Enhancing Dynamic Hand Gesture Recognition through Optimized Feature Selection using Double Machine Learning

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Abstract

Causal machine learning combines causal inference and machine learning to understand and utilize causal relationships in data. While traditional machine learning focuses on missions of prediction and pattern recognition, causal machine learning goes a step further by revealing causal relationships between variables. In this research, we employ the double machine learning method to identify variables in the gesture recognition problem where independent variables have causal relationships with the final gesture. These variables are then selected for further classification and analysis. By comparing this approach with traditional feature selection methods, we find that the variables selected using double machine learning are more useful for classification and yield excellent results across different machine learning classification models. This new double machine learning based approach provides a valuable reference for researchers during the feature selection stage.

CCS Concepts

• **Computing Methodologies**; • **Causal Reasoning and Diagnostics**; • **Machine Learning**;

Keywords

Leap Motion Controller, Hand Gesture Recognition, Feature Selection, Causal Effect, Double Machine Learning

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1 Introduction

With the rapid development of computer and Internet technology, human-computer interaction (HCI) has received widespread attention. Nowadays, people's interaction is gradually shifting from using keyboards, mice, and touchscreens as input devices to using touchless interaction. In this development process, gesture recognition is becoming popular and accepted by the public as a novel touchless interaction method [1]. In general, gesture recognition is divided into two methods. One is the usage of computer vision-based recognition techniques, where hand images are captured by one or more cameras, and deep learning algorithms such as neural networks and convolutional neural networks are used for categorization [2]. The other method is sensor-based, which involves using digital gloves and 3D depth sensors to collect data. Although research on sensor-based methods began earlier than computer vision-based recognition techniques, their practical applications are very limited because these methods require wearable devices such as digital gloves to track and estimate the position and orientation of the hand and fingers [3].

The advent of 3D depth sensor tools, such as the leap motion controller (LMC), provides a low-cost and more effective method for detecting and tracking hand movements. The LMC can output data such as hand orientation, fingertip position, bone position, and other points of interest. Marin et al. used three feature datasets collected by the LMC (fingertip distance, fingertip angle, and fingertip height) and found that the accuracy of static gesture recognition based on LMC reached 80% [4]. The LMC is also promising for other specialized fields. Ameur et al. defined 11 dynamic gestures for medical image manipulation based on the problem of touchless interaction in aseptic areas in healthcare and used 3D positional information as input features for models [5]. Additionally, the same research team released a dataset containing more samples and richer spatial-frequency features [6]. With the increasing accuracy of data acquisition, the LMC can provide data on skeletal movements. Boulahia et al. extended the existing action recognition feature set HIF3D and used the LMC to acquire a new dataset containing the 3D coordinates of 46 joints (23 joints on one hand), aiming to create a closer representation of the whole body and gestures through the skeleton data [7]. Subsequently, Li et al. proposed a skeleton-based gesture recognition enhancement method, showing that the static gesture recognition accuracy was as high as 94%, and the dynamic gesture recognition rate, combined with the initial FC strategy, reached more than 90% [8].

However, as the richness of LMC data types increases, the number of variables available in studies gradually rises. When dealing with high dimensional LMC data, feature selection becomes particularly important as it can significantly reduce the time cost and complexity of the analysis process. In recent years, research on feature selection has become popular, with various statistical based methods such as recursive feature elimination (RFE), chi-square, and genetic algorithms. These methods can help reduce data dimensions and improve the efficiency of model training [9]. Additionally, causal machine learning leverages the strong fit of machine learning models to describe the individual variables that have a positive or negative effect on the final dependent variable outcome through changes in treatment effect values [10]. Yan et al. demonstrated in their paper that the causal uplift model can be useful for the complementary refinement of SHAP graphs for interpretable machine learning [11]. In this research, we propose a relatively novel approach for feature selection. We use the double machine learning model to determine whether there is a significant difference in the treatment effect of a single variable on the dependent variable while controlling for other variables. We evaluate the effectiveness of this screening method by comparing double machine learning with other variable selection methods.

The remainder of this research is organized as follows: In section 2, we provide a detailed description of the environment setup, the dataset, feature selection methods, and machine learning methods. In section 3, we present the detailed experimental procedure and results. Finally, we summarize the research in the last section.

