

Digital Image & Video Processing

Final Project Report: Face Detection Project



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Introduction

This project focuses on developing a complete end-to-end face-detection system using classical image-processing techniques in MATLAB. The goal was to design a robust detector that performs reliably across different subjects and lighting conditions without relying on deep-learning models. The system is divided into two major phases: an offline training phase, where color-based skin models, geometric priors, and an average face template are learned from a set of labeled images, and an online detection phase, where the trained model is applied to new input images to locate human faces. During training, RGB and HSV skin histograms were constructed using ground-truth reference masks, and statistical information such as face area, vertical position, and a normalized face template was computed. During detection, the model is used to generate a skin-likelihood map, followed by morphological processing, connected-component analysis, template matching, and a multi-stage filtering pipeline to produce accurate bounding boxes. This structured approach allows the system to achieve high accuracy while maintaining interpretability and computational simplicity.

Flowchart of the project

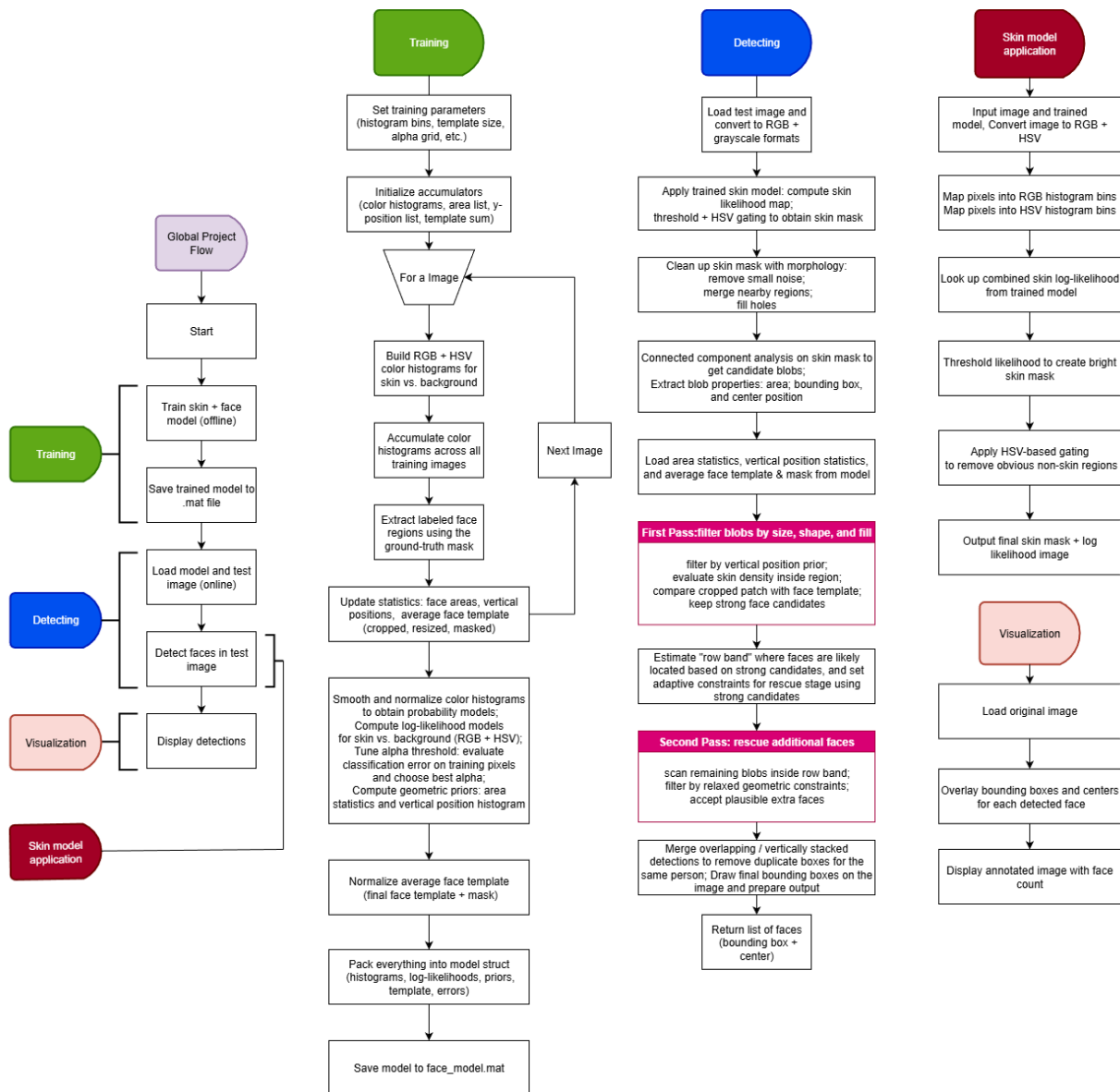


Figure 1 Flowchart

Global Project Flow

The overall system was divided into an offline training phase and an online detection phase, as summarized in Figure 1. During the training phase, a set of labeled face images and corresponding ground-truth masks were used to learn a probabilistic skin model, geometric priors, and an average face template. The resulting model was stored in a MATLAB .mat file for later reuse. During the detection phase, this pre-trained model was loaded and applied to unseen test images to locate faces. The detection pipeline produced a set of face bounding boxes and center locations, which were overlaid on the input image for visualization.

Offline Training

In the training lane of the flowchart, the process began with the selection of training parameters such as histogram bin counts, template size, and the search grid for the decision threshold. Accumulators were then initialized to store RGB and HSV color histograms for skin and background, as well as lists of face areas, normalized vertical positions, and the running sum of face templates. For each training image, the corresponding ground-truth mask was used to separate skin from background. RGB and HSV color histograms were computed for both classes and accumulated across all images. Labeled face regions were extracted from the mask and used to update geometric statistics (area and vertical position) and to construct an average face template by cropping, resizing, masking with an ellipse, and summing over all faces. After all images were processed, the color histograms were smoothed and normalized to obtain probability models, a log-likelihood classifier was derived, and the alpha threshold was tuned by minimizing misclassification on the training pixels. Finally, area statistics, a vertical position histogram, and a normalized average face template were computed and packed into a single model structure, which was saved to `face_model.mat`.

Online Detection

The detecting lane in the flowchart describes the online stage. First, a test image was loaded and converted into RGB and grayscale formats. The pre-trained model was then applied to compute a skin-likelihood image and a corresponding binary skin mask. This mask underwent a sequence of morphological operations in order to remove small noise, merge nearby regions, and fill interior holes. Connected component analysis was then performed on the cleaned mask, and for each candidate region, basic properties such as area, bounding box, and centroid were extracted. Using the learned area statistics, vertical position priors, and the face template from the training phase, a first pass of filtering was performed to select high-confidence faces based on geometric criteria, skin density, and template correlation. The vertical positions of these strong detections were used to estimate a likely “row band” where faces were located, and a second pass was executed within this band to rescue additional plausible faces using relaxed constraints. Finally, overlapping or vertically stacked detections corresponding to the same subject were merged before the resulting bounding boxes and centers were returned.

Skin Model Application and Visualization

The skin model application lane represents the subroutine that maps an input image to a binary skin mask using the trained color model. The input image was converted to RGB and HSV spaces, and each pixel was mapped into the corresponding histogram bins stored in the model. The pre-computed log-likelihoods in RGB and HSV were combined with the trained threshold to generate a per-pixel skin-likelihood image, which was then normalized for debugging display. A brightness-based threshold and an HSV-based gating step were applied to reject obvious non-skin regions and produce the final skin mask. In the visualization lane, the original test image was reloaded, the detected face bounding boxes and centers were drawn on top, and an annotated image with the total face count was displayed. This completed the end-to-end pipeline from offline model training to online face detection and visualization.

