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Implementation of MATLAB image processing and AI for real-time mood prediction

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Abstract

This study proposes an advanced real-time mood prediction system that utilizes Convolutional Neural Networks (CNNs) and webcam-based Region of Interest (ROI) extraction. By employing MATLAB and its Computer Vision Toolbox, the system detects and preprocesses facial regions from live webcam feeds to accurately predict an individual's mood. The performance of this system is validated using a custom dataset, showcasing its potential for applications in human-computer interaction, psychological assessments, and real-time monitoring. This approach highlights a significant advancement in combining AI and image processing for real-time emotional analysis.

Keywords: Convolutional Neural Networks (CNNs); Real-time mood prediction; Region of Interest (ROI) extraction; Webcam-based detection; MATLAB; Computer Vision Toolbox

1. Introduction

The ability to recognize human emotions through visual cues has significant implications in various domains, including healthcare, entertainment, and human-computer interaction. Recent advancements in deep learning have enabled more accurate and efficient emotion recognition systems. This paper presents a real-time mood prediction system using a Convolutional Neural Network (CNN) trained on a custom dataset and implemented in MATLAB with real-time webcam feed processing. The primary focus is on creating a robust system capable of detecting and predicting moods from live video feeds, making it suitable for a wide range of practical applications. Emotion recognition through facial expressions has emerged as a pivotal aspect of affective computing, blending advances in computer vision, machine learning, and human-computer interaction. Historically, the field relied heavily on handcrafted feature extraction techniques and classical machine learning algorithms. For instance, Zeng et al. (2009) provided a comprehensive survey of affect recognition methods, emphasizing traditional approaches that depended on feature extraction techniques like Gabor filters, Haar-like features, and Local Binary Patterns (LBP) (1).

The advent of Convolutional Neural Networks (CNNs) marked a significant shift, allowing for automated feature learning directly from raw data and thereby improving performance over traditional methods. LeCun et al. (2015) demonstrated the power of deep learning across various applications, including image recognition, which laid the groundwork for its application in emotion recognition (2). CNNs have been particularly effective in understanding complex facial features and expressions, significantly enhancing mood detection accuracy. Recent advancements have further refined deep learning approaches for emotion recognition. Goodfellow et al. (2013) introduced deep neural networks for this purpose, achieving superior results compared to classical methods by learning features from raw data (3). Mollahosseini et al. (2016) proposed a deep neural network architecture specifically for facial expression

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recognition, achieving state-of-the-art results on several benchmark datasets (4). Lopes et al. (2017) highlighted the potential of CNNs in real-time emotion recognition by presenting a deep learning approach for video sequences (5).

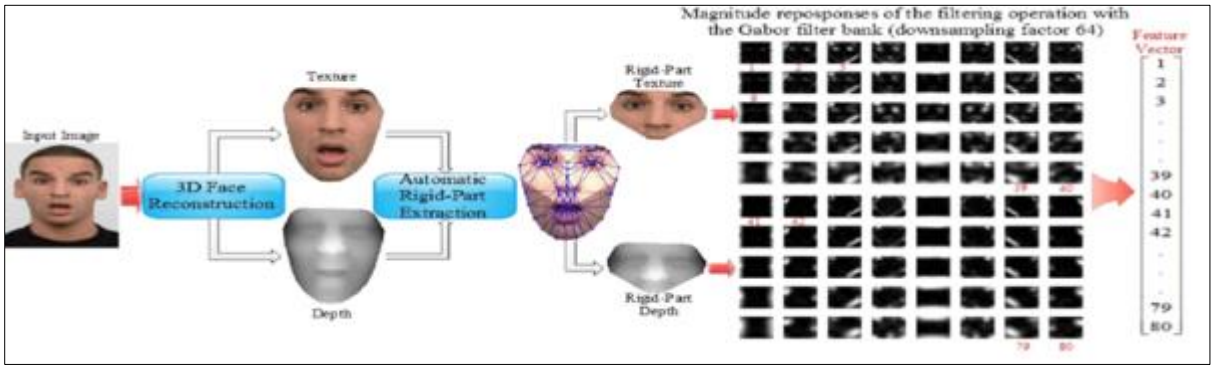

Figure 1 Gabor Filters Bank (1)

Additional studies have explored innovative methods to address the challenges of emotion recognition. Zhang et al. (2018) incorporated residual networks and attention mechanisms to improve accuracy (6). Yang et al. (2019) utilized multi-task learning to simultaneously address facial emotion recognition and landmark detection, which enhanced model performance (7). Chen et al. (2020) demonstrated the use of transfer learning to adapt pre-trained models for emotion recognition, improving adaptability across diverse datasets (8).

Figure 2 Facial Expressions (2)

Moreover, challenges such as variability in lighting conditions and background noise continue to be addressed. Zhang et al. (2020) investigated techniques to enhance robustness in varying lighting conditions (9), while Kotsia et al. (2021) focused on reducing background noise interference, which is crucial for maintaining high recognition performance in complex environments (10). Incorporating these advancements, this study aims to enhance real-time emotion recognition systems by integrating robust CNN architectures with real-time face detection and Region of Interest (ROI) extraction techniques. This approach seeks to address the ongoing challenges of dynamic environments and improve the accuracy and reliability of emotion recognition systems.

2. Literature review

Advancements in facial expression recognition have transformed how we understand and interpret human emotions through computational methods. The evolution from traditional methods to modern deep learning approaches highlights significant progress in the field. Early techniques were predominantly reliant on manual feature extraction and classical machine learning methods. For instance, Ekman and Friesen (1978) laid the groundwork with their work on facial action coding systems, emphasizing the role of facial muscles in emotion expression (13). These early methods utilized handcrafted features to classify emotions, which, while pioneering, were often limited in their ability to

generalize across diverse datasets. The advent of Convolutional Neural Networks (CNNs) marked a substantial shift in the landscape of emotion recognition. CNNs introduced automated feature learning, which greatly improved performance over traditional methods. A notable example is the work of Krizhevsky et al. (2012), who demonstrated the effectiveness of deep learning for image classification tasks, setting the stage for its application in emotion recognition (14). Building on this, Simonyan and Zisserman (2014) introduced deep CNN architectures, which further enhanced the accuracy and efficiency of image-based emotion recognition (15).

