Cairo University
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Pattern Recognition

Hand Gesture Recognition

Submitted to

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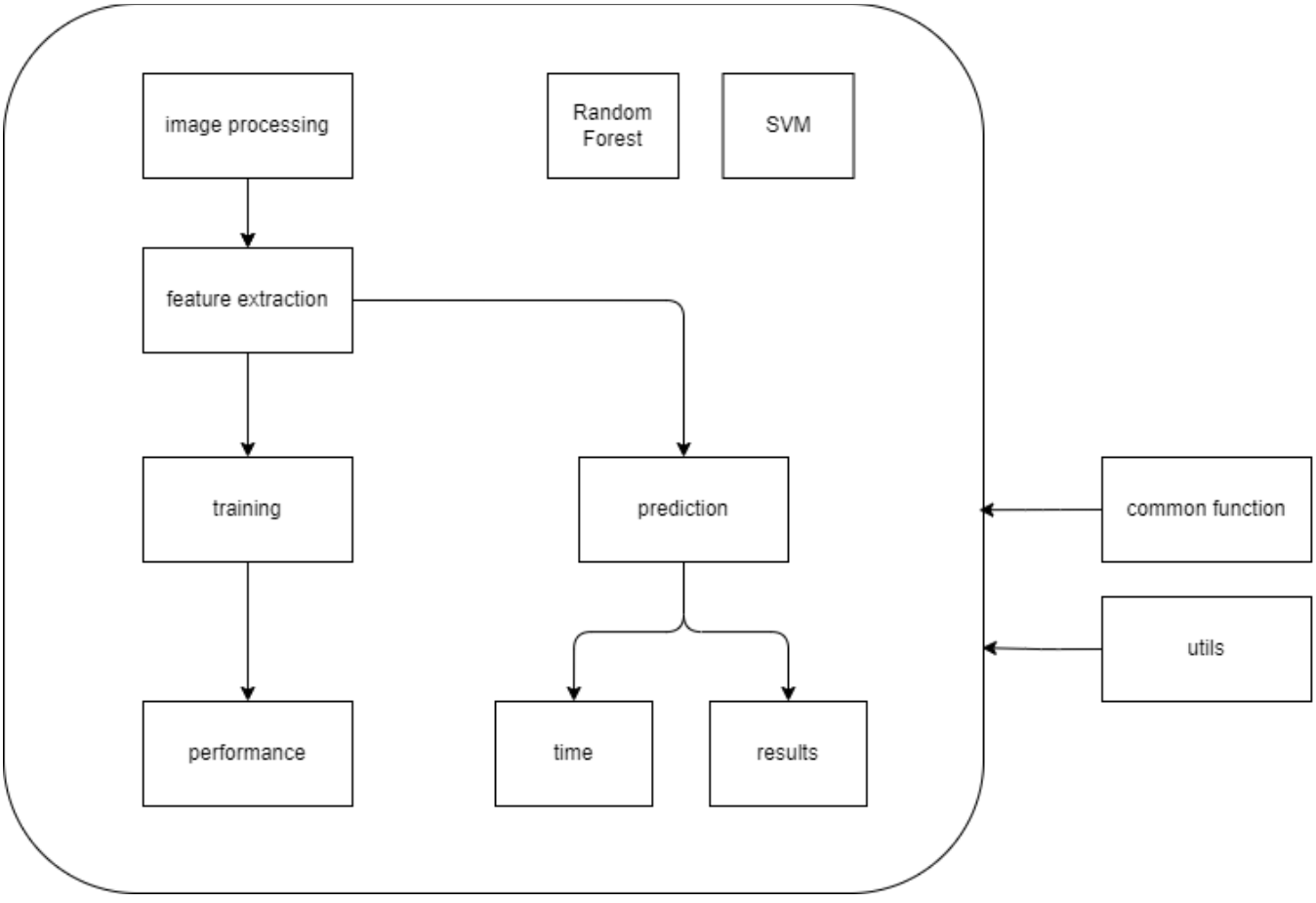
Work distribution:

Ahmed Hosny	**SVM** **HOG – LBP** **Tunning modules**
Ahmed Madbouly	**Image processing**
Eman Shahda	**Random Forest** **Shi Thomas** **Voting Algorithm**
Nour Ziad	**ML Pipeline** **ORB – SIFT** **Voting algorithm**

Project Pipeline:



Our machine learning pipeline consists of the following steps:

Data preprocessing: The raw data is preprocessed to prepare it for machine learning. This includes tasks such as cleaning the data, removing background, handling missing values, and transforming the data into a format that can be used by the machine learning algorithm.