Detection Results

Image & face number	# Faces detected	# Faces failed to detect	False Positive	Correction Rate
person1, 10	10	0	0	100%
person2, 13	13	0	0	100%
person3, 13	13	0	0	100%
person4, 9	9	0	0	100%
person5, 13	13	0	0	100%
person6, 12	12	0	0	100%
person7, 10	10	1	1	80%
person8, 11	11	0	0	100%
training1, 21	18	3	0	85.7%
training2, 24	24	0	0	100%
training3, 25	24	1	0	96%
training4, 24	24	0	0	100%
training5, 24	23	1	0	95.8%
			Overall Accuracy:	96.7%

Detected faces: 10



Figure 2 person1

Detected faces: 13



Figure 3 person2

Detected faces: 13

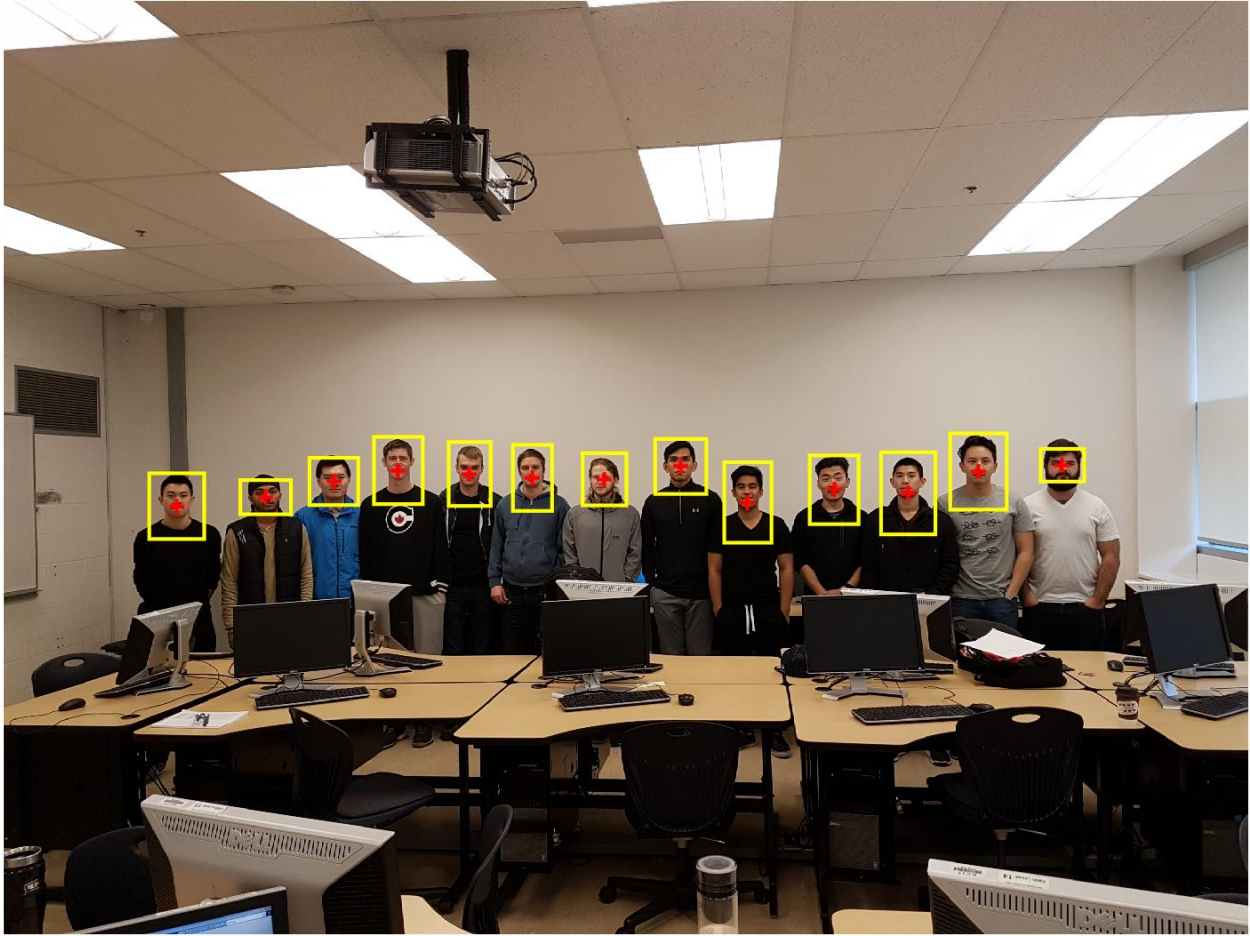


Figure 4 person3

Detected faces: 9

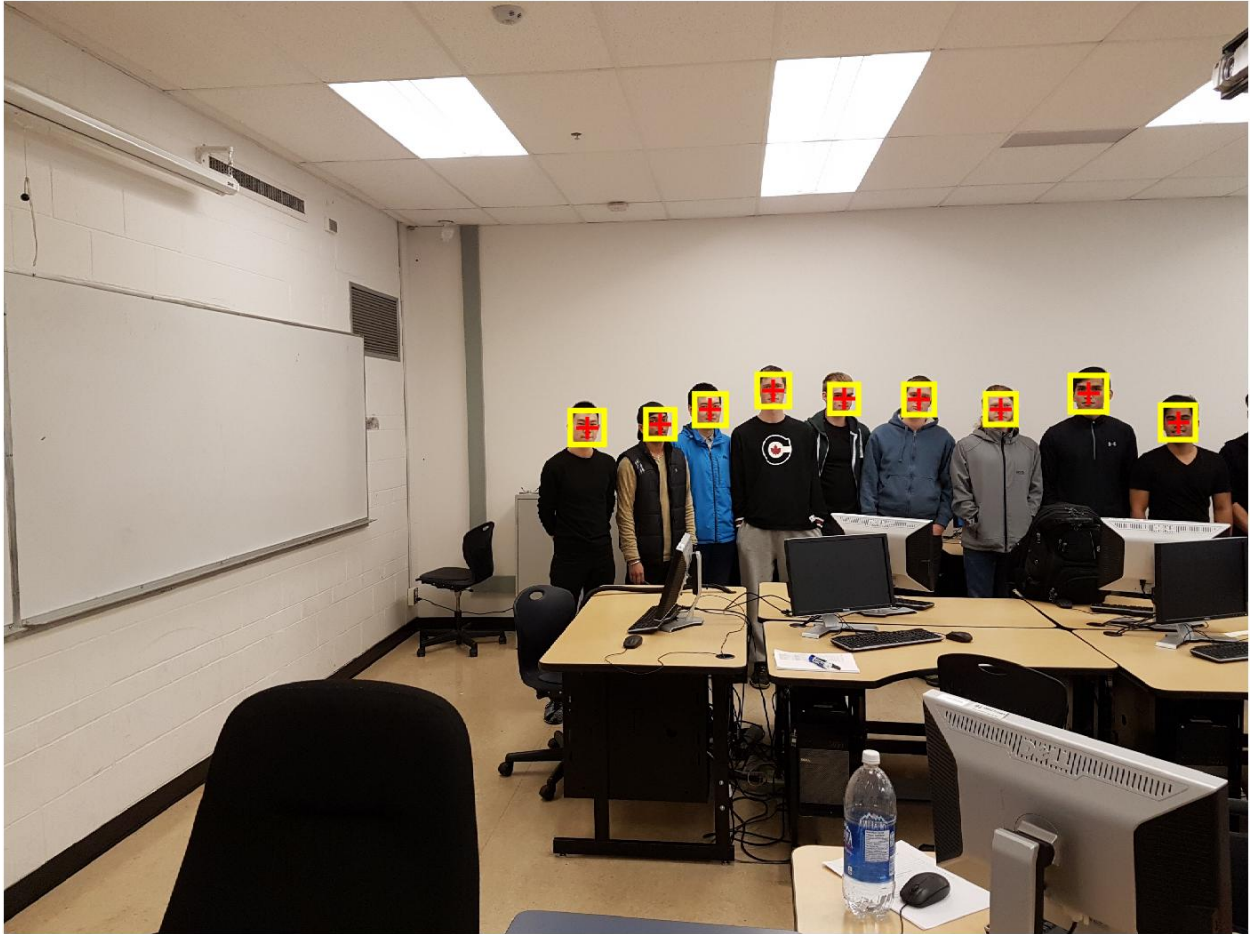


Figure 5 person4

Detected faces: 13



Figure 6 person5

Detected faces: 12



Figure 7 person6

Detected faces: 10



Figure 8 person7

Detected faces: 11

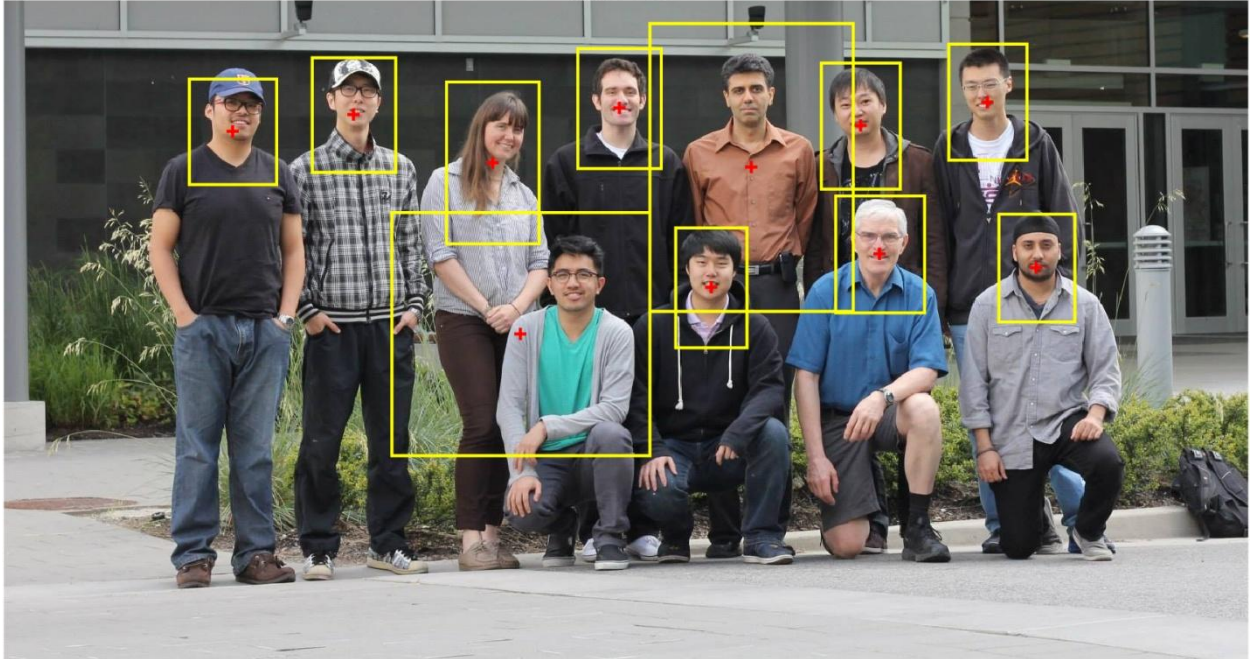


Figure 9 person8

Detected faces: 18

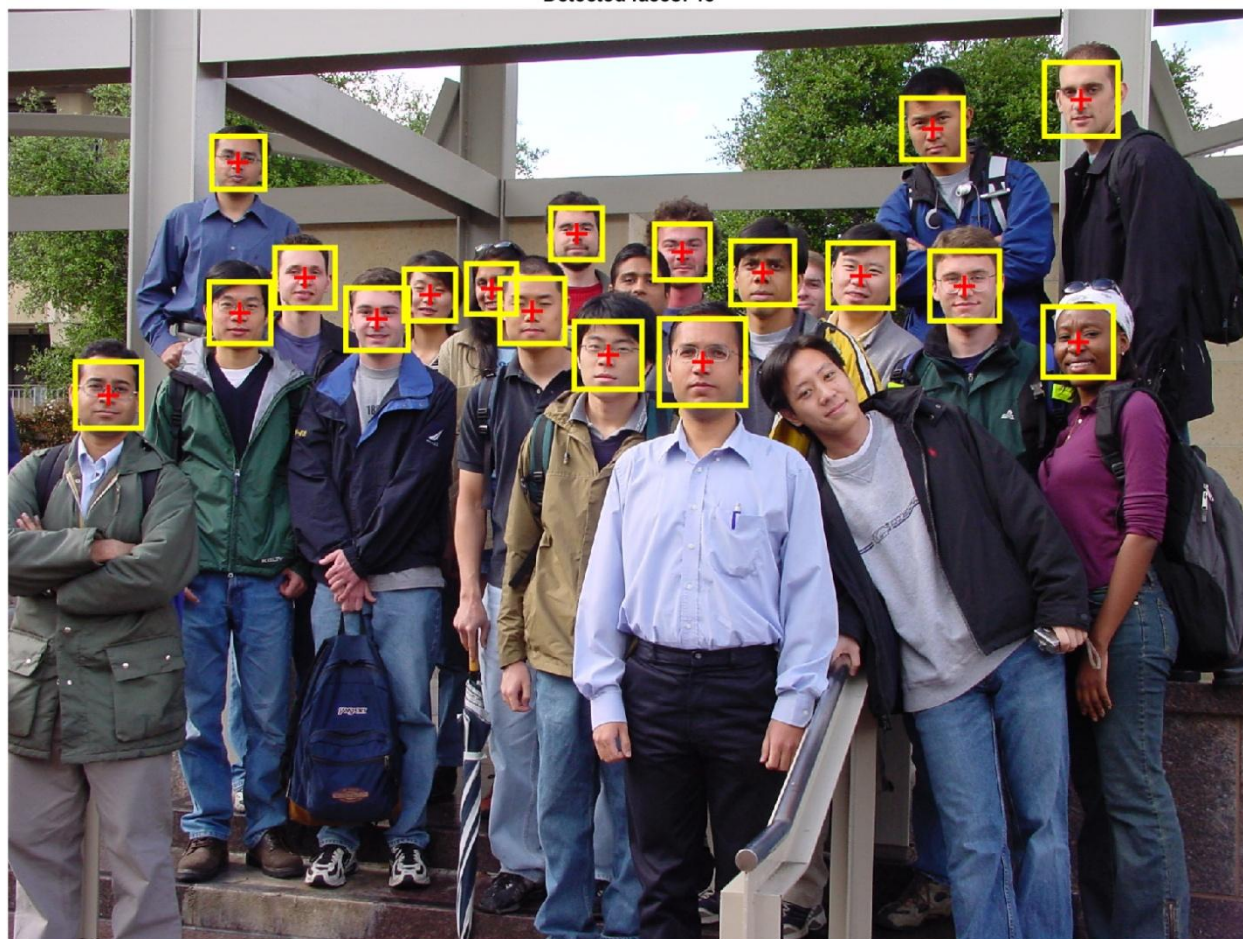


Figure 10 training1

Detected faces: 24

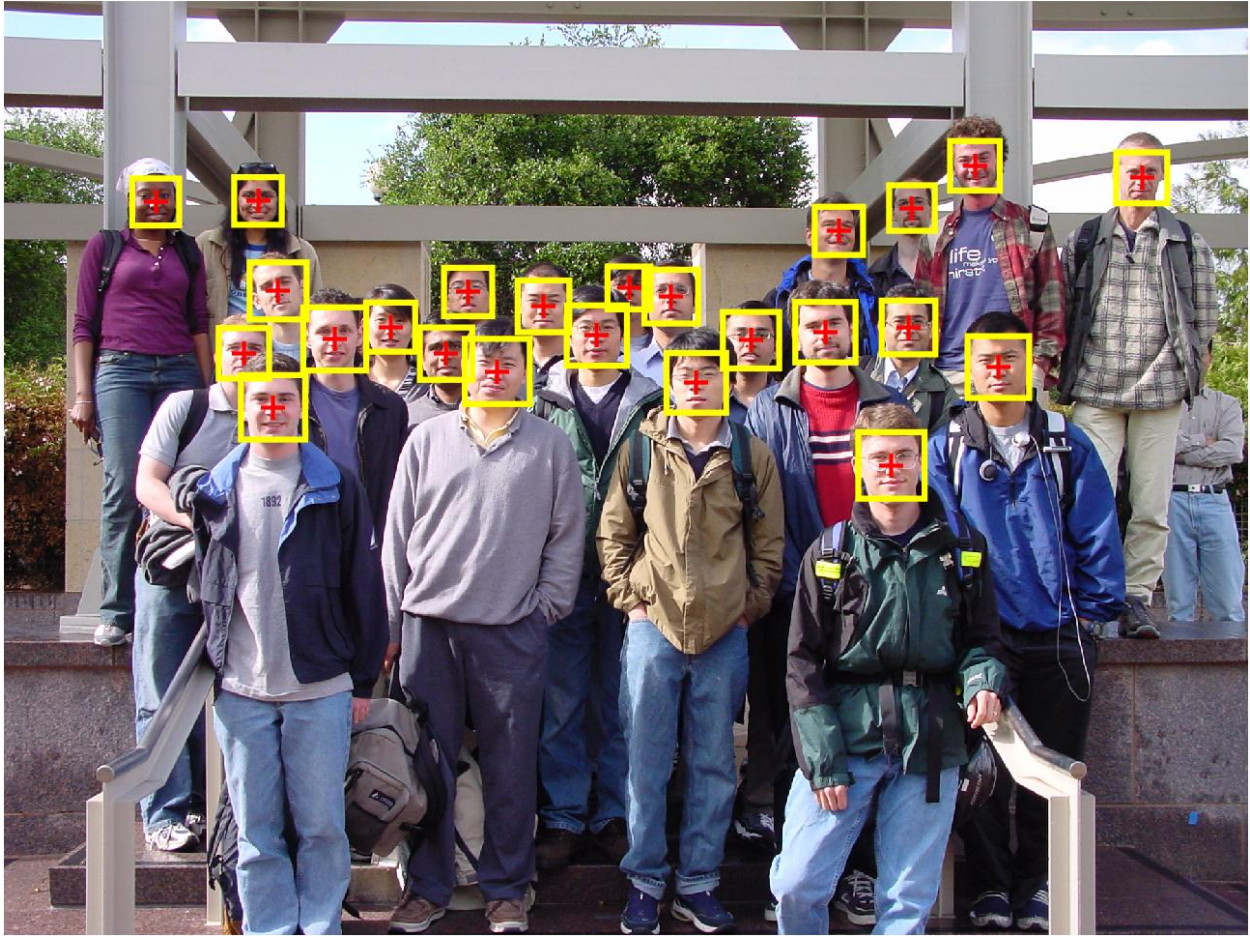


Figure 11 training2