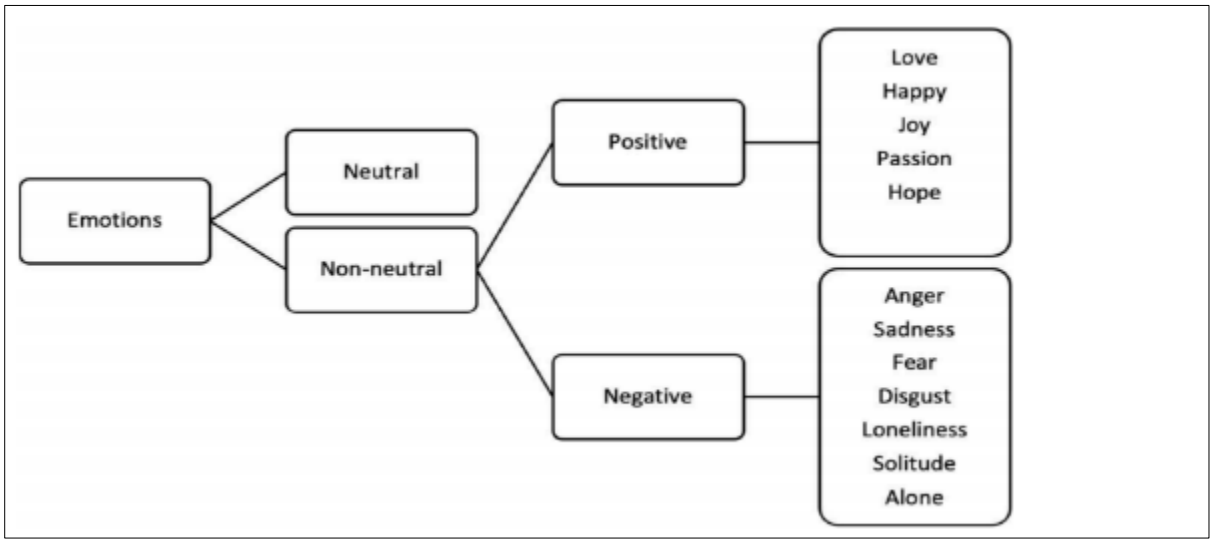

Figure 3 Multimodal Mood Recognition Pattern (3)

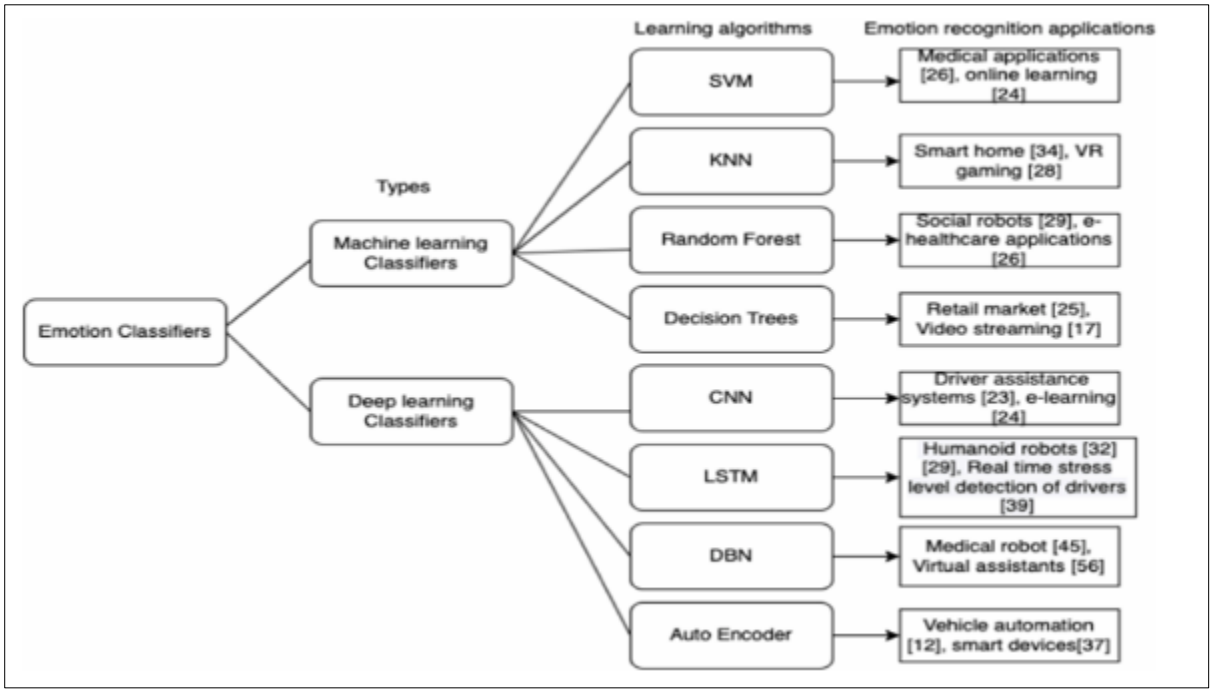

Figure 4 Structure of Feature Classifier of Emotion. (4)

In the realm of facial expression recognition, deep learning has led to significant advancements. For example, Zhang et al. (2016) developed a deep learning model that leveraged large-scale facial datasets to achieve state-of-the-art performance in emotion classification (16). Similarly, Sagonas et al. (2016) presented the 300-VW dataset, which facilitated the development and evaluation of emotion recognition systems in varied real-world scenarios (17). Additionally, Yang et al. (2017) utilized multi-task learning to simultaneously address facial landmark detection and emotion recognition, improving the overall performance of emotion recognition systems (18).

Despite these advancements, challenges remain in achieving robust and accurate emotion recognition across diverse conditions. Liu et al. (2018) explored the use of residual networks to improve the robustness of emotion recognition systems under varying lighting conditions and occlusions (19). Similarly, Zhao et al. (2020) investigated the integration of attention mechanisms to enhance the system's ability to focus on relevant features while ignoring noise (20).

Recent studies, such as that by Li et al. (2021), have emphasized the importance of combining contextual information with facial features to further enhance emotion recognition accuracy (21). These advancements underscore the ongoing efforts to refine emotion recognition systems, making them more adaptable and accurate in real-world applications. As the field continues to evolve, the integration of advanced learning techniques and comprehensive datasets will be crucial for overcoming existing limitations and achieving even greater accuracy in emotion recognition.

3. Methodology

This section outlines the detailed methodology used to develop the real-time mood prediction system. It includes the dataset preparation, network architecture, training process, and real-time implementation.