Feature engineering: Feature engineering involves selecting and transforming the relevant features in the data that are most predictive of the target variable. This can include techniques such as dimensionality reduction, scaling, and normalization.

Model selection: Once the data is preprocessed and the features are engineered, the next step is to select an appropriate machine learning algorithm for the task at hand. This can include techniques such as decision trees, random forests, support vector machines, or neural networks.

Model training: The selected machine learning algorithm is then trained on the preprocessed data and the engineered features. This involves adjusting the parameters of the algorithm to minimize the error between the predicted and actual values.

Model evaluation: Once the model is trained, it is evaluated on a separate test set to assess its performance. This involves calculating metrics such as accuracy, precision, recall, and F1 score. Also calculating the confusion matrix on the test set

How To Run:

you can use run.bat file to run the code with the following configuration

run (pip install -r requirements.txt) to install all required packages

if you want to train new model

==> run.bat 1 --path_of_dataset --model_name_to_save --debug_flag

if you want to test on given model

==> run.bat 2 --path_to_testset --model_name_to_run --debug_flag

Preprocessing module:

The **image_pre_processing** function is the main function that performs the image preprocessing steps. It takes an input image as a parameter and returns the preprocessed result.

1. Resizing: The input image is first resized to a smaller size to make the preprocessing faster and take less time while maintaining its aspect ratio.
2. Brightness Calculation: The algorithm calculates the average brightness of the resized image. This value is used to determine which method to use for binary conversion in the next step.
3. Binary Conversion: Based on the calculated brightness value, the algorithm decides whether to use a "high contrast" or "low/medium contrast" binary conversion method.
    - If the average brightness is high, indicating a well-lit image, the algorithm applies a "high contrast" binary conversion method. It converts the image to a different color space(YUV), enhances the contrast using histogram equalization, and applies a thresholding operation to obtain a binary image.
    - If the average brightness is low to medium, indicating a darker image, the algorithm uses a "low/medium contrast" binary conversion method. It converts the image to a different color space, applies thresholding operations, and performs morphological operations (such as erosion and dilation) to refine the binary image.
4. Edge detection: to perform this step firstly we reduce the size of the image a bit to avoid dealing with the whole image as an one contour , then blur the image to remove noise , finally apply canny edge detection
5. Contour Extraction: The algorithm extracts the contours from the binary image. Contours represent the boundaries of objects or regions of interest in the image. This step helps in isolating and segmenting important features.
6. Filtering and Smoothing: The algorithm applies filters and smoothing techniques to reduce noise and refine the extracted contours. This step helps to remove any unwanted artifacts and improve the overall quality of the image.
7. Result Generation: Finally, the algorithm generates the preprocessed result. It applies additional filtering or transformations to enhance the image quality.

The resulting image is typically resized to a standardized size for consistency and compatibility with further analysis or processing tasks.

By performing these preprocessing steps, the algorithm aims to enhance the quality of the input image, improve contrast and clarity, and extract meaningful features.

Feature Extraction/Selection Module:

Hog Transform is a feature extraction technique

. Here's a breakdown of the parameters used in the hog_features function:

orientations: This parameter specifies the number of gradient orientation bins to use when calculating the histogram for each cell. In this case, orientations=6 means that the gradients will be quantized into 6 orientation bins.

pixels_per_cell: This parameter specifies the size of each cell in pixels. In this case, pixels_per_cell=(16, 16) means that each cell will be 16 pixels wide and 16 pixels tall.

cells_per_block: This parameter specifies the number of cells per block. In this case, cells_per_block=(3, 3) means that each block will be 3 cells wide and 3 cells tall.

The hog_features function likely takes in the image as input and returns a feature vector that represents the image. The feature vector is likely calculated by following the steps I mentioned in my previous answer, including gradient computation, cell formation, histogram calculation, block normalization, and feature vector concatenation.

Model Selection/Training Module:

SVM: this code creates an SVM object with a polynomial kernel of degree 4 and a low regularization parameter, which may result in a more generalized model. The coef0 parameter is set to 1, which gives more importance to higher-degree polynomials. The gamma parameter is set to 0.1, which may result in a more complex decision boundary that is sensitive to changes in the input data. The random_state parameter is set to 0 to ensure reproducibility of the results.

Model parameter:

kernel='poly': This specifies that the SVM should use a polynomial kernel function.