Detected faces: 24



Figure 12 training3

Detected faces: 24

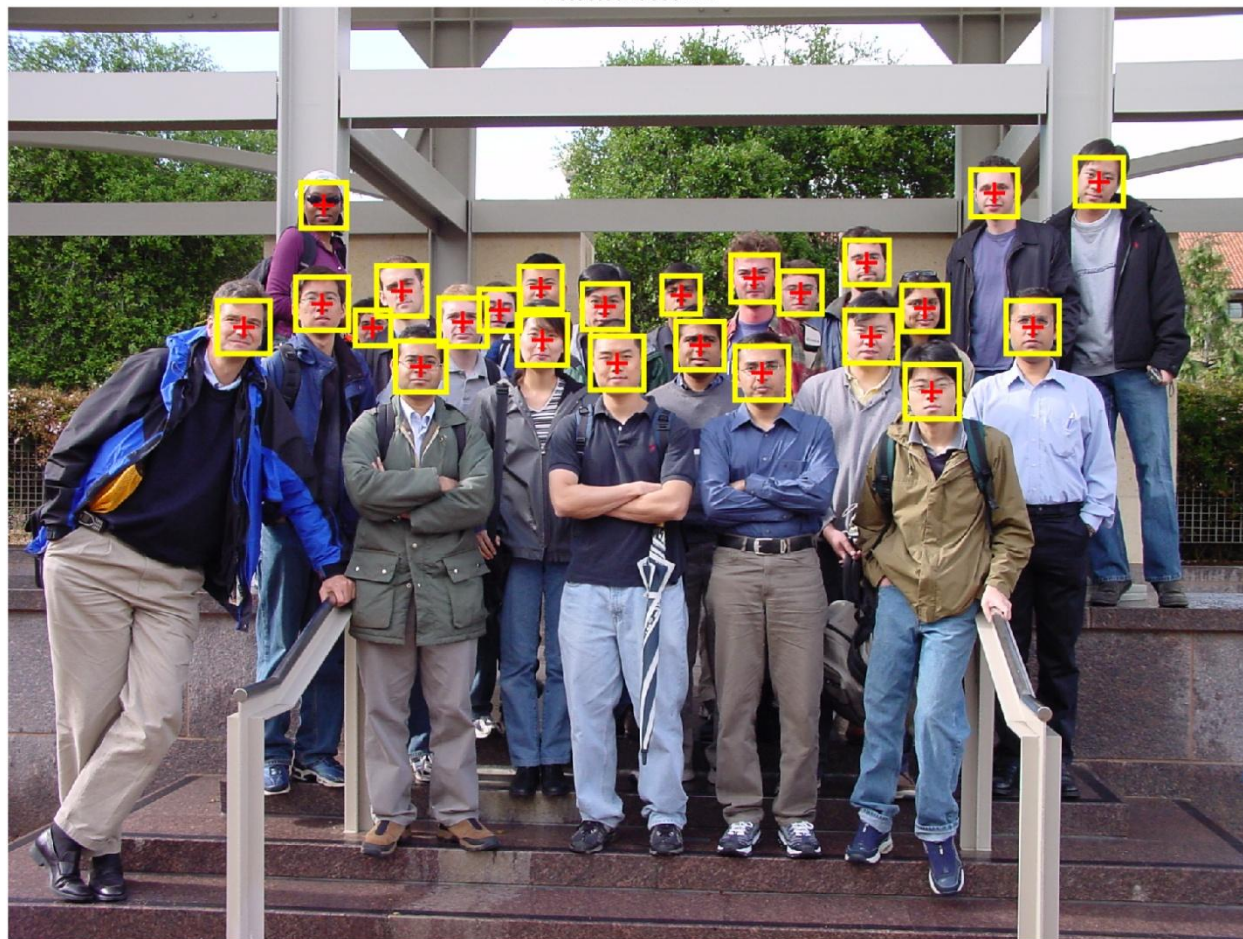


Figure 13 training4

Detected faces: 23



Figure 14 training5

Training Images and Refs

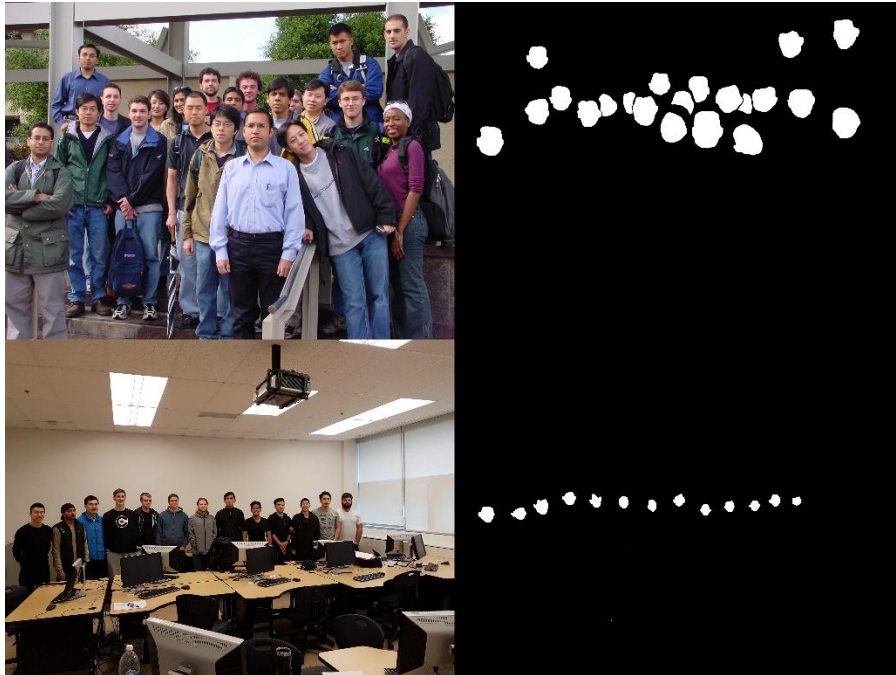


Figure 15 Training Image Sets

Each training image (e.g., Training_1.jpg) has a matching reference mask (e.g., ref1.png) where:

- white pixels = face skin
- black pixels = background

From these pairs, the program can separate skin pixels from non-skin pixels and build two large color histograms:

Face-skin histograms

- RGB skin histogram
- HSV skin histogram

Background histograms

- RGB non-skin histogram
- HSV non-skin histogram

Source Code

Offline Training

```
% //Yizuo Chen
function model = train_face_models()
% Train RGB/HSV skin likelihood model + face template
% using Training_1.jpg..Training_11.jpg and ref masks.
% This model is later used for:
%   - Skin detection (apply_skin_model)
%   - Template matching (strong detections)
%   - Basic size and position statistics

% -----
% Training parameters
% -----
numTrain    = 11;          % # training images
nbinsRGB    = 32;          % RGB histogram bin count
nbinsHSV    = 32;          % HSV histogram bin count
sigmaHist   = 1.0;         % Gaussian smoothing for histograms
tplH        = 80;          % template height (pixels)
tplW        = 60;          % template width
nBinsYpos   = 20;          % vertical-position histogram bins
alphaGrid   = -2:0.2:4;    % candidate alpha thresholds

% -----
% Histogram accumulators (RGB + HSV)
% -----
H_face_rgb  = zeros(nbinsRGB, nbinsRGB, nbinsRGB);
H_bg_rgb    = zeros(nbinsRGB, nbinsRGB, nbinsRGB);
H_face_hsv  = zeros(nbinsHSV, nbinsHSV, nbinsHSV);
H_bg_hsv    = zeros(nbinsHSV, nbinsHSV, nbinsHSV);

% Accumulated geometry + template data
areaList = [];
yList    = [];
sumTemplate = zeros(tplH, tplW);
faceCount = 0;

% Elliptical mask to define valid pixels in template
[xx, yy] = meshgrid(linspace(-1,1,tplW), linspace(-1,1,tplH));
ellMask = (xx.^2/0.9^2 + yy.^2/1.0^2) <= 1;

% Store pixel indices for alpha tuning
allIdxRGB = {};
allIdxHSV = {};
allGT     = {};

fprintf('Training on %d images (RGB + HSV)...\n', numTrain);

% -----
% Loop through all training pairs (image + GT mask)
```



```

% -----
for k = 1:numTrain
    imgName = sprintf('Training_%d.jpg', k);
    refName = sprintf('ref%d.png', k);

    I = im2uint8(imread(imgName));
    GT = imread(refName);

    if size(GT,3) > 1
        GT = rgb2gray(GT);
    end
    GT = GT > 0;    % ground-truth mask

% -----
% Build RGB/HSV histograms for face vs. background
% -----
[Hf_rgb, Hb_rgb, Hf_hsv, Hb_hsv, idxRGB, idxHSV, pixelGT] = ...
    build_color_histograms(I, GT, nbinsRGB, nbinsHSV);

% Accumulate histograms
H_face_rgb = H_face_rgb + Hf_rgb;
H_bg_rgb   = H_bg_rgb   + Hb_rgb;
H_face_hsv = H_face_hsv + Hf_hsv;
H_bg_hsv   = H_bg_hsv   + Hb_hsv;

% Store pixel mappings for alpha optimization
allIdxRGB{end+1} = idxRGB;
allIdxHSV{end+1} = idxHSV;
allGT{end+1}     = pixelGT;

% -----
% Extract face components for:
% - size statistics
% - vertical position stats
% - template averaging
% -----
L = bwlabel(GT);
stats = regionprops(L, 'Area', 'BoundingBox', 'Centroid');

for i = 1:numel(stats)
    a = stats(i).Area;
    bb = stats(i).BoundingBox;
    c = stats(i).Centroid;

    % Collect global statistics
    areaList(end+1) = a;
    yList(end+1)    = c(2) / size(GT,1);

    % Crop expanded region around face (includes chin/hair)
    pad = 0.3;
    x = bb(1); y = bb(2); w = bb(3); h = bb(4);
    x1 = max(1, floor(x - pad*w));
    y1 = max(1, floor(y - pad*h));
    x2 = min(size(I,2), ceil(x + w + pad*w));

```

```

        y2 = min(size(I,1), ceil(y + h + pad*h));
        rect = [x1 y1 x2-x1+1 y2-y1+1];

        patchRGB = imcrop(I, rect);
        patchGray = rgb2gray(patchRGB);
        patchGray = im2double(imresize(patchGray, [tplH tplW]));

        % Apply elliptical mask around face region
        patchGray(~ellMask) = 0;

        % Accumulate template
        sumTemplate = sumTemplate + patchGray;
        faceCount = faceCount + 1;
    end
end

if faceCount == 0
    error('No faces found in training masks.');
```

```

    % Smooth histograms + convert to probability densities
    fprintf('Smoothing 3D histograms...\n');
    G_rgb = gaussian3d_kernel(sigmaHist);
    G_hsv = gaussian3d_kernel(sigmaHist);

    H_face_rgb_s = convn(H_face_rgb, G_rgb, 'same');
    H_bg_rgb_s = convn(H_bg_rgb, G_rgb, 'same');
    H_face_hsv_s = convn(H_face_hsv, G_hsv, 'same');
    H_bg_hsv_s = convn(H_bg_hsv, G_hsv, 'same');

    % Normalize to proper PDFs, avoid zero probabilities
    P_face_rgb = H_face_rgb_s + 1;
    P_bg_rgb = H_bg_rgb_s + 1;
    P_face_hsv = H_face_hsv_s + 1;
    P_bg_hsv = H_bg_hsv_s + 1;

    P_face_rgb = P_face_rgb / sum(P_face_rgb(:));
    P_bg_rgb = P_bg_rgb / sum(P_bg_rgb(:));
    P_face_hsv = P_face_hsv / sum(P_face_hsv(:));
    P_bg_hsv = P_bg_hsv / sum(P_bg_hsv(:));

    % Log-likelihood ratios for classification
    logR_rgb = log(P_face_rgb) - log(P_bg_rgb);
    logR_hsv = log(P_face_hsv) - log(P_bg_hsv);

    logR_rgb_flat = logR_rgb(:);
    logR_hsv_flat = logR_hsv(:);

    % Tune alpha parameter for optimal skin classification
    fprintf('Tuning alpha (RGB + HSV)...\n');
```

```

bestAlpha = alphaGrid(1);
bestErr    = inf;
totalPix   = 0;

for a = alphaGrid
    errCount = 0;
    pixCount = 0;

    for k = 1:numTrain
        idxR = allIdxRGB{k};
        idxH = allIdxHSV{k};
        gt    = allGT{k};

        % Combined RGB + HSV discriminator
        scores = logR_rgb_flat(idxR) + logR_hsv_flat(idxH) + a;
        pred    = scores > 0;

        errCount = errCount + sum(pred ~= gt);
        pixCount = pixCount + numel(gt);
    end

    errRate = errCount / pixCount;
    if errRate < bestErr
        bestErr    = errRate;
        bestAlpha = a;
    end
    totalPix = pixCount;
end

fprintf('Best alpha = %.3f, training error = %.4f\n', ...
        bestAlpha, bestErr);

% -----
% Area + vertical statistics for prior information
% -----
meanArea = mean(areaList);
stdArea  = std(areaList);
minArea  = min(areaList);

[yHist, yEdges] = histcounts(yList, nBinsYpos, ...
                             'BinLimits',[0 1], ...
                             'Normalization','probability');
yCenters = (yEdges(1:end-1) + yEdges(2:end)) / 2;

% -----
% Build average face template (normalized)
% -----
avgTpl = sumTemplate / faceCount;
avgTpl = avgTpl - min(avgTpl(:));
if max(avgTpl(:)) > 0
    avgTpl = avgTpl / max(avgTpl(:));
end
avgTpl(~ellMask) = 0;