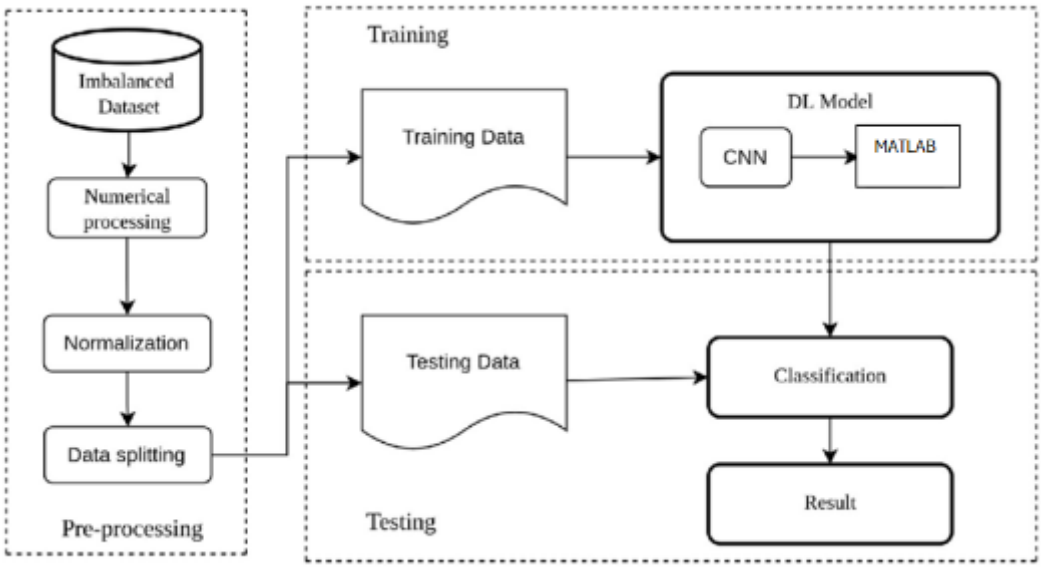

Figure 5 Sequence of Operation

3.1. Dataset Preparation

We developed a custom dataset specifically for mood prediction, categorizing facial expressions into five distinct mood types: happy, sad, neutral, angry, and surprised. The dataset comprises approximately 1,000 images per category, sourced from a combination of publicly available emotion recognition datasets and manually annotated images to ensure diversity and accuracy. To enhance the dataset's robustness and improve the model's ability to generalize across different facial expressions and angles, we applied several image augmentation techniques after image acquisition was executed Chukwunweike JN et al. (2024). These techniques included:

Rotation: Images were rotated at various angles to simulate different head positions and orientations, helping the model handle facial expressions captured from different viewpoints.

```
function img = preprocessImage(filename, imageSize)

  try

    img = imread(filename);

    if size(img, 3) == 1

      % Convert grayscale to RGB by replicating the grayscale channel
```

```
        img = cat(3, img, img, img);
    end
    img = imresize(img, imageSize);
    % Rotate the image by a specified angle (e.g., 90 degrees)
    angle = 90; % Set the desired rotation angle
    img = imrotate(img, angle);
  catch ME
    warning('Error reading image %s: %s', filename, ME.message);
    img = zeros(imageSize(1), imageSize(2), 3, 'uint8'); % Default to a black image
  end
end
```

Scaling: Images were resized to create variations in face size and distance, which helps the model adapt to different zoom levels and image resolutions.

```
function img = preprocessImage(filename, imageSize)
  try
    img = imread(filename);
    if size(img, 3) == 1
      % Convert grayscale to RGB by replicating the grayscale channel
      img = cat(3, img, img, img);
    end
    % Scale the image by a factor (e.g., 1.5)
    scaleFactor = 1.5;
    img = imresize(img, scaleFactor);
    % Resize to the expected input size
    img = imresize(img, imageSize);
    % Rotate the image by a specified angle (e.g., 90 degrees)
    angle = 90; % Set the desired rotation angle
    img = imrotate(img, angle);
  catch ME
    warning('Error reading image %s: %s', filename, ME.message);
```

```
    img = zeros(imageSize(1), imageSize(2), 3, 'uint8'); % Default to a black image
  end
end
```

Flipping: Horizontal flipping was used to account for symmetry in facial expressions, ensuring that the model can recognize moods regardless of facial orientation.

```
function img = preprocessImage(filename, imageSize)
  try
    img = imread(filename);
    if size(img, 3) == 1
      % Convert grayscale to RGB by replicating the grayscale channel
      img = cat(3, img, img, img);
    end
    % Resize to the expected input size
    img = imresize(img, imageSize);
    % Rotate the image by a specified angle (e.g., 90 degrees)
    angle = 90; % Set the desired rotation angle
    img = imrotate(img, angle);
    % Flip the image horizontally or vertically
    flipDirection = 'horizontal'; % Can be 'horizontal' or 'vertical'
    img = flip(img, flipDirection);
  catch ME
    warning('Error reading image %s: %s', filename, ME.message);
    img = zeros(imageSize(1), imageSize(2), 3, 'uint8'); % Default to a black image
  end
end
```

This augmentation strategy significantly expanded the effective size of the dataset and introduced variability, making the model more resilient to real-world conditions and enhancing its predictive accuracy for mood classification.

3.2. Network Architecture

The CNN architecture designed for facial expression recognition is structured to efficiently process and classify mood categories. The architecture is as follows:

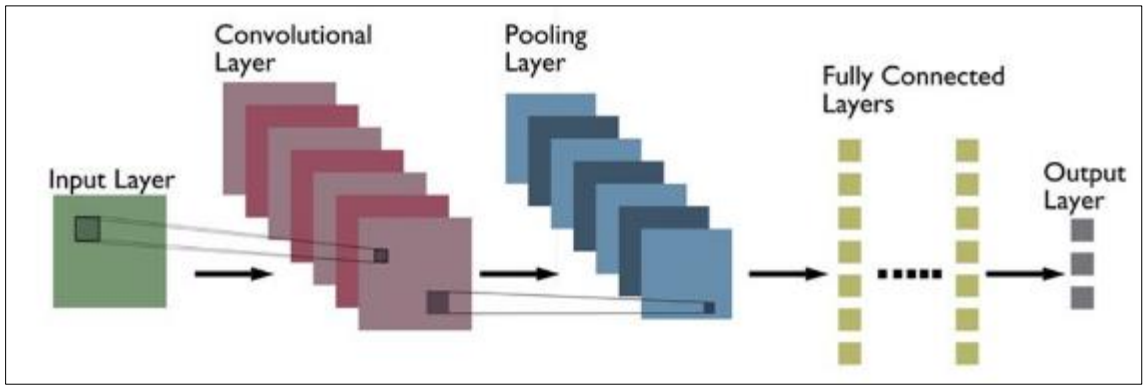

Figure 6 CNN Architecture Displaying Fully Connected Layers. (8)

