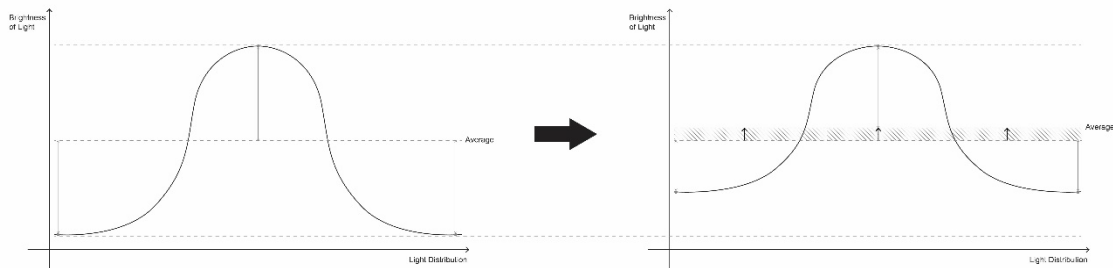


Computer Vision Report

Description of Task

Problem Statement and Goal of Computer Vision

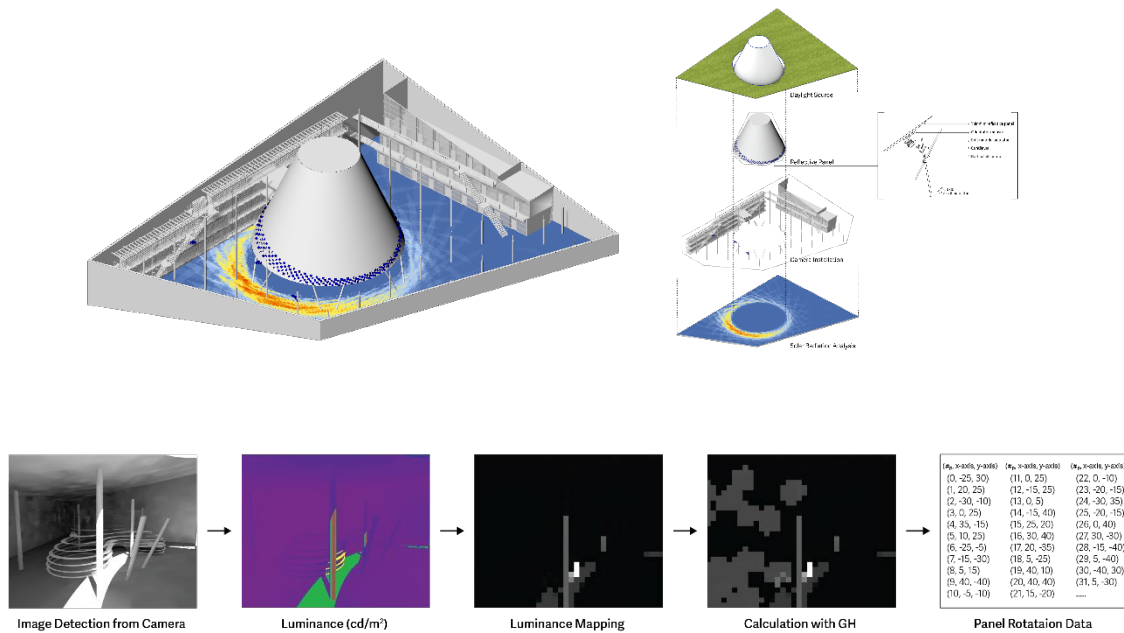
The integration of computer vision aims to tackle the problem of an inefficient distribution of daylight in the library. The solution consists of 140 reflective panels with adjustable rotation angles that reflect rays of light from the central skylight around the cone. The rotation angles are derived from the calculation of the best possible scenario of redistributing the skylight across the dark/shadowed areas of the interior space. With the panel dataset registered in each class, computer vision will be able to make the adjustments of panel angles based on the changes in the layout of the furniture within a certain proximity.



Overall Workflow

Step 1. Creation of base configuration for AI training and the calculation of panel optimization

The images of the current situation will be used for determining certain classes of furniture layouts for the initial dataset of the base configuration. Then, the software would take a picture from each class for every hour of the year and generate luminance maps in pair. This luminance map would serve as an input for the calculation for the optimization of panel rotation angles using grasshopper. Optimized result for every hour throughout the year will be stored in a registry.

