the sensitive measure, in which more information is included

III. PROPOSED HAND GESTURE RECOGNITION METHOD

The general block scheme of hand gesture recognition includes the following components, which are static hand gesture dataset, binary and skeleton image formation, feature labeling and extraction, classifier models, and performance evaluation. This general blcok-scheme is presented in Fig. 1, all major components are marked with green color.

Static hand gesture images are stored in the images dataset. They are used to train the classifier and evaluate the accuracy of the classification task. These RGB images of hand gestures are first passed into a block that can form the binary and skeleton images from them. All the proposed skeletonization and denoise methods are embedded in this block.

Next, feature extraction is conducted based on these obtained binary and skeleton images. For each pair of binary image and skeletal image, there are nine geometry features should be extracted, and they together compose a feature vector. Next, manual labeling for each pair of binary and skeleton images is also required to get the truth labels that corresponding to each feature vector. These feature vector can passed to the trained classifier for prediction. By comparing the predicted label and the truth label to compute the accuracy. In the classification module, there are six different well-known classifiers for optional, which includes decision tree(DT) [31], knearest neighbors (KNN) [32], naïve Bayes (NB) [33], support vector machine (SVM) [34], ensemble learning (EL) [35], multilayer perceptron (MLP) [36].

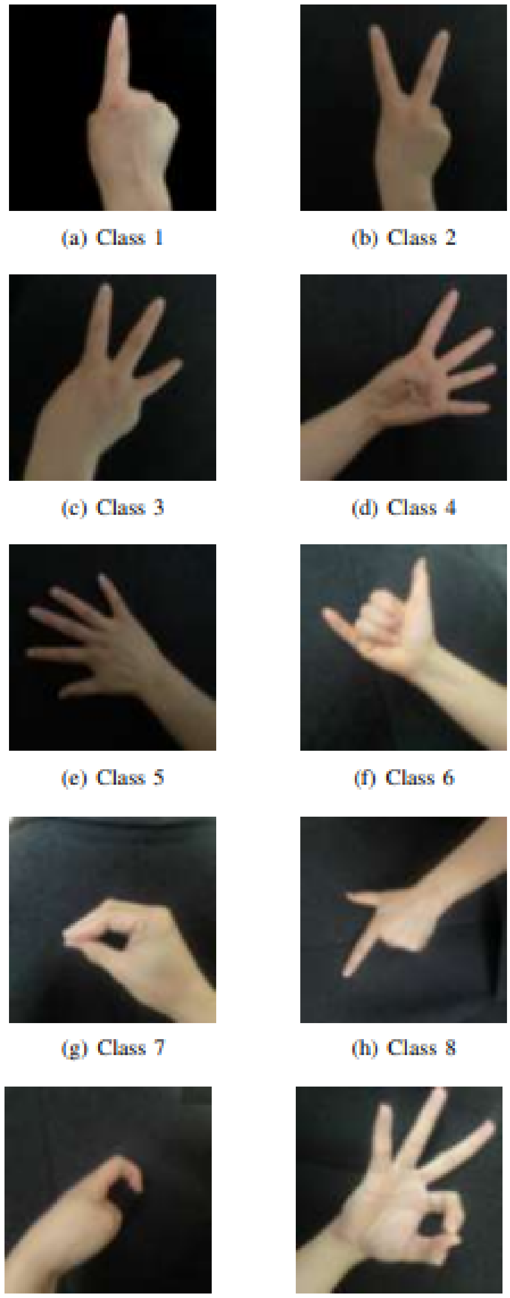
A. *Creation of the Hand Gesture Dataset*

All static hand gesture images that in dataset are captured with the iPhone 11. The resolution of images are $3024 \times 3024 \times 3$. Since directly processing these images is time-consuming, resize operation is used to converting these images into $95 \times 95 \times 3$ images. The dataset consists of ten different classes, example pictures are shown in Fig. 2.

In each one class, there are more than 100 different images. As a result, the total amount of our dataset is over 1000 images. These images are randomly divided into train-validation group and testing group. The number of images in testing group is equal to 20% of the initial image set, and the number of images in train-validation group is 80% of the initial image set.

B. *Forming Binary Image and Skeleton Image using Hybrid Combining Denoising Techniques and Skeletonization Methods*

The skeleton and pattern images are extracted from the original images by using different combinations of



(a) Class 1 (b) Class 2 (c) Class 3 (d) Class 4 (e) Class 5 (f) Class 6 (g) Class 7 (h) Class 8 (i) Class 9 (j) Class 10

Figure 1: Example of the Ten Class of Hand Gestures.

skeletonization method and denoise methods . There are six hybrid methods are used, which including ZS+ATFM, OPTA+ATFM, OPCA+ATFM, ZSM+ATFM, MOPCA+ATFM, and MOPCA+ATFM+DCEM. The time consumption of these methods is listed in Tab. I.