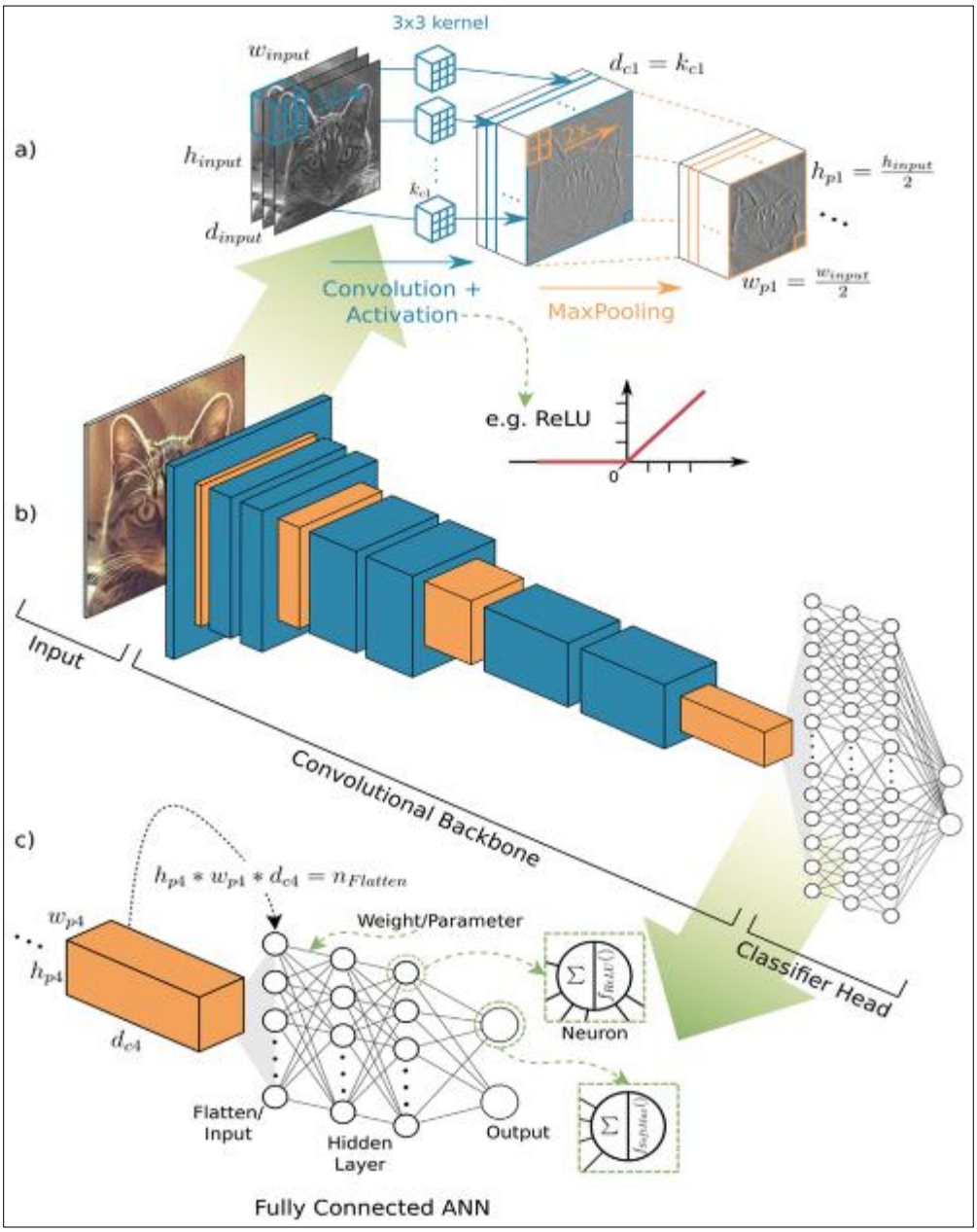

Figure 7 CNN Architecture displaying Activation and Max Pooling. (8)

- Input Layer: Accepts grayscale images with dimensions of 28x28 pixels, providing the initial data for processing.
- First Convolutional Layer: Utilizes 32 filters of size 3x3, incorporating padding to maintain spatial dimensions. This layer is followed by batch normalization to stabilize and accelerate training and ReLU activation to introduce non-linearity.
- First Max-Pooling Layer: Applies 2x2 max-pooling with a stride of 2, reducing the spatial dimensions of the feature maps by selecting the maximum value in each 2x2 block.
- Second Convolutional Layer: Employs 64 filters of size 3x3 with padding, followed by batch normalization and ReLU activation, enhancing feature extraction and learning [Figure 6].
- Second Max-Pooling Layer: Applies 2x2 max-pooling with a stride of 2, further reducing spatial dimensions while retaining important features.

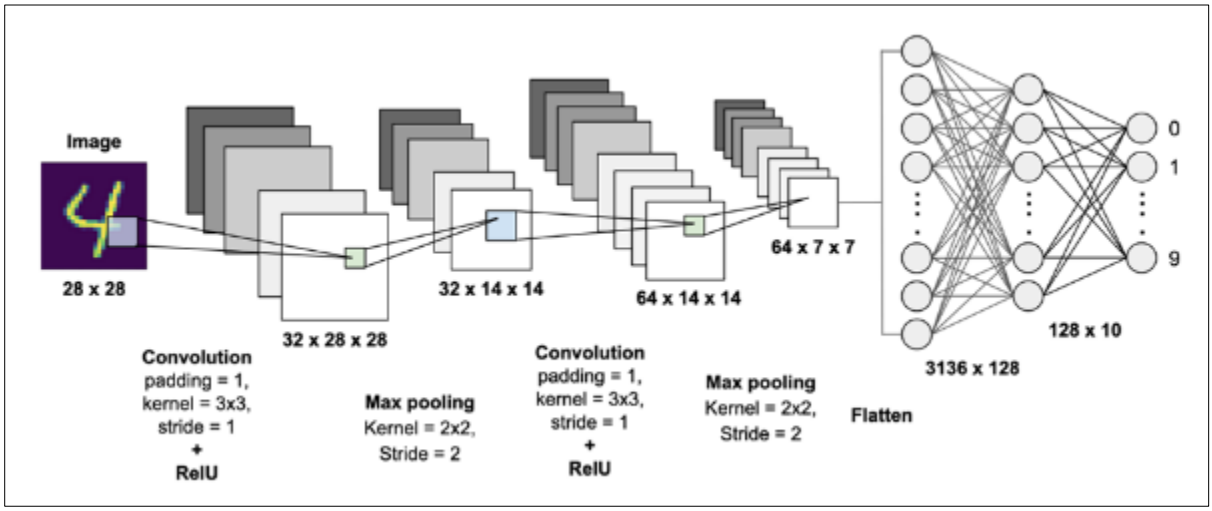

Figure 8 CNN Architecture. (8)