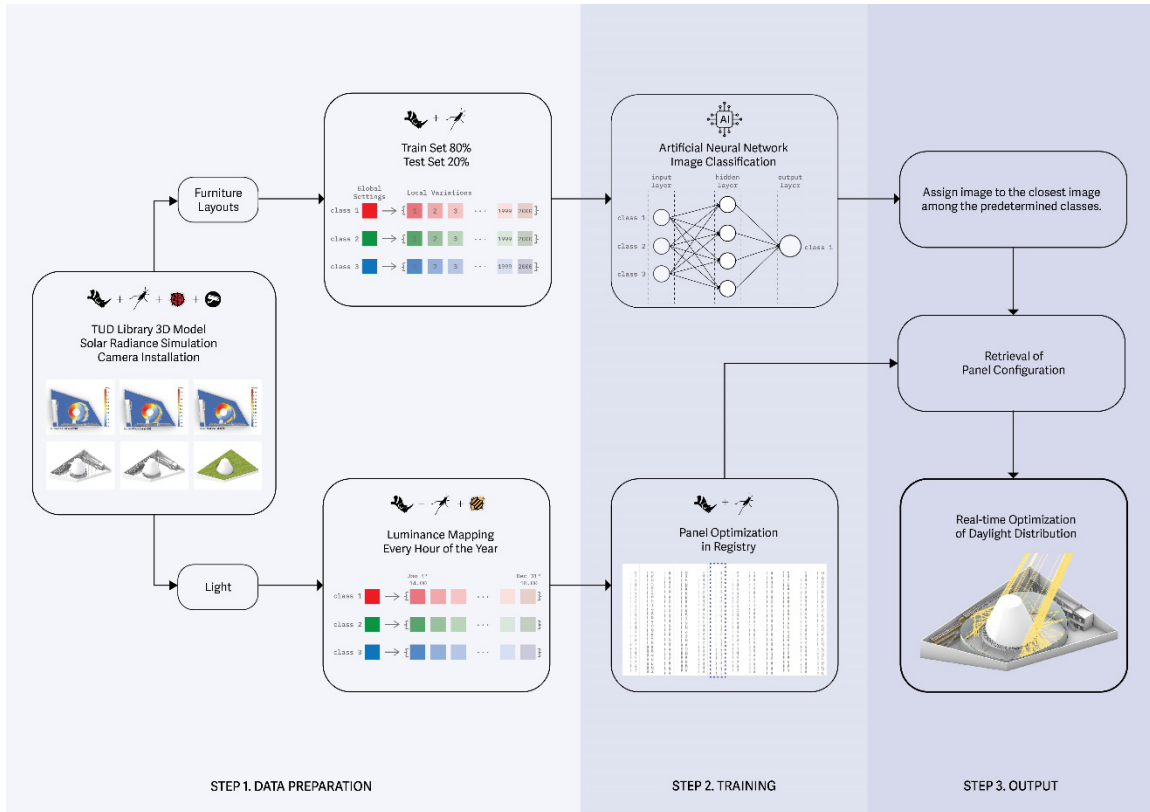


Step 2. Integration of computer vision

AI network is trained to figure out to which base configuration is the closest to the varied configuration.

Step 3. Retrieval of panel configuration out of registry

When the class is recognized, the system will retrieve the panel data out of the registry for the recognized class and optimize their angles for the concrete hour.



Pipeline

Computer Vision Task

The problem will be solved by 'image classification' which associates one or more labels, in this case single-label classification, to a given image.

Data Preparation

Input 1. Base configuration of furniture layouts (classification)

A set of cameras are mounted across the focus-area that indicates lighting discomfort the most based on the solar radiance analysis. The images detected by the cameras scan the current situation. Based on this analysis, certain classes of furniture layouts are determined and stored as an initial dataset of base configuration for step 2.