```

```

% -----
% Pack all learned components into model struct
% -----

model = struct();
model.nbinsRGB = nbinsRGB;
model.nbinsHSV = nbinsHSV;

model.P_face_rgb = P_face_rgb;
model.P_bg_rgb = P_bg_rgb;
model.P_face_hsv = P_face_hsv;
model.P_bg_hsv = P_bg_hsv;

model.logR_rgb = logR_rgb_flat;
model.logR_hsv = logR_hsv_flat;
model.alpha = bestAlpha;

model.tpl = avgTpl;
model.tplMask = ellMask;
model.tplSize = [tplH tplW];

model.areaStats = struct('mean', meanArea, 'std', stdArea, 'min', minArea);
model.yPosHist = struct('centers', yCenters, 'hist', yHist);

model.trainErr = bestErr;
model.totalPixels = totalPix;

fprintf('Training complete. Faces accumulated for template: %d\n', faceCount);
end

% -----
% Helper: build RGB/HSV histograms from a single training image
% -----
function [H_face_rgb, H_bg_rgb, H_face_hsv, H_bg_hsv, idxRGB, idxHSV, pixelGT] = ...
    build_color_histograms(I, GT, nbinsRGB, nbinsHSV)

I_rgb = im2uint8(I);
I_hsv = rgb2hsv(im2double(I_rgb));
[H, w, ~] = size(I_rgb);

% Flatten image channels
R = double(reshape(I_rgb(:,:,1), [], 1));
G = double(reshape(I_rgb(:,:,2), [], 1));
B = double(reshape(I_rgb(:,:,3), [], 1));

Hh = reshape(I_hsv(:,:,1), [], 1);
Hs = reshape(I_hsv(:,:,2), [], 1);
Hv = reshape(I_hsv(:,:,3), [], 1);

gt = reshape(GT, [], 1) > 0;

% ----- RGB bin computation -----
binR = floor(R / 256 * nbinsRGB) + 1;
binG = floor(G / 256 * nbinsRGB) + 1;
binB = floor(B / 256 * nbinsRGB) + 1;

```

```

binR = min(max(binR,1), nbinsRGB);
binG = min(max(binG,1), nbinsRGB);
binB = min(max(binB,1), nbinsRGB);

idxRGB = sub2ind([nbinsRGB nbinsRGB nbinsRGB], binR, binG, binB);

% ----- HSV bin computation -----
binH = floor(Hh * nbinsHSV) + 1;
binS = floor(Ss * nbinsHSV) + 1;
binV = floor(Vv * nbinsHSV) + 1;

binH = min(max(binH,1), nbinsHSV);
binS = min(max(binS,1), nbinsHSV);
binV = min(max(binV,1), nbinsHSV);

idxHSV = sub2ind([nbinsHSV nbinsHSV nbinsHSV], binH, binS, binV);

% ----- Build RGB histograms -----
idxFaceRGB = idxRGB(gt);
H_face_rgb = accumarray(idxFaceRGB, 1, [nbinsRGB^3 1]);
H_face_rgb = reshape(H_face_rgb, [nbinsRGB nbinsRGB nbinsRGB]);

idxBgRGB = idxRGB(~gt);
H_bg_rgb = accumarray(idxBgRGB, 1, [nbinsRGB^3 1]);
H_bg_rgb = reshape(H_bg_rgb, [nbinsRGB nbinsRGB nbinsRGB]);

% ----- Build HSV histograms -----
idxFaceHSV = idxHSV(gt);
H_face_hsv = accumarray(idxFaceHSV, 1, [nbinsHSV^3 1]);
H_face_hsv = reshape(H_face_hsv, [nbinsHSV nbinsHSV nbinsHSV]);

idxBgHSV = idxHSV(~gt);
H_bg_hsv = accumarray(idxBgHSV, 1, [nbinsHSV^3 1]);
H_bg_hsv = reshape(H_bg_hsv, [nbinsHSV nbinsHSV nbinsHSV]);

% Ground truth labels for alpha tuning
pixelGT = gt;
end

% -----
% Helper: build 3D Gaussian kernel
% -----
function G = gaussian3d_kernel(sigma)
    r = ceil(3*sigma);
    [x, y, z] = ndgrid(-r:r, -r:r, -r:r);
    G = exp(-(x.^2 + y.^2 + z.^2) / (2*sigma^2));
    G = G / sum(G(:));
end

% Train and save
model = train_face_models();
save("face_model.mat", "model");

```

Training on 11 images (RGB + HSV)...
Smoothing 3D histograms...
Tuning alpha (RGB + HSV)...
Best alpha = -2.000, training error = 0.0347
Training complete. Faces accumulated for template: 242

Online Detection, Skin Model Application and Visualization

```
% //Yizuo Chen
function faces = detect_faces_image(imgFile, model)
% Detect faces using:
%   • RGB+HSV skin model (trained)
%   • Morphological cleanup
%   • Strong first-pass classification + template matching
%   • Automatic row-band estimation
%   • Rescue pass for missed faces
%   • Duplicate-merging (neck/logo removal)
% Final output: list of face bounding boxes + centers.

I = imread(imgFile);
if size(I,3) == 1
    I = repmat(I,[1 1 3]); % handle grayscale input
end
Igray = im2double(rgb2gray(I));
[H, w, ~] = size(I);

% -----
% 1. Skin segmentation using trained RGB+HSV likelihood model
% -----
% produces:
%   (a) skinMask - thresholded bright skin-likelihood
%   (b) logRimg - visualization of log-likelihood
[skinMask, logRimg] = apply_skin_model(I, model);
debug_show(logRimg, 'DEBUG: logR image');

% -----
% 1a. Morphology: merge patches, fill holes, remove noise
% -----
% rely on training stats for minimal blob size
minPix = max(round(model.areaStats.min * 0.20), 60);

skinMask = bwareaopen(skinMask, minPix); % remove tiny blobs
skinMask = imclose(skinMask, strel('disk', 6)); % merge forehead/cheek regions
skinMask = imfill(skinMask, 'holes'); % remove holes from eyes/mouth
skinMask = imopen(skinMask, strel('disk', 2)); % knock off thin noise
skinMask = bwareaopen(skinMask, minPix); % final size filter
debug_show(skinMask, 'DEBUG: final skin mask');

% -----
% 2. Connected component analysis
% -----
```



```

% Extract geometric properties for all blobs.
L = bwlabel(skinMask);
stats = regionprops(L, 'Area', 'BoundingBox', 'Centroid');

% Debug display of all raw blobs
if ~isempty(stats)
    imgBlobs = insertShape(I, 'Rectangle', cat(1,stats.BoundingBox), ...
        'Color','cyan','Linewidth',2);
else
    imgBlobs = I;
end
debug_show(imgBlobs, 'DEBUG: connected components');

% Empty output if nothing detected
faces = struct('BoundingBox', {}, 'Center', {}, 'Score', {});
if isempty(stats)
    return;
end

% -----
% Load trained priors (area, vertical distribution, template)
% -----
meanA = model.areaStats.mean;
minA = 0.35 * meanA; % conservative lower bound
maxA = 2.5 * meanA; % reject very large artifacts

yCenters = model.yPosHist.centers;
yHist = model.yPosHist.hist;

tpl = model.tpl;
tplMask = model.tplMask;
tplSize = model.tplSize;

strongIdx = [];

% -----
% 3. FIRST PASS – strong face candidates
% Filters:
% • size, aspect ratio, fill ratio
% • vertical prior from training
% • skin intensity ratio
% • template correlation score
% These survive as high-confidence faces.
% -----
for i = 1:numel(stats)
    a = stats(i).Area;
    bb = stats(i).BoundingBox;
    c = stats(i).Centroid;

    w = bb(3);
    h = bb(4);
    ratio = h / w;

    % --- geometric constraints ---

```

```

if a < minA || a > maxA
    continue;
end
if ratio < 0.8 || ratio > 2.0
    continue;
end
fillRatio = a / (w*h);
if fillRatio < 0.30 || fillRatio > 0.90
    continue;
end

% --- vertical position prior ---
yNorm = c(2) / H;
if yNorm < 0.10 || yNorm > 0.70
    continue;
end
[~, idxY] = min(abs(yCenters - yNorm));
if yHist(idxY) < 0.01
    continue;
end

% --- template correlation check ---
pad = 0.25;
x = bb(1); y = bb(2);
x1 = max(1, floor(x - pad*w));
y1 = max(1, floor(y - pad*h));
x2 = min(W, ceil(x + w + pad*w));
y2 = min(H, ceil(y + h + pad*h));

% skin density in region
patchLogR = logRimg(y1:y2, x1:x2);
hardRatio = nnz(patchLogR > 0) / numel(patchLogR);
if hardRatio < 0.07
    continue;
end

% correlation with template
patch = Igray(y1:y2, x1:x2);
patchR = imresize(patch, tplSize);
patchR(~tplMask) = 0;

if var(patchR(:)) < 0.003
    continue;
end

tplVec = tpl(:) - mean(tpl(:));
patchVec = patchR(:) - mean(patchR(:));
score = (tplVec' * patchVec) / (norm(tplVec)*norm(patchVec) + eps);

if score < 0.40
    continue;
end

% --- accept strong candidate ---