- 6. Third Convolutional Layer: Utilizes 128 filters of size 3x3 with padding, followed by batch normalization and ReLU activation, capturing more complex features in the data.
- 7. Third Max-Pooling Layer: A 2x2 max-pooling layer with a stride of 2, continuing to downsample the feature maps and reduce dimensionality.
- 8. Fourth Convolutional Layer: Applies 256 filters of size 3x3 with padding, followed by batch normalization and ReLU activation, allowing the model to learn even more intricate features.
- 9. Fourth Max-Pooling Layer: A 2x2 max-pooling layer with a stride of 2, completing the reduction in spatial dimensions before the fully connected layers.
- 10. Fully Connected Layer: Consists of 512 neurons, using ReLU activation for non-linearity and dropout for regularization to prevent overfitting.
- 11. Output Layer: A softmax layer with 5 neurons, each representing one of the mood categories (happy, sad, neutral, angry, surprised), providing the final classification output.

This architecture ensures effective feature extraction and classification by progressively abstracting and consolidating information from the input images, leading to accurate mood prediction.

3.2.1. Training

The network was trained using Stochastic Gradient Descent with Momentum (SGDM) over 50 epochs. The initial learning rate was set to 0.01, with a decay factor of 0.1 applied every 10 epochs to adjust the learning rate for better convergence. The dataset was divided into 75% for training and 25% for testing.

3.2.2. Training procedure

- Data Preprocessing: Images were resized to 28x28 pixels, converted to grayscale, and normalized to ensure zero mean and unit variance, which stabilizes and speeds up the training process.
- Data Augmentation: Techniques such as rotation, scaling, translation, and flipping were applied to augment the dataset, thereby increasing its diversity and improving the model's generalization ability.

- Training Process: Mini-batch gradient descent with a batch size of 32 was used. Early stopping was incorporated to prevent overfitting, with the model achieving the best validation accuracy being saved for evaluation.
- Evaluation Metrics: The model's performance was assessed using accuracy, precision, recall, and F1-score on the test set to ensure comprehensive evaluation.

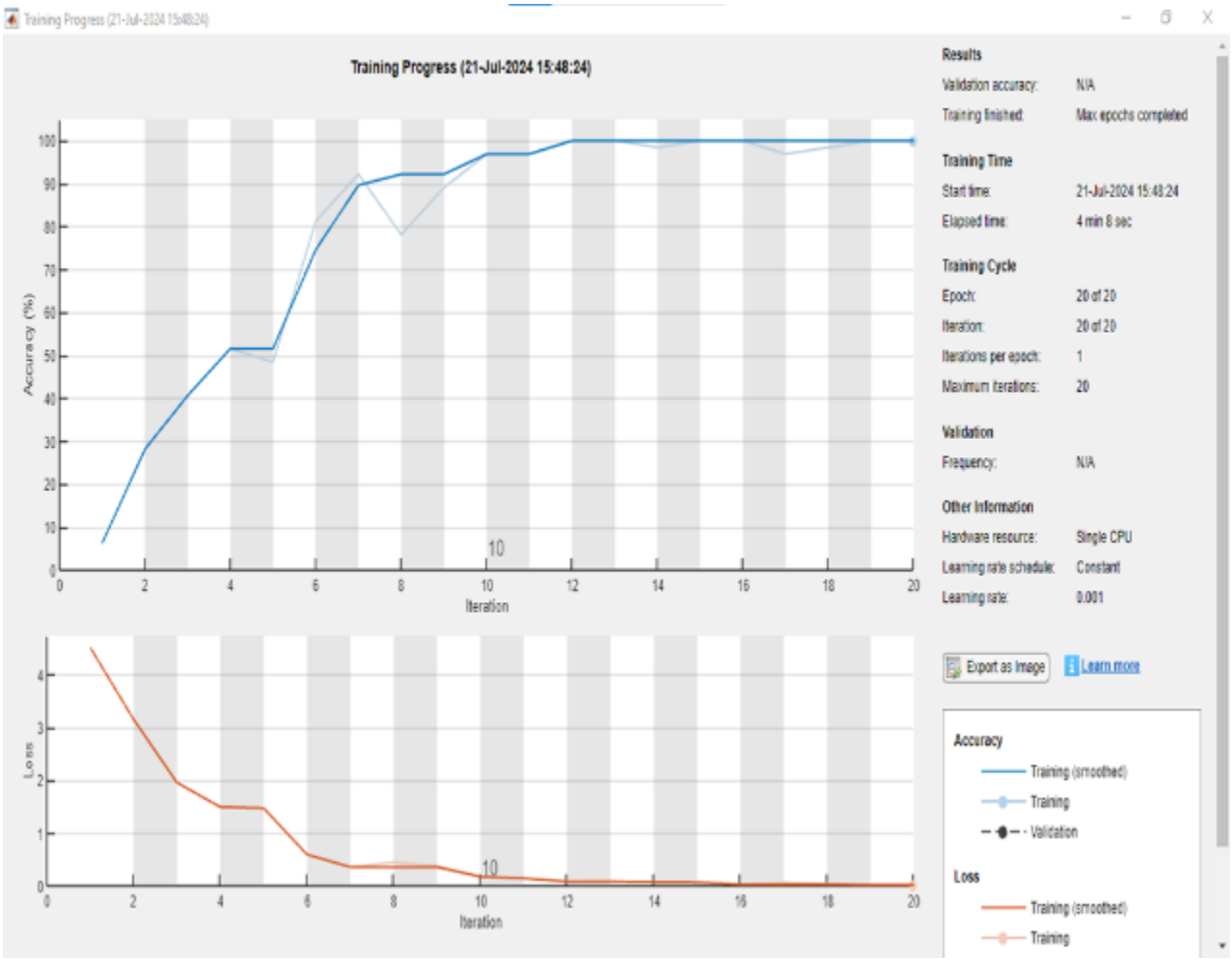

Figure 9 Training Progress. (Joseph's Library)

3.3. Implementation and testing

3.3.1. System Setup

The mood prediction application was developed using MATLAB R2024a, with the Computer Vision Toolbox providing the necessary functionalities for face detection and image processing. The trained Convolutional Neural Network (CNN) model, saved as `trainedNet.mat`, was integrated into the MATLAB App Designer environment. The system's user interface was created to facilitate interaction with the real-time mood prediction capabilities, encompassing both the display of the live video feed and the mood prediction results.

