Table II
HYPERPARAMETER OF DIFFERENT CLASSIFIERS

Classifier	**Hyperparameter**	**Setting**
DT	Maximum number of splits	100
	Split criterion	Gini
KNN	Number of neighbors	1
	Distance metric	Euclideam
	Distance weight	Equal
NB	Kernal Type	Gaussian
SVM	Kernal Type	Quadratic
	Box constraint level	1
	Kernel scale mode	Auto
EL	Ensemble Method	Bagged Trees
	Learning Type	Decision Tree
	Maximum number of splits	99
	Number of learners	30
	Learning rate	0.1
	Subspace dimension	1
MLP	Number of fully connected layers	1
	Layer size	25
	Activation	Relu
	Iteration limit	1000

Where m is the number of the pair of feature vectors x and its corresponding true label y. $f(x)$ is predicted label for feature vector x

IV. EXPERIMENTAL RESULTS

Two separate experiments are conducted for the purpose of evaluating the performance of the proposed recognition method. In the first experiment, the recognition experiment is conducted on five hand gesture classes, which include Class 1 to Class 5. Whereas in the second experiment, the recognition experiment is conducted on all ten hand gesture classes.

A. Performance evaluation of static hand gesture Classification for five classes

In order to explore the influence of the features on the classification task for five classes, an experiment of the feature selection has been conducted based on the classifiers of KNN and SVM, in which we removed one feature from the feature vector and conducted the classification task by using remaining features. Experimental results are shown in Tab. III.

Table III
CLASSIFICATION ACCURACY COMPARISON FOR 8 AND 9 FEATURES AND 5 CLASSES

Feature Deleted	**Classification Accuracy**			
	Train/Validation Set		**Test Set**	
	KNN	**SVM**	**KNN**	**SVM**
NEP	92.30%	97.00%	88.80%	97.80%
NCP	93.80%	97.90%	90.30%	98.50%
EIH	94.80%	97.60%	94.00%	99.30%
AVRD	94.40%	97.20%	94.00%	99.30%
RDTE	95.30%	97.90%	92.50%	99.30%
NVCP	96.40%	97.90%	96.30%	99.30%
ADTPE	95.90%	97.40%	97.00%	99.30%
DPSP	94.40%	97.40%	97.00%	99.30%
AAEP	94.60%	97.40%	94.80%	99.30%
Full Features	99.40%	97.80%	94.00%	99.30%

From Table III, it is clear that the deletion of the NEP or the deletion of NCP may decrease the accuracy of the classification result in both KNN and SVM. Deleting the NVCP, ADTPE, and AAEP may improve the accuracy of the KNN classification, whereas deleting them may not change the performance of the SVM classification. The reason for that is the KNN classifier used in our experiment only considers the closest neighbors.

Next, the influence of the different skeleton extractions on the accuracy of all six classifiers is also studied. The results are shown in Tab. IV and Tab. V.

From Tab. IV and Tab. V, it is obvious that skeletonization methods can affect the accuracy of the classification. Among the methods with ATFM denoise operation, the proposed three skeletonization methods: ZSM, OPCA, and MOPCA, have higher accuracy of classification over ZS and OPTA in all six classifiers, in which the MOPCA has the highest average accuracy, which is 96.15% and 97.17% on the validation set and testing set respectively.

In addition, the denoising methods influence the performance of classification. For example, we can see that the average accuracy of MOPCA with ATFM+DCEM is 96.67% and 97.55% on the validation and testing sets, respectively, which is 2% higher than that of MOPCA with ATFM

From the perspective of the classifiers, the decision tree and ensemble learning are the top two best classifiers in the task of five classes classification on all skeletons extracted by different methods, which have up to 98.5% and up to 98.3% accuracy on the validation set, respectively. For the testing set, both have up to 100% accuracy of classification. In contrast, the naïve Bayes has the worst performance in terms of accuracy, which has only

Table IV
CLASSIFICATION ACCURACY EVALUATION ON TRAIN/VALIDATION SET THAT HAS 5 DIFFERENT CLASSES

Classifier Models	ZS+ ATFM	OPTA+ ATEM	ZSM+ ATFM	OPCA+ ATFM	MOPCA+ ATFM	MOPCA+ATFM +DCEM
DT	88.4%	82.4%	93.0%	92.9%	97.4%	98.5%
NB	73.6%	73.8%	87.3%	87.5%	96.6%	95.7%
SVM	86.2%	78.5%	93.1%	87.3%	96.8%	97.8%
KNN	81.5%	71.8%	87.9%	83.6%	93.2%	94.4%
EL	90.7%	83.7%	95.5%	97.3%	97.3%	98.3%
MLP	85.4%	74.0%	88.4%	83.0%	95.6%	96.3%
Mean	84.3%	77.3%	90.8%	86.8%	96.1%	96.6%