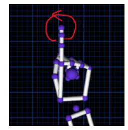
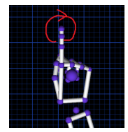
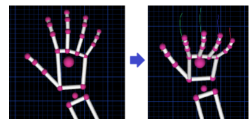
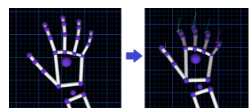
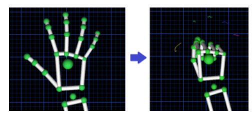
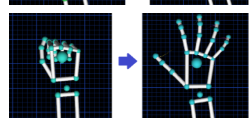
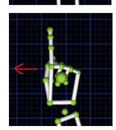
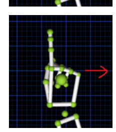
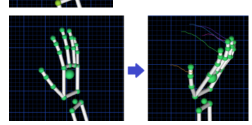
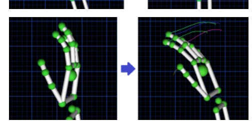
2 Materials and methods

This section discusses the collection of data and information about the variables of interest. Next, we introduce the double machine learning feature selection method in this research. Finally, we briefly describe the machine learning classification methods employed in the experiments.

2.1 Gesture dataset collection

We collected all data in a controlled indoor environment. The LMC was placed on a flat tabletop in front of a whiteboard, on which we drew a 3x3 grid, with each square measuring 10x10 cm. The LMC was connected to a laptop computer via a USB cable, and a researcher monitored and controlled the data collection process.

Table 1: Description of Hand Gestures

Movement of Gestures	Description
	Index rotate with counterclockwise direction
	Index rotate with clockwise direction
	Release up
	Release down
	Grip in
	Grip out
	Index swipe left
	Index swipe right
	Hand swipe right
	Hand swipe left

During the experiment, participants placed their hands on the LMC and pointed their fingers toward the whiteboard as the initial hand position. A total of 12 participants (7 females and 5 males) took part in this experiment. The experiment involved 10 different movement of gestures, with each participant repeating each movement 10 times, all 10 movement of gestures were listed in Table 1.

2.2 Structure of the gesture dataset

For the collected raw data, we define three types of feature sets: single-finger features, two-finger features, and bone-finger features.

For single-finger features, we focus on the 3D spatial characteristics of the hand and fingers. The variables involved in single-finger features include hand position, hand direction and normal, fingertips position, and fingertips direction. We divide these into two datasets: fset_mean, which contains the mean of the variables, and fset_std, which contains the standard deviation of the variables. For the two-finger features dataset fset_dist, we include the euclidean distance between the fingertip and the palm center, as well as the distance between adjacent fingertips, to evaluate the performance of distance-based gesture recognition features. For the bone-finger features, the positions of the distal and intermediate phalanges (the value of 'prev_joint', which is the position of the end of the bone closest to the wrist in the LMC API) are extracted as bone-based 3D spatial variables. The final bone-finger feature set fset_bones_mean includes hand position, hand direction and normal, fingertips position, fingertips direction, distal phalanges position, and intermediate phalanges position.

2.3 Feature selection methods and classification algorithms

In the area of big data, feature selection methods play a crucial role in data preprocessing for machine learning and data mining. By identifying and selecting the most informative features, feature selection methods not only significantly improve model performance but also reduce computational complexity and the risk of overfitting. In practical projects, there are several common methods for feature selection. One such method is the variance threshold (VAR) [12], which is based on the principle that the variance of each feature indicates the degree of data dispersion. Features with smaller variances provide less information. We achieve feature selection by calculating the variance of each feature and removing those below a certain threshold. Another method is select from model (SFM), a model-based feature selection technique. It evaluates the importance of features by learning the parameters of the model or the importance of the variables, deciding which features to retain. The random forest model is often used for this purpose. A different approach is principal component analysis (PCA), which focuses on compressing feature dimensions rather than selecting features [13]. PCA simplifies the data structure by projecting high-dimensional data into a low-dimensional space while retaining the main information of all features.

We propose a novel approach: feature selection based on double machine learning (DML). In traditional causal inference studies, DML is a method for estimating heterogeneous treatment effects, assuming that we can observe all potential factors or variables, defined as confounders X. T stands for the treatment variable, while Y denotes the potentially affected dependent variable. In reality, confounders X may be too high in dimension for satisfactory modeling. The DML approach combines two machine learning predictive models in the final stage to create a model for calculating heterogeneous treatment effects. This method allows any machine learning algorithm to be used for both prediction tasks [14].