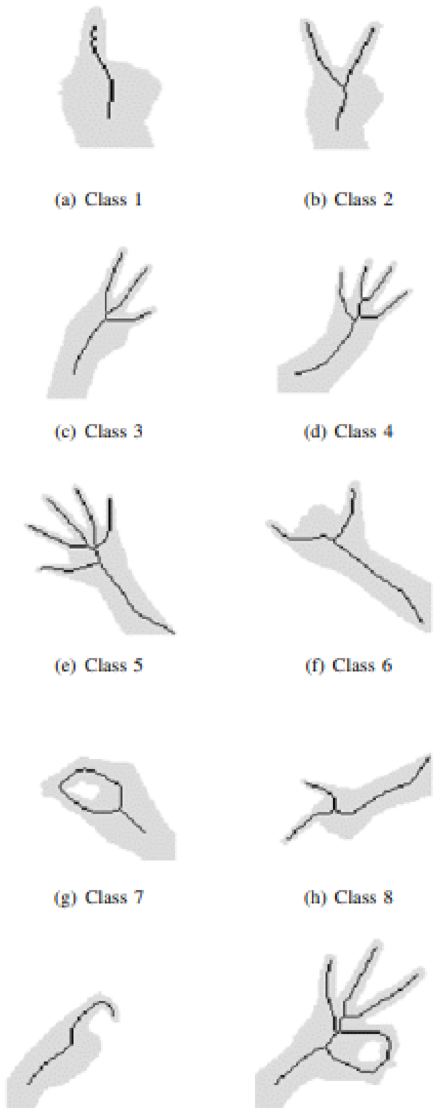
From Tab. I, it is noted that ZS+ATFM, OPTA+ATFM, ZSM+ATFM, MOPCA+ATFM, and MOPCA+ATFM+DCEM respectively spend more 38%, 22%, 33%, 0.4%, and 5% time when compared with the method of OPTA+ATFM. Besides, we can learned the use of DCEM may take extra 0.02 seconds.

In Fig. 3, we listed example skeletons extracted from

Table 1:
TIME CONSUMPTION OF SIX METHODS

Skeleton Image Extract algorithm	Average Time of
ZS+ATFM	0.704
OPTA+ATFM	0.624
OPCA+ATFM	0.510
ZSM+ATFM	0.682
MOPCA+ATFM	0.512
MOPCA+ATFM+DCEM	0.536

he images that are shown in Fig 2 by using the skeletonization method MOPCA with both ATFM and DCEM.



(a) Class 1 (b) Class 2 (c) Class 3 (d) Class 4 (e) Class 5 (f) Class 6 (g) Class 7 (h) Class 8 (i) Class 9 (j) Class 10

Figure 2: Skeleton examples of ten hand gesture classes.

C. *Feature extraction based on Skeleton and Binary Images*

After a skeletal image and its pattern image are obtained from an input image, it is necessary to transform the skeletal images along with its pattern image to a 9-dimension feature vector used in the later classification. This 9-dimension vector includes the following significant geometrical features: the number of endpoints (NEP); the number of cross points (NCP); the existence of the inner hole (EIH); the average virtual-real distance rate between each pair of endpoints (AVRD); the number of virtual cross points (NVCP); Rate of the deviation of the thick of the endpoints (RDTE); Average distance between the thickest point in a pattern image and each endpoint in the skeletal image(ADTPE); distance between pattern thickest point and skeletal thickest point (DPSP); average angle of the endpoint (AAEP). Each dimension of this feature vector is manually selected with respect to the topology of these different classes.

The NEP is obtained by summarizing the number of these foreground pixels, which have only one neighbor foreground pixel in its 8-neighborhood window in the skeletal image.

The NCP is obtained by summarizing the number of these foreground pixels, which have more than two neighbor foreground pixels in its 8-neighborhood window in the skeletal image.

The EIH is an important geometry feature with only two values, 0 or 1. The inner hole denotes that the hole should be enclosed by the skeleton. Ideally, only Class 7 and Class 10 have the inner hole. One method to judge the existence of the inner hole for these hand images is to compute the number of closed areas in the skeleton image.

The AVRD describes the similarity of the real connecting line between endpoints to the virtual closet straight line between them. For each pair of endpoints, the real connecting line and its distance can be obtained using breadth-first search (BFS) algorithms, and the distance of the virtual line is calculated using the Euclidean distance formula. Then the average value is easily obtained.

The NVCP is obtained by summarizing the total number of points at the intersection of the virtual line and the real line.

Before presenting the definition of RDTE, ADTPE, and DPSP, the concept of thickness is first introduced. The thickness of a pixel is defined by the distance between this pixel and its closest pixel located on the boundary in the pattern image. Boundary pixels comprise the foreground pixel, whose four neighbors have at least one background pixel.