Table V
CLASSIFICATION ACCURACY EVALUATION ON TEST SET THAT HAS 5 DIFFERENT CLASSES

Classifier Models	ZS+ ATFM	OPTA+ ATEM	ZSM+ ATFM	OPCA+ ATFM	MOPCA+ ATFM	MOPCA+ATFM +DCEM
DT	85.8%	82.1%	93.3%	94.0%	96.3%	100.0%
NB	79.9%	75.4%	86.6%	82.8%	95.8%	94.0%
SVM	90.3%	78.4%	91.8%	86.6%	97.0%	99.3%
KNN	85.1%	75.4%	86.6%	82.8%	97.8%	94.0%
EL	90.3%	82.8%	93.3%	94.0%	98.3%	100.0%
MLP	85.1%	68.7%	82.8%	88.1%	97.8%	98.0%
Mean	86.0%	77.1%	89.0%	88.0%	97.1%	97.5%

95.7% in the validation set and 94.00% in the testing set. Regarding training time, when skeletonization is set as MOPCA+ATFM+DCEM, the average time consumed by the decision tree is about 0.6s, which is faster than ensemble learning, which consumes about 4.2s. In Fig. 5, training Time consumed by different classifiers in 5 classes is presented.

For five classes classification task, the best combination method is using MOPCA skeletonization to extract the skeleton, using ATFM and DCEM to offset the noise's influence, and selecting decision tree to predict the class of the static hand gesture. The overall accuracy can reach 98.5%, and the train time is 0.6435s.

B. Performance evaluation of static hand gesture Classification for 10 classes

Similar to the previous section, the experiment of the feature selection has been conducted based on the classifiers of KNN and SVM once more. The only difference is that the current experiment considered more classes, which increased from 5 to 10. Experimental results of the feature selection are shown in Tab. VI

By comparing Tab. VI and Tab. III, it is notable that the overall accuracy of classification is significantly reduced with the increasing number of classes since there are more complicated hand gestures are considered. In addition, the importance of each feature is also altered. For example, in Tab. III, we knew that the deletion of the NEP and NCP might significantly worsen the accuracy; however, in Tab. VI, the degree of the influence caused by them is much slightly when compared with the feature of AAEP. On the other hand, removing the NVCP and

Table VI
CLASSIFICATION ACCURACY COMPARISON FOR 8 AND 9 FEATURES AND 10 CLASSES

Feature Deleted	Classification Accuracy			
	Validation Set		Test Set	
	KNN	SVM	KNN	SVM
NEP	81.30%	79.70%	85.00%	80.60%
NCP	81.80%	81.10%	84.80%	81.00%
EIH	82.60%	81.50%	84.40%	81.60%
AVRD	82.50%	80.50%	85.70%	79.70%
RDTE	84.50%	80.90%	85.70%	82.70%
NVCP	84.40%	80.90%	88.20%	82.70%
ADTPE	82.50%	78.70%	83.10%	79.30%
DPSP	83.80%	81.20%	85.20%	81.90%
AAEP	73.20%	74.40%	73.40%	78.10%
Full Features	82.70%	81.60%	84.40%	81.00%

RDTE may increase the classification accuracy on both KNN and SVM.

Similar to the previous section, the influence of the different skeletonization methods and the different classifiers on the accuracy are explored in static hand gesture classification. The accuracy of 10 classes on the validation and testing sets are presented in Tab. VII and Tab. VIII, respectively. Training time consumed by different classifiers on ten classes is shown in Fig. 6.

From Tab. VII and Tab. VIII, we can see that the average accuracy of classification based on skeletons extracted by distinct methods are all decreased to some extent when comparing with the results in Tab. IV and Tab. V. However, the MOPCA+DCEM+ATFM method still outperforms other methods. For example, for classifying ten types of static hand gesture tasks, the average accuracy of classification of the MOPCA+DCEM+ATFM