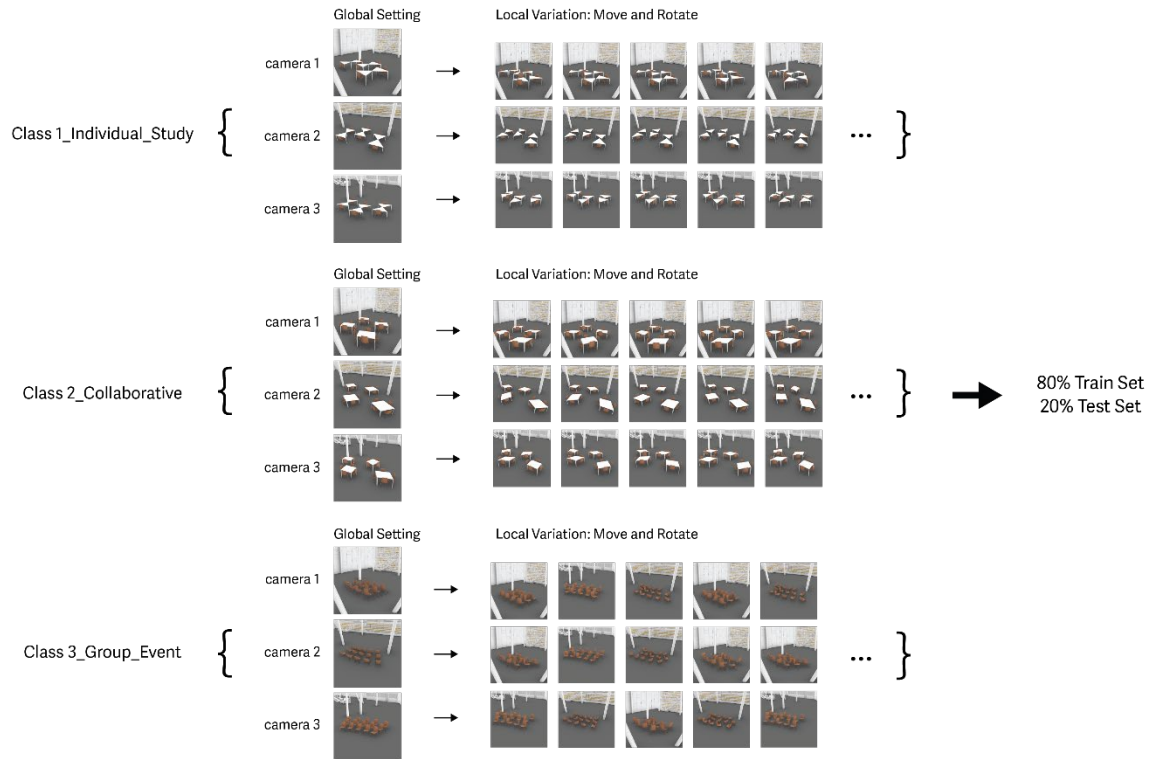
Input 2. Train set (80%) and Test set (20%)

Along with the certain classes within the base dataset (global settings), the installed cameras picture different variations of these classes (local variations). By variation, the furniture is distributed with the

same strategy defining the class, but the concrete exact position of camera angle and rotation of the individual furnishings may vary.

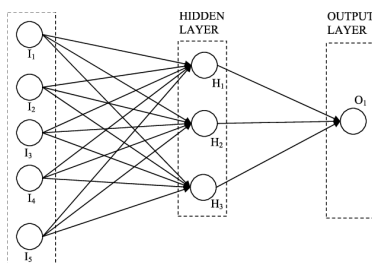
Output 3. Finding the most similar furniture arrangement

A neural network would be trained on the image dataset so that it is able to assign the images with local variations to the closest image among the predetermined class.



Machine Learning Model

Collected from the data in the previous step, the Artificial Neural Network is constructed with the trainset. This ML model learns from the training data sets to optimize itself for better accuracy over time. After the training, the ML model is ready to predict the unseen data. Thus, ANN could be used to predict the outputs.



Data

Data

During the data preparation step, the data needed for the AI training are image datasets indicating base furniture configurations from different camera angles and slightly varied furniture configurations from different camera angles. The variation would be move and rotate. During the process of producing the datasets synthetically, it was crucial that there are no overlapping images in the variations.

Data Annotation

Data annotation for image classification is 'labelling.' By labelling each image with assigned classes, the AI network classifies and gets the output as 'predicted: class x.'

Software

Pretrained Script

The software for the training will be two pretrained scripts. One is Resnet 18 and the other VGG 16. Resnet tries to take only the new information from the previous training block for the next training layer. This way, it reduces the risk of increasing the inaccuracy in each training blocks. VGG16 uses 3 by 3-pixel filter which is much smaller than the usual filter sizes of other training models. Thus, it increases the accuracy of image classification significantly.

Training Result