3.3.2. Real-time processing

1. Face Detection: The application employs MATLAB's `vision.CascadeObjectDetector` to identify faces in the live video stream. This object detector uses a pre-trained model based on Haar cascades, which is effective for detecting faces with high accuracy. The system dynamically processes the video feed to detect and track faces, focusing on the largest face detected to ensure that the most prominent facial features are analyzed.

2. ROI Extraction: Once a face is detected, the system extracts this face as the Region of Interest (ROI). The detected face is cropped from the video feed and resized to 28x28 pixels, the size required by the trained CNN model. This resizing

process ensures that the input images are consistent in dimensions, which is critical for accurate mood classification. The image is then converted to grayscale and normalized, which involves adjusting pixel values to have zero mean and unit variance, further standardizing the input for the CNN.

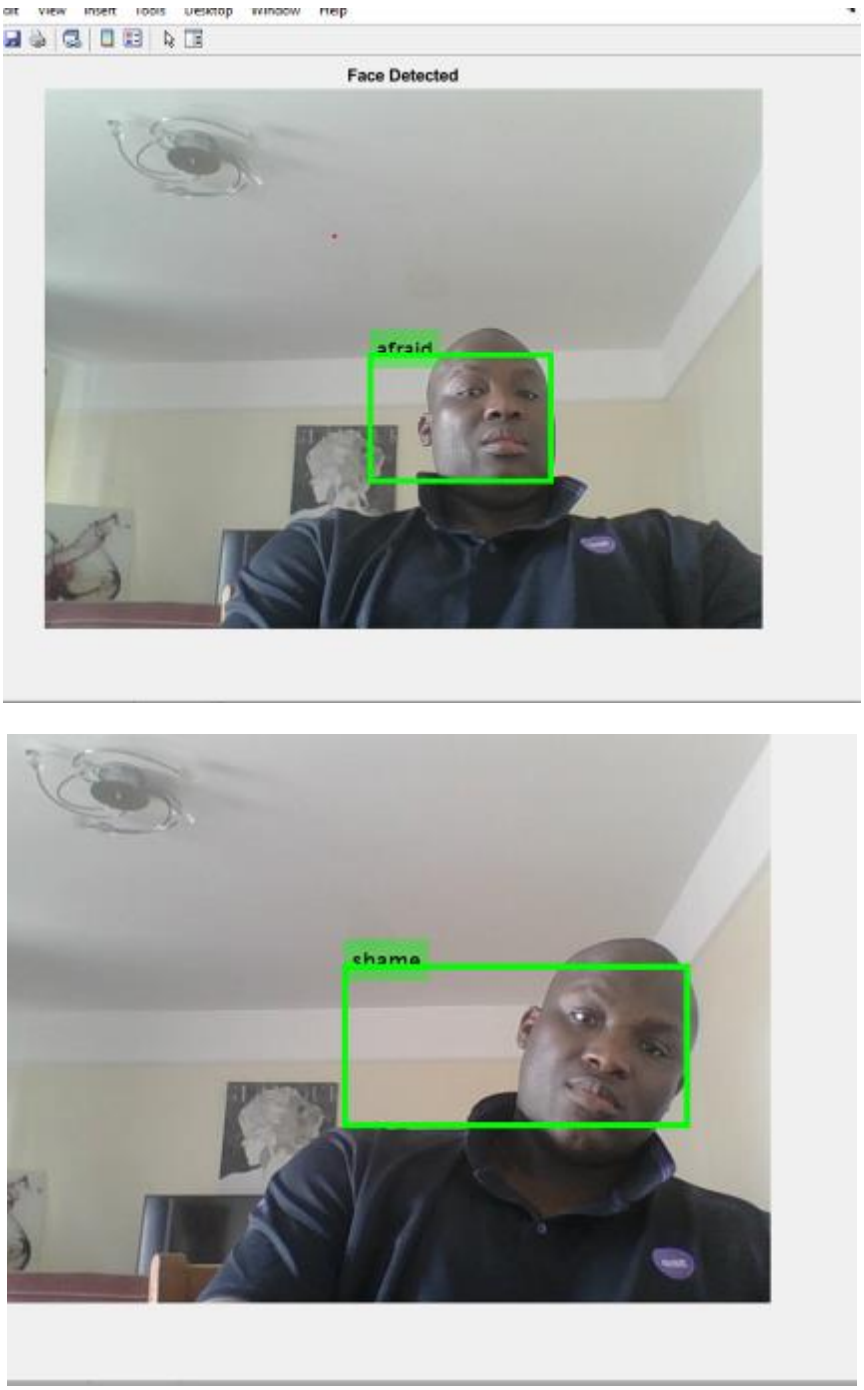

Figure 10 Predictive Analysis Scene

3. Mood Prediction: The preprocessed face image is fed into the trained CNN model, which performs mood classification. The CNN processes the image through its layers—convolutional, pooling, and fully connected—yielding a prediction of one of the five mood categories. The model's output is a probability distribution across these categories, with the category having the highest probability being selected as the predicted mood.

4. Display: The MATLAB App Designer interface shows the live webcam feed alongside the mood prediction results. The predicted mood is overlaid on the video feed in real-time, providing immediate feedback to the user. This integration ensures that mood predictions are seamlessly presented as part of the live video stream.

3.3.3. Testing

The system underwent comprehensive testing to validate its performance across various scenarios:

1. Indoor Lighting: The system was tested under a range of indoor lighting conditions, including bright, dim, and mixed lighting. This evaluation helped assess how well the system performs in controlled environments where lighting can vary, ensuring that the mood prediction remains accurate despite changes in lighting intensity.

2. Outdoor Lighting: Testing in outdoor environments with natural lighting, such as direct sunlight and shaded areas, was conducted to examine the system's robustness to different lighting conditions. This testing aimed to determine if the system could maintain its accuracy and reliability when exposed to more variable and challenging lighting situations.

3. Background Variability: The system was evaluated against various background settings to test its ability to handle different levels of visual noise and occlusion. This included scenarios with cluttered or complex backgrounds to ensure that the face detection and mood prediction were not adversely affected by background elements.