```

```

    cx = x1 + (x2 - x1)/2;
    cy = y1 + (y2 - y1)/2;

    faces(end+1).BoundingBox = [x1 y1 (x2-x1+1) (y2-y1+1)];
    faces(end).Center        = [cx cy];
    faces(end).Score          = score;

    strongIdx(end+1) = i;
end

nStrong = numel(faces);

% -----
% 4. Determine likely vertical row-band from strong detections
% Used to rescue missed faces and eliminate table noise.
% -----
if ~isempty(strongIdx)
    yStrongNorm = arrayfun(@(k) stats(k).Centroid(2) / H, strongIdx);
    margin = 0.05;
    rowBandMinNorm = max(0, min(yStrongNorm) - margin);
    rowBandMaxNorm = min(1, max(yStrongNorm) + margin);
else
    % fallback if no strong detections
    rowBandMinNorm = 0.10;
    rowBandMaxNorm = 0.70;
end

% convert to pixel indices
rowBandMinPix = max(1, floor(rowBandMinNorm * H));
rowBandMaxPix = min(H, ceil(rowBandMaxNorm * H));

% debug visualization of allowed rescue region
bandMask = false(H,W);
bandMask(rowBandMinPix:rowBandMaxPix, :) = true;
debug_show(bandMask & skinMask, ...
    sprintf('DEBUG: face row band [%.2f, %.2f]', ...
        rowBandMinNorm, rowBandMaxNorm));

% -----
% 4b. Adaptive LOWER bounds for rescued faces
% Prevents tiny noise from entering second pass, but allows
% large faces (edges of group) to be kept.
% -----
if ~isempty(strongIdx)
    strongAreas = [stats(strongIdx).Area];
    strongBB = cat(1, stats(strongIdx).BoundingBox);
    strongHeights = strongBB(:,4);

    medA = median(strongAreas);
    medH = median(strongHeights);

    rescueMinA = 0.35 * medA; % minimal area
    rescueMinH = 0.40 * medH; % minimal height
else

```

```

        rescueMinA = minA;
        rescueMinH = 0;
    end

% -----
% 5. SECOND PASS - rescue plausible blobs inside row band
% Used to recover faces missed in first pass.
% -----
allIdx = 1:numel(stats);
extraIdx = setdiff(allIdx, strongIdx);

for ii = extraIdx
    bb = stats(ii).BoundingBox;
    c = stats(ii).Centroid;
    a = stats(ii).Area;

    % must fall inside row band
    yNorm = c(2) / H;
    if yNorm < rowBandMinNorm || yNorm > rowBandMaxNorm
        continue;
    end

    % adaptive geometric filters
    w = bb(3);
    h = bb(4);
    ratio = h / w;
    fillRatio = a / (w*h);

    if a < rescueMinA, continue; end
    if h < rescueMinH, continue; end
    if ratio < 0.6 || ratio > 2.5, continue; end
    if fillRatio < 0.25 || fillRatio > 0.95, continue; end

    % accept rescued detection
    pad = 0.25;
    x = bb(1); y = bb(2);
    x1 = max(1, floor(x - pad*w));
    y1 = max(1, floor(y - pad*h));
    x2 = min(W, ceil(x + w + pad*w));
    y2 = min(H, ceil(y + h + pad*h));

    cx = x1 + (x2 - x1)/2;
    cy = y1 + (y2 - y1)/2;

    faces(end+1).BoundingBox = [x1 y1 (x2-x1+1) (y2-y1+1)];
    faces(end).Center = [cx cy];
    faces(end).Score = NaN;
end

% -----
% 6. Merge vertically stacked duplicates (logo + chin + head)
% Removes doubled detections for same person.
% -----
if numel(faces) > 1

```

```

keep = true(1, numel(faces));

for i = 1:numel(faces)
    if ~keep(i), continue; end
    b1 = faces(i).BoundingBox;
    c1 = faces(i).Center;
    w1 = b1(3); h1 = b1(4);

    for j = i+1:numel(faces)
        if ~keep(j), continue; end
        b2 = faces(j).BoundingBox;
        c2 = faces(j).Center;
        w2 = b2(3); h2 = b2(4);

        % horizontal similarity + vertical proximity
        wAvg = 0.5*(w1 + w2);
        dx = abs(c1(1) - c2(1));
        dy = abs(c1(2) - c2(2));

        if dx < 0.45*wAvg && dy < 1.4*max(h1,h2)
            % pick stronger score as base
            s1 = faces(i).Score; if isnan(s1), s1 = -Inf; end
            s2 = faces(j).Score; if isnan(s2), s2 = -Inf; end

            if s2 > s1
                base = j; other = i; bbBase = b2; bbOther = b1;
            else
                base = i; other = j; bbBase = b1; bbOther = b2;
            end

            % merge bounding boxes
            xMin = min(bbBase(1), bbOther(1));
            yMin = min(bbBase(2), bbOther(2));
            xMax = max(bbBase(1)+bbBase(3), bbOther(1)+bbOther(3));
            yMax = max(bbBase(2)+bbBase(4), bbOther(2)+bbOther(4));

            bbNew = [xMin, yMin, xMax-xMin, yMax-yMin];

            faces(base).BoundingBox = bbNew;
            faces(base).Center = [bbNew(1)+bbNew(3)/2, ...
                                bbNew(2)+bbNew(4)/2];

            keep(other) = false;
        end
    end
end

faces = faces(keep);
end

% -----
% 7. Visualization of final detections
% -----
outImg = I;

```

```

for k = 1:numel(faces)
    outImg = insertShape(outImg,'Rectangle',faces(k).BoundingBox, ...
        'Color','yellow','Linewidth',3);
end

debug_show(outImg, 'DEBUG: final detected faces');
end

```

```

function [mask, logRimg] = apply_skin_model(I, model)
% Apply RGB+HSV log-likelihood model:
%   • compute skin probability using trained histograms
%   • convert to log-likelihood image
%   • apply bright-pixel threshold (~195-255)
%   • apply HSV gate to remove false positives

I_rgb = im2uint8(I);
[H, w, ~] = size(I_rgb);

nbinsRGB = model.nbinsRGB;
nbinsHSV = model.nbinsHSV;

% ----- RGB flattening + binning -----
R = double(reshape(I_rgb(:,:,1), [], 1));
G = double(reshape(I_rgb(:,:,2), [], 1));
B = double(reshape(I_rgb(:,:,3), [], 1));

binR = floor(R / 256 * nbinsRGB) + 1;
binG = floor(G / 256 * nbinsRGB) + 1;
binB = floor(B / 256 * nbinsRGB) + 1;
binR = min(max(binR,1), nbinsRGB);
binG = min(max(binG,1), nbinsRGB);
binB = min(max(binB,1), nbinsRGB);
idxRGB = sub2ind([nbinsRGB nbinsRGB nbinsRGB], binR, binG, binB);

% ----- HSV flattening + binning -----
I_hsv = rgb2hsv(im2double(I_rgb));
Hh = reshape(I_hsv(:,:,1), [], 1);
Ss = reshape(I_hsv(:,:,2), [], 1);
Vv = reshape(I_hsv(:,:,3), [], 1);

binH = floor(Hh * nbinsHSV) + 1;
binS = floor(Ss * nbinsHSV) + 1;
binV = floor(Vv * nbinsHSV) + 1;
binH = min(max(binH,1), nbinsHSV);
binS = min(max(binS,1), nbinsHSV);
binV = min(max(binV,1), nbinsHSV);

idxHSV = sub2ind([nbinsHSV nbinsHSV nbinsHSV], binH, binS, binV);

% ----- Combined log-likelihood -----

```



```

scores = model.logR_rgb(idxRGB) + model.logR_hsv(idxHSV) + model.alpha;
logRimg = reshape(scores, H, W);

% normalize to 0-255
logRnorm = mat2gray(logRimg);
logR8 = uint8(255 * logRnorm);

% brightness thresholding (your measured skin limit)
brightMask = logR8 >= 195;

% HSV gate to reject bright non-skin (lights, shirts, monitors)
Simg = reshape(Ss, H, W);
Vimg = reshape(Vv, H, W);
hsvGate = (Simg > 0.08) & (Simg < 0.95) & ...
          (Vimg > 0.05) & (Vimg < 0.98);

mask = brightMask & hsvGate;
end