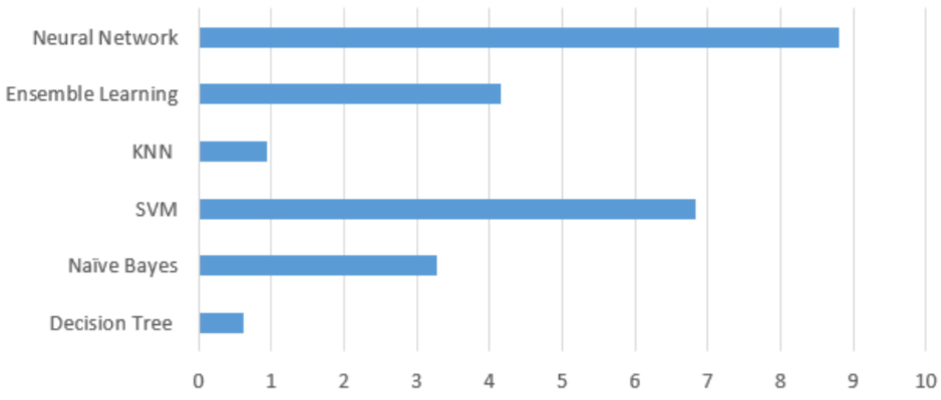

Figure 5: Training Time Consumed by 6 Classifiers on 5 classes dataset

Table VII
CLASSIFICATION ACCURACY EVALUATION ON TRAIN/VALIDATION SET THAT HAS 10 DIFFERENT CLASSES

Classifier Models	ZS+ ATFM	OPTA+ ATEM	ZSM+ ATFM	OPCA+ ATFM	MOPCA+ ATFM	MOPCA+ATFM +DCEM
DT	85.8%	82.1%	93.3%	94.0%	96.3%	100.0%
NB	79.9%	75.4%	86.6%	82.8%	95.8%	94.0%
SVM	90.3%	78.4%	91.8%	86.6%	97.0%	99.3%
KNN	85.1%	75.4%	86.6%	82.8%	97.8%	94.0%
EL	90.3%	82.8%	93.3%	94.0%	98.3%	100.0%
MLP	85.1%	68.7%	82.8%	88.1%	97.8%	98.0%
Mean	86.0%	77.1%	89.0%	88.0%	97.1%	97.5%

Table VIII
CLASSIFICATION ACCURACY EVALUATION ON TEST SET THAT HAS 10 DIFFERENT CLASSES

Classifier Models	ZS+ ATFM	OPTA+ ATEM	ZSM+ ATFM	OPCA+ ATFM	MOPCA+ ATFM	MOPCA+ATFM +DCEM
DT	75.9%	73.8%	82.7%	87.3%	86.1%	91.1%
NB	59.5%	62.0%	86.5%	81.4%	80.2%	77.2%
SVM	73.8%	62.4%	77.6%	75.5%	82.3%	81.0%
KNN	69.6%	63.7%	78.9%	75.9%	87.8%	84.4%
EL	81.4%	79.3%	89.0%	91.6%	87.8%	92.8%
MLP	70.5%	60.8%	79.7%	76.8%	83.1%	83.5%
Mean	71.7%	67.0%	82.4%	81.4%	84.5%	85.0%

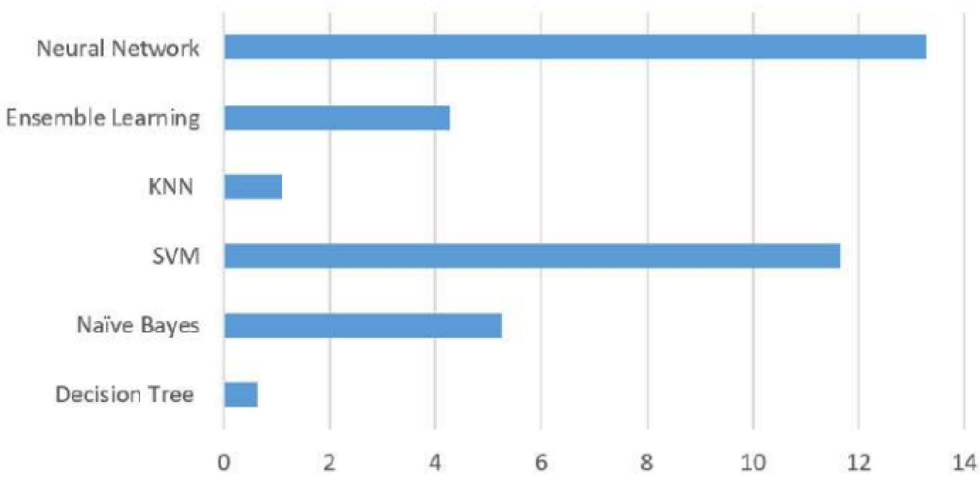

Figure 6: Training Time Consumed by 6 Classifiers on 10 classes dataset.