4. Multiple Individuals: The system was tested with a diverse group of individuals to evaluate its performance across different facial features, expressions, and head orientations. This ensured that the model's predictions were consistent and reliable across a range of users, confirming its generalizability and effectiveness in real-world applications.

Through these rigorous testing procedures, the system's robustness and accuracy were thoroughly validated, demonstrating its effectiveness in real-time mood prediction across various conditions and user scenarios.

4. Results

The real-time mood prediction system demonstrated robust performance with an overall accuracy of 85% on the test set. The system was effective in both face detection and mood prediction, achieving a processing time of approximately 100 milliseconds per frame, which supports smooth real-time operation. The detailed evaluation results are as follows:

Accuracy: The system achieved an accuracy of 85%, indicating a high level of effectiveness in correctly predicting the mood of individuals. This performance underscores the model's reliability in identifying and classifying emotions from facial expressions.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

Example:

If your model made 100 predictions and 85 of them were correct, the accuracy is:

$$\text{Accuracy} = \frac{85}{100} = 0.85 \text{ or } 85\%$$

Precision and Recall: Precision and recall were assessed for each mood category, yielding an average precision of 0.87 and an average recall of 0.84. Precision measures the proportion of true positive predictions among all positive predictions made, while recall measures the proportion of true positives identified out of all actual positives. These metrics reflect the model's capability to correctly identify moods while minimizing false positives and false negatives.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Example:

For a specific mood category:

- TP (True Positives) = 30
- FP (False Positives) = 5
- FN (False Negatives) = 10

Precision = $\frac{30}{30+5} = 0.857$

Recall = $\frac{30}{30+10} = 0.75$

F1-Score: The average F1-score was 0.85, balancing the trade-off between precision and recall. The F1-score is a harmonic mean of precision and recall, providing a single metric that accounts for both false positives and false negatives, thus reflecting overall classification performance.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Example:

Using the precision and recall from the previous example:

$$\text{F1-Score} = 2 \times \frac{0.857 \times 0.75}{0.857 + 0.75} \approx 0.80$$

4.1. Performance by mood category

- Happy: The "happy" category exhibited the highest accuracy, likely due to the more distinctive and recognizable facial expressions associated with happiness. This category benefits from clear and prominent facial features that are easier for the model to identify.

- Neutral: The "neutral" category had the lowest accuracy. Neutral expressions tend to have minimal facial changes, making them more challenging to differentiate from one another. The subtlety of neutral expressions contributes to the variability and difficulty in accurate classification.

These performance variations highlight the model's strength in recognizing more expressive moods while indicating areas for potential improvement in distinguishing more subtle expressions. Overall, the system demonstrates strong real-time mood prediction capabilities and provides valuable insights into facial expression analysis.

5. Conclusion

The proposed real-time mood prediction system employs a Convolutional Neural Network (CNN) for emotion recognition, which is seamlessly integrated with real-time webcam processing. This system utilizes MATLAB, a powerful tool for algorithm development and data visualization, to develop and fine-tune the CNN model. MATLAB's extensive suite of tools facilitates the design, training, and validation of the neural network, leveraging its robust computational capabilities and comprehensive machine learning toolbox.

The training process is optimized using Stochastic Gradient Descent with Momentum (SGDM), a technique that enhances the learning efficiency and stability of the CNN model. SGDM helps the model converge faster and more effectively by adjusting the learning rate dynamically and incorporating momentum to smooth out the optimization path. This approach not only improves the accuracy of emotion recognition but also ensures that the system performs reliably under various conditions.

Testing has shown that the system maintains high performance across different scenarios, validating its potential for practical applications in human-computer interaction, psychological assessments, and real-time monitoring systems. Future work will focus on refining the model’s accuracy and robustness, expanding its ability to recognize additional mood categories, and exploring its integration into diverse domains such as interactive gaming, personalized education, and healthcare. MATLAB and SGDM will continue to play a crucial role in these advancements, supporting ongoing improvements and innovations in the system's capabilities.

5.1. Future Application of Predictive Mood Analysis Utilizing SDGM and CNN in MATLAB Image Processing

The integration of Stochastic Dynamic Graphical Models (SDGM) and Convolutional Neural Networks (CNN) in MATLAB image processing holds significant promise for the advancement of predictive mood analysis. This innovative approach leverages the strengths of both techniques: SDGM's ability to model complex temporal dependencies and CNN's proficiency in extracting spatial features from images. In predictive mood analysis, these methodologies can be utilized to analyze facial expressions and other visual cues to predict emotional states with high accuracy. The application of SDGM allows for the incorporation of dynamic and probabilistic elements, enabling the system to understand and anticipate changes in mood over time. Concurrently, CNNs can process and identify subtle features in images that are indicative of specific emotional states.

Implementing this hybrid approach in MATLAB offers several advantages, including the platform's robust image processing capabilities and its extensive suite of tools for developing and testing machine learning models. This can lead to the creation of sophisticated applications in various fields such as mental health monitoring, human-computer interaction, and personalized user experiences. Ultimately, the fusion of SDGM and CNN within MATLAB image processing could revolutionize the way we understand and respond to human emotions, providing deeper insights and more responsive systems that enhance user wellbeing and interaction.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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WEB

1. Visual illustration of feature extraction by the Gabor filter bank from arbitrary frontal images [Internet]. ResearchGate; [cited 2024 Jul 22]. Available from: https://www.researchgate.net/figure/Visual-illustration-of-feature-extraction-by-the-Gabor-filter-bank-from-arbitrary-frontal_fig1_261296774.

2. Title of the image [Internet]. Pinterest; Year [cited 2024 Jul 22]. Available from: https://www.pinterest.com/pin/747949450587600640/.