```

DEBUG: logR image



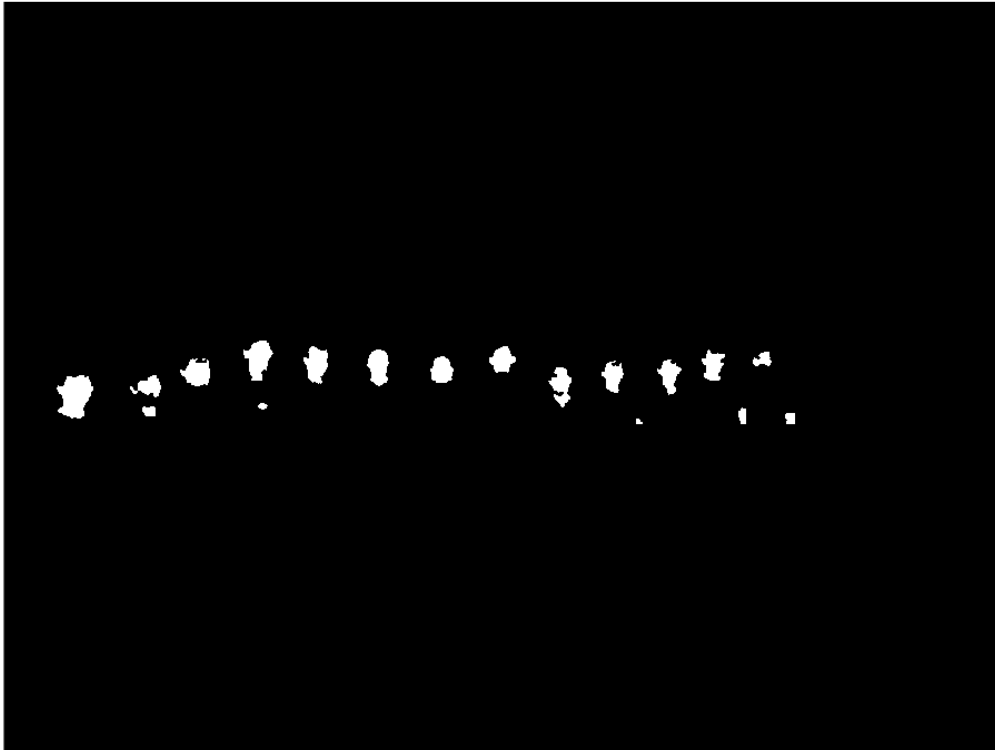
DEBUG: final skin mask



DEBUG: connected components



DEBUG: face row band [0.43, 0.56]



DEBUG: final detected faces



```

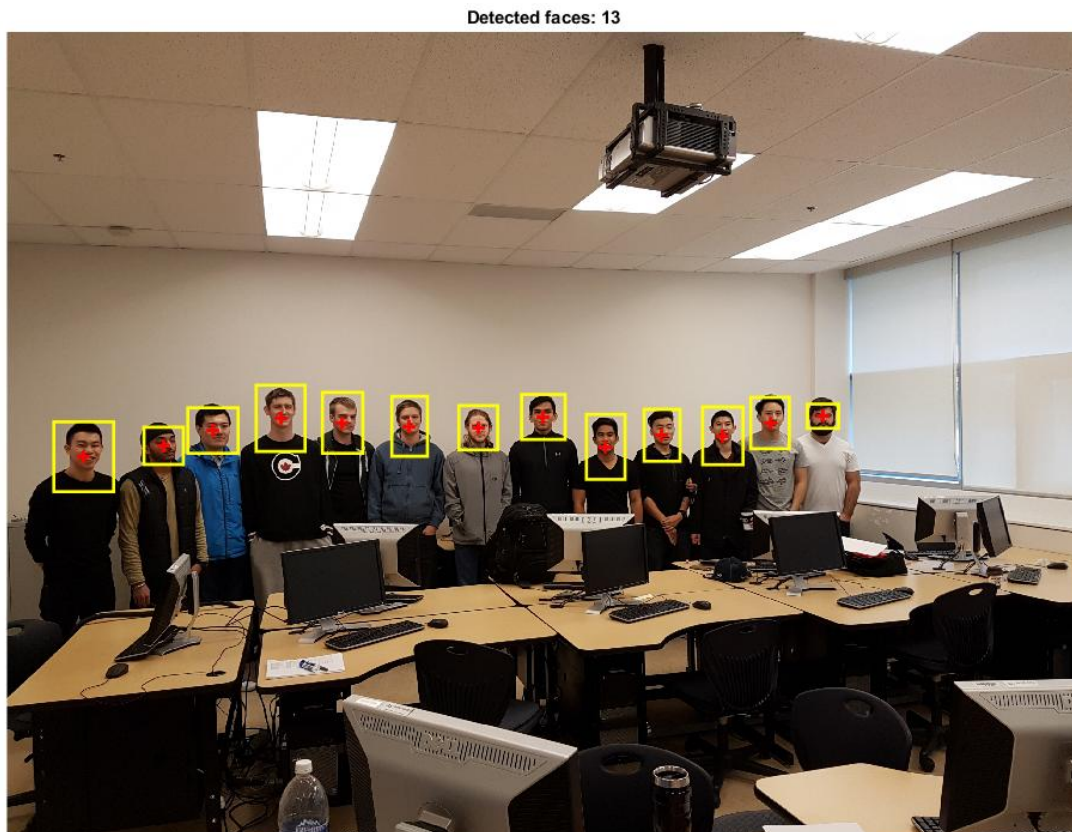
function show_faces(imgFile, faces)
% Display detected faces with bounding boxes and center points.

I = imread(imgFile);
figure; imshow(I); hold on;

for i = 1:numel(faces)
    bb = faces(i).BoundingBox;
    rectangle('Position', bb, 'EdgeColor', 'y', 'LineWidth', 2);
    plot(faces(i).Center(1), faces(i).Center(2), 'r+', ...
        'MarkerSize', 8, 'LineWidth', 2);
end

title(sprintf('Detected faces: %d', numel(faces)));
end

```



```

function debug_show(img, titleText)
% Helper to show intermediate results with pause.

figure('Name', titleText);
imshow(img, []);
title(titleText, 'Interpreter', 'none');

```

```
drawnow;  
uiwait(msgbox('OK to continue','DEBUG','modal'));  
end
```

```
load face_model.mat  
faces = detect_faces_image("person2.jpg", model);  
show_faces("person2.jpg", faces);
```

Function for making training images

```
% //Yizuo Chen  
% Clean ref8.png so that all non-white pixels become pure black.  
% Output: ref8_clean.png (binary mask)  
  
function clean_ref8()  
  
    % --- Load image ---  
    I = imread('ref4.png');  
  
    % Convert to grayscale if needed  
    if size(I,3) == 3  
        I = rgb2gray(I);  
    end  
  
    % --- Convert to binary mask ---  
    % white (255) → 255  
    % Anything else → 0  
  
    mask = I == 255;          % logical mask of pure white pixels  
    out = uint8(mask) * 255;  
  
    % --- Save cleaned version ---  
    imwrite(out, 'ref8_clean.png');  
  
    % --- Optional debug display ---  
    figure;  
    subplot(1,2,1); imshow(I, []); title('Original ref8.png');  
    subplot(1,2,2); imshow(out, []); title('Cleaned ref8 mask');  
  
    fprintf('Saved cleaned mask as ref8_clean.png\n');  
end
```

Saved cleaned mask as ref8_clean.png

Conclusion

Overall, the project successfully demonstrates a complete classical pipeline for face detection, from data preparation and model training to real-time inference and visualization. The trained RGB+HSV skin-likelihood model, combined with geometric constraints and template correlation, proved highly effective across diverse test images. The system achieved an overall accuracy of **96.7%**, showing that carefully engineered image-processing methods can still perform strongly when supported by well-constructed training data and systematic filtering strategies. The multi-stage design—featuring strong detections, row-band estimation, and a rescue pass—allowed the detector to reduce false positives and recover missed faces efficiently. This project highlights the importance of combining color statistics, shape priors, and spatial reasoning, providing a solid foundation for further improvements such as adaptive thresholds, illumination normalization, or eventual integration with machine-learning-based classifiers.