For a given skeleton with n endpoints, all endpoints can form a set SEP , in which the i-th endpoint is denoted as SEPi . The thickness of SEPi can be denoted as TEPi . The set formed by all TEPi is denoted as TSEP . Then,

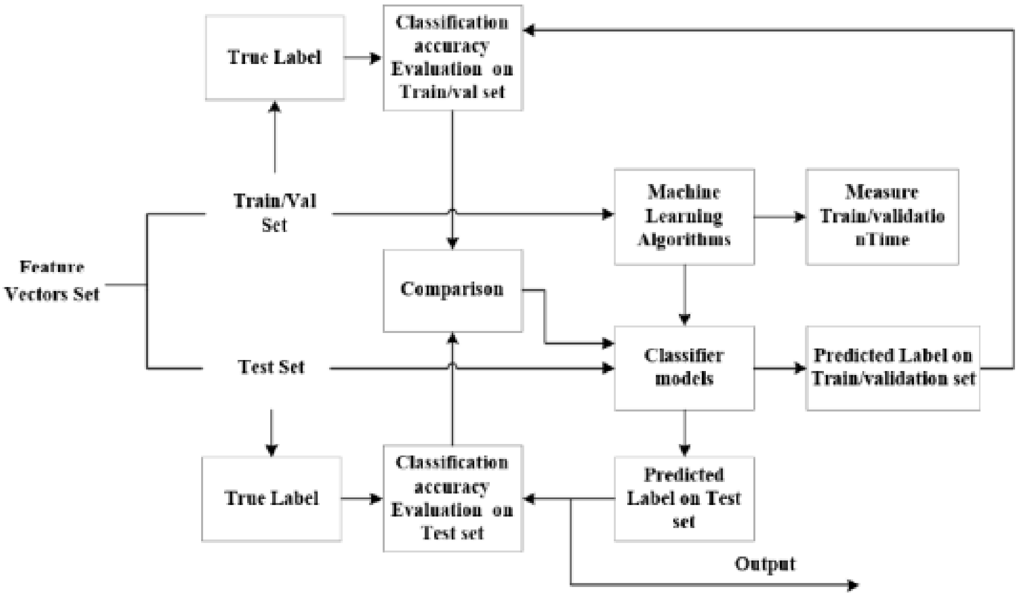


Figure 3: Classification Models and Performance Evaluation.

the RDTE for this skeleton can be computed by using the following formula

$$\text{RDTE} = \begin{cases} 0 & n \leq 1 \\ \sum_i^n \sqrt{\frac{(T_{EP_i} - \frac{1}{n}\sum_i^n T_{EP_i})^2}{\max(T_{S_{EP}}) - \min(T_{S_{EP}})}} & n > 1 \end{cases}$$

We suppose the coordinates of the thickest pixel in the pattern image are Px and Py, and its thickness is Tp. We suppose that in a skeletal image, there are n endpoints. The coordinates of the i-th endpoint are denoted as EPix and EPiy . Then, the ADTPE can be calculated by using the following formula:

$$\text{AMDTE} = \begin{cases} 0 & n \leq 1 \\ \sum_i^n \sqrt{\frac{(T_{EP_i} - \frac{1}{n}\sum_i^n T_{EP_i})^2}{\max(T_{S_{EP}}) - \min(T_{S_{EP}})}} & n > 1 \end{cases}$$

Supposing the coordinate of the thickest pixel in the pattern image is Px and Py, and the coordinate of the thickest pixel in the skeletal image is Sx and Sy, the DPSP can be calculated according to the following formula:

$$\text{DPSP} = \sqrt{(P_x - S_x)^2 + (P_y - S_y)^2}$$

Before obtaining the value of the AAEP, the main axis is defined by the thickest point in the pattern image and the farthest endpoint in the skeletal image from that point. Based on that, it is easy to calculate the relative angle of the remaining endpoint to these axes, and the AAEP is the mean of these angles. If the number of endpoints is less than 2, the AAEP is set as 0.

D. *Classifier Models and Performance Evaluation*

The obtained feature vectors of the images from the training set of the dataset and their labels are passed to classifiers metioned, then conduct the learning process. The hyperparameter of these classifiers is listed in Tab. II.

Then, the classifier's learning result are evaluated by considering the accuracy of these classifiers on the test set.

Here, our aim is to explore the relationship between the accuracy of the classifiers and the different skeleton extracted by different methods, the relationship between the accuracy of the classifiers, and the difference in the feature selection. In addition, we also study the difference between distinct classifiers and their performance under a different number of classes. The general block diagram is shown in Fig. 4.

There are many criteria to evaluate the classifier's performance, such as accuracy, F1, precision, recall, roc, and so on. Here, we only take accuracy as the evaluation criteria for simplification. The formula of accuracy is described in the following:

$$\text{Accuracy} = \sum_i^m I(x_i; y_i)$$

$$\text{I}(\text{x}_i; y_i) = \begin{cases} 1 & f(x_i) = y_i \\ 0 & f(x_i) \neq y_i \end{cases}$$