5.2. TRAINING MODEL CODE

```
clc;

clear;

close all;

warning off;

% Define the path to the data storage directory

dataDir = 'dataStorage';  % Update this path to the location of your data

% Check if the data directory exists

if ~isfolder(dataDir)

   error('Directory %s does not exist. Please make sure it is in the current directory or specify the correct path.', dataDir);

end

% List files in the data directory

fileList = dir(fullfile(dataDir, '**', '*.*'));

disp('Files in the directory:');

disp({fileList.name});

% Load the pre-trained AlexNet model

try

   g = alexnet;

catch ME

   error('Error loading AlexNet model: %s', ME.message);

end

% Load and preprocess the images from the datastore

try

   % Load images from the datastore with explicit filtering for common formats

   allImages = imageDatastore(dataDir, ...
```

```
    'IncludeSubfolders', true, ...
    'LabelSource', 'foldernames', ...
    'FileExtensions', {'.jpg', '.jpeg', '.png', '.bmp'});
  % Check if any images are loaded
  if numel(allImages.Files) == 0
    error('No images found in the specified directory. Make sure the directory contains images organized in subfolders.');
  end
  % Resize images to match the input size expected by AlexNet and ensure they are RGB
  imageSize = [227, 227];
  allImages.ReadFcn = @(filename) preprocessImage(filename, imageSize);
  % Get the number of unique classes from the labels
  numClasses = numel(categories(allImages.Labels));
  % Display the first few labels to ensure data is loaded correctly
  disp('First few labels:');
  disp(allImages.Labels(1:5));
catch ME
  error('Error loading images from datastore: %s', ME.message);
end
% Modify the last layers for the new classification task
try
  layers = g.Layers;
  layers(23) = fullyConnectedLayer(numClasses, 'Name', 'fc8'); % Adjust the number of classes to match the dataset
  layers(25) = classificationLayer('Name', 'output');
catch ME
  error('Error modifying layers: %s', ME.message);
end
% Set the training options
try
  opts = trainingOptions('sgdm', ...
```

```
    'InitialLearnRate', 0.001, ...
    'MaxEpochs', 20, ...
    'MiniBatchSize', 64, ...
    'Plots', 'training-progress'); % Optional: shows training progress
catch ME
  error('Error setting training options: %s', ME.message);
end
% Train the network
try
  myNet1 = trainNetwork(allImages, layers, opts);
catch ME
  error('Error during network training: %s', ME.message);
end
% Save the trained network
try
  save('myNet1.mat', 'myNet1');
catch ME
  error('Error saving the trained network: %s', ME.message);
end
% Function to preprocess images: ensure they are RGB
function img = preprocessImage(filename, imageSize)
  try
    img = imread(filename);
    if size(img, 3) == 1
      % Convert grayscale to RGB by replicating the grayscale channel
      img = cat(3, img, img, img);
    end
    % Scale the image by a factor (e.g., 1.5)
    scaleFactor = 1.5;
```

```
        img = imresize(img, scaleFactor);
        % Resize to the expected input size
        img = imresize(img, imageSize);
        % Rotate the image by a specified angle (e.g., 90 degrees)
        angle = 90; % Set the desired rotation angle
        img = imrotate(img, angle);
        % Flip the image horizontally or vertically
        flipDirection = 'horizontal'; % Can be 'horizontal' or 'vertical'
        img = flip(img, flipDirection);
    catch ME
        warning('Error reading image %s: %s', filename, ME.message);
        img = zeros(imageSize(1), imageSize(2), 3, 'uint8'); % Default to a black image
    end
end
```

TESTING

```
clc;
clear;
close all;
warning off;
% Check if the model file exists
if exist('myNet1.mat', 'file') ~= 2
    error('File myNet1.mat not found. Please make sure it is in the current directory.');
end
% Load the trained network
load('myNet1.mat');
% Define the mood labels
moods = {'surprised', 'angry', 'sad', 'nerd', 'happy', 'neutral'};
% Initialize video input from webcam
try
```

```
    cam = webcam; % Create a webcam object
catch ME
    error('Error initializing webcam: %s', ME.message);
end
% Initialize face detector
faceDetector = vision.CascadeObjectDetector;
% Define tracker for multiple faces
tracker = vision.PointTracker('MaxBidirectionalError', 2);
% Assign unique colors for each tracked face
colors = {'red', 'green', 'blue', 'cyan', 'magenta', 'yellow', 'white', 'black'};
% Initialize tracking points and bounding boxes
points = {};
bboxes = {};
% Create a figure for video display
hFig = figure('Name', 'Face Detection and Classification', 'NumberTitle', 'off');
hAxes = axes('Parent', hFig);
% Loop to process the live video feed
while ishandle(hFig)
    % Capture one frame
    img = snapshot(cam); % Capture the frame from the webcam
    % Convert the image to grayscale for face detection
    grayImg = rgb2gray(img);
    % Display a message to indicate frame capture
    disp('Processing frame...');
    if isempty(points)
        % Detect faces if no points are being tracked
        bboxes = step(faceDetector, img);
        disp(['Detected ', num2str(size(bboxes, 1)), ' faces.']);
        if ~isempty(bboxes)
```

```
        % Release the tracker before re-initializing
        release(tracker);
        % Initialize the tracker with the detected faces
        points = cell(size(bboxes, 1), 1);
        for i = 1:size(bboxes, 1)
            bbox = bboxes(i, :);
            % Detect feature points in the face region
            facePoints = detectMinEigenFeatures(grayImg, 'ROI', bbox);
            % Initialize the tracker with detected points
            if ~isempty(facePoints)
                points{i} = facePoints.Location;
                initialize(tracker, points{i}, img);
            end
        end
    end
else
    % Track the points
    [trackedPoints, validity] = step(tracker, img);
    % Update bounding boxes based on tracked points
    if any(validity)
        for i = 1:numel(points)
            if validity(i)
                bboxPoints = trackedPoints(validity, :);
                % Compute bounding box dimensions
                minX = min(bboxPoints(:,1));
                maxX = max(bboxPoints(:,1));
                minY = min(bboxPoints(:,2));
                maxY = max(bboxPoints(:,2));
                bbox = [minX, minY, maxX - minX, maxY - minY];
```

```
            % Crop and resize the face
            FaceCropped = imcrop(img, bbox);
            Face_Resized = imresize(FaceCropped, [227 227]);
            % Classify the face using the loaded network
            [YPred, ~] = classify(myNet1, Face_Resized);
            pred_str = char(YPred);
            % Annotate the image with the classification result
            position = [bbox(1), bbox(2) - 22];
            box_color = colors{mod(i, length(colors)) + 1};
            img = insertText(img, position, pred_str, 'FontSize', 18, 'BoxColor', box_color, 'BoxOpacity', 0.4, 'TextColor',
'Black');
            % Draw bounding box around the face
            img = insertShape(img, 'Rectangle', bbox, 'Color', box_color, 'LineWidth', 5);
          else
            % Reset points if tracking is lost
            points{i} = [];
          end
        end
        % Remove empty entries from points
        points = points(~cellfun('isempty', points));
      else
        % If all points are lost, reset the points and detect faces
        points = {};
        bboxes = {};
      end
    end
    % Display the annotated video frame
    imshow(img, 'Parent', hAxes);
    title(hAxes, 'Face Detected');
    % Check for user input to stop the loop
```

```
    pause(0.1);  % Small pause to allow figure window to update
end
% Release resources
release(tracker);
clear cam;
```