C=0.1: This is the regularization parameter, which controls the trade-off between minimizing the training error and minimizing the complexity of the model. A smaller value of C results in a more regularized model that prefers simpler decision boundaries.

random_state=0: This is the random seed used by the random number generator. Setting a fixed value for random_state ensures that the results are reproducible.

coef0=1: This is a parameter that determines the importance of high-degree polynomials in the kernel function. A higher value of coef0 gives more importance to higher-degree polynomials.

degree=4: This is the degree of the polynomial kernel function. A higher value of degree allows the SVM to fit more complex decision boundaries.

gamma=0.1: This is a parameter that controls the sensitivity of the SVM to changes in the input data. A smaller value of gamma results in a smoother decision boundary.

Random Forest: we also created a random forest classifier object with 100 decision trees and a fixed random seed of 0. The RandomForestClassifier() function also has other optional parameters that can be used to further customize the random forest, such as max_depth to control the depth of the decision trees, max_features to control the number of features considered for each split, and criterion to specify the function used to measure the quality of each split.

Model parameter:

n_estimators=100: This is the number of decision trees to create in the random forest. A higher value of n_estimators typically results in better performance, but also increases the computational cost. The default value is 100.

random_state=0: This is the random seed used by the random number generator. Setting a fixed value for random_state ensures that the results are reproducible.

Voting Algorithm:

voting classifier using three different base classifiers - K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF) - and returns the trained voting classifier. Here's a breakdown of the code:

The function takes two arguments - Xtrain and ytrain - which are the training data and corresponding labels, respectively.

Three different base classifiers are defined and initialized with specific hyperparameters. The KNeighborsClassifier is set with 5 neighbors, the SVC uses a polynomial kernel, has a regularization parameter of 0.1, a degree of 4, a gamma value of 10.0, and is set to use probability estimates. The RandomForestClassifier uses 100 trees, with no maximum depth, a minimum number of samples per leaf of 1, and a minimum number of samples per split of 5.

A VotingClassifier is initialized with the three base classifiers as its estimators. The voting parameter is set to 'soft', which means the predicted probabilities of each classifier are used to calculate an average probability for the final prediction.

The fit method is called on the VotingClassifier object, passing in the training data and labels to train the model.

The trained VotingClassifier object is returned from the function.

The commented out lines at the end of the code show how to make predictions using the trained model and calculate the accuracy of the predictions.

Performance Analysis Module:

for performance analysis model we used many approaches to calculate the model performance

Confusion Matrix: This is a table that is often used to evaluate the performance of a classification model. It is a matrix that summarizes the actual and predicted classifications made by a classifier on a set of test data. A confusion matrix displays the number of instances that are correctly and incorrectly classified by the classifier, organized by true class and predicted class.

Accuracy: This metric measures the proportion of correctly classified instances out of all instances. It is calculated as (TP + TN) / (TP + TN + FP + FN), where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives.

Precision: This metric measures the proportion of true positives out of all predicted positives. It is calculated as TP / (TP + FP).

Recall: This metric measures the proportion of true positives out of all actual positives. It is calculated as TP / (TP + FN).

F1 score: This metric is the harmonic mean of precision and recall and is a good measure of overall performance. It is calculated as 2 * (precision * recall) / (precision + recall).

Enhancements and Future work:

Hand gesture recognition is an important application of computer vision and has various potential applications, such as in virtual reality, robotics, and human-computer interaction. Here are some possible enhancements and future work that can be done in the field of hand gesture recognition:

Improvement on image processing: so that we can decrease the noise and extracted purely the hand of the image such that we can use another feature extraction techniques like shi-thomas which highly affected by noise or any miss detection in the background, or even sift which doesn't get affected by scaling or orientation

Improvement of classifier model: we can combine more than a classifier to get a larger accuracy value (code sample provided in combine.py)

Improvement of accuracy: One of the main challenges in hand gesture recognition is achieving high accuracy, especially for complex gestures with subtle variations. Future work can focus on developing more accurate algorithms by using advanced machine learning techniques such as deep learning and convolutional neural networks.

Real-time gesture recognition: Real-time gesture recognition is important for many applications, such as gaming and virtual reality. Future work can focus on developing algorithms that can recognize gestures in real-time using efficient algorithms and hardware.

Robustness to lighting and background variations: Hand gesture recognition systems can be affected by variations in lighting and background, which can lead to incorrect classification. Future work can focus on developing algorithms that are robust to lighting and background variations by using advanced image processing techniques.

Gesture recognition for sign language: Hand gesture recognition can be used for sign language recognition, which can help improve communication for the hearing-impaired.

Future work can focus on developing algorithms that can recognize sign language gestures with high accuracy.

Gesture recognition for robotics: Hand gesture recognition can be used for controlling robots and other devices. Future work can focus on developing algorithms that can recognize hand gestures and translate them into commands for controlling robotic devices.