As shown in Figure 1, T and X simultaneously affect the variable Y, while X also influences the variation of T. In DML, we treat both Y and T as dependent variables and calculate the variability of the effect on Y under different T by estimating the effect of features on

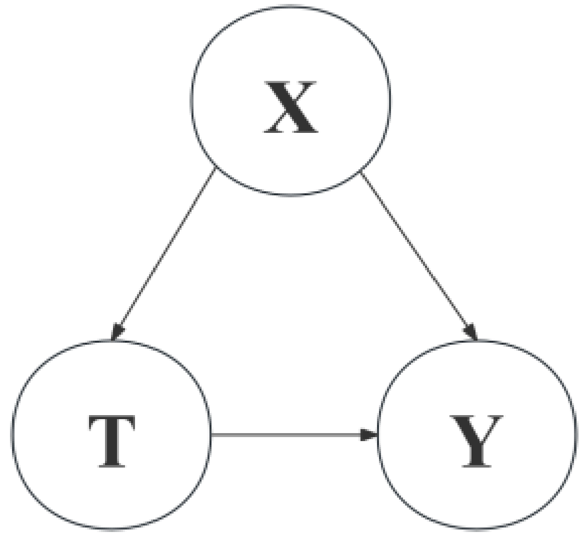


Figure 1: Structure of X, T and Y

the dependent variable. First, we build two independent machine learning models to predict Y and T, respectively, with X as the dependent variable. The formulas are shown below.

$$E(Y|X) = ML_1(X)$$

$$E(T|X) = ML_2(X)$$

We can then obtain the coefficient θ, also known as the conditional average treatment effect (CATE), by calculating the residuals of Y and T and performing the corresponding regression.

$$Y - ML_1(X) = \theta \cdot [T - ML_2(X)] + \varepsilon$$

When CATE shows a significant positive or negative difference, we can assume that the variable T has a significant effect on the results. In this research, we treat each variable in the four datasets (fset_mean, fset_std, fset_dist, fset_bones_mean) as variable T individually, while categorizing all remaining independent variables as variable X. We detect whether each variable has a significant CATE difference by training the DML model. Eventually, we select the variables with significant CATE differences for the next step of machine learning classification tasks. To test the superiority of the DML-based feature selection method, we also compare its classification effects with those of the three traditional feature selection methods mentioned above.

In terms of machine learning models, we select six traditional models for analysis: logistic regression (LR), k-nearest neighbors (KNN), random forest (RF), extra trees (ET), histogram-based gradient boosting (Hist-GB), and light gradient boosting machine (LightGBM). These models are widely used in various fields [15]. During the analysis, 80% of the data is used to train the model, and the remaining 20% is used to test the model. Four classification metrics are involved: accuracy, precision, recall, and f1 score. These metrics estimate the error between the actual gesture and the model's

Table 2: Average Classification Results for different Dataset

Dataset	accuracy	precision	recall	f1 score
fset_mean	95.122 ± 3.827	95.554 ± 3.222	95.122 ± 3.827	95.108 ± 3.812
fset_std	72.153 ± 7.090	73.203 ± 7.109	72.153 ± 7.090	72.169 ± 7.135
fset_dist	89.184 ± 8.459	89.787 ± 8.079	89.184 ± 8.459	89.155 ± 8.449
fset_bones_mean	95.937 ± 3.203	96.239 ± 2.983	95.937 ± 3.203	95.893 ± 3.295

Table 3: Average Classification Results for different Machine Learning Models

Machine Learning	accuracy	precision	recall	f1 score
LR	80.625 ± 11.005	81.801 ± 10.970	80.625 ± 11.005	80.563 ± 11.051
KNN	85.755 ± 13.495	86.524 ± 13.012	85.755 ± 13.495	85.692 ± 13.492
RF	90.182 ± 10.402	90.663 ± 9.993	90.182 ± 10.402	90.203 ± 10.346
ET	91.641 ± 9.194	92.041 ± 8.880	91.641 ± 9.194	91.630 ± 9.173
Hist-GB	90.260 ± 9.843	90.626 ± 9.600	90.260 ± 9.843	90.269 ± 9.803
LightGBM	90.130 ± 9.461	90.518 ± 9.244	90.130 ± 9.461	90.131 ± 9.429

predicted gesture. When these metrics are closer to 1, it indicates better classification performance.

3 Experiment Results

This section lists the predictions under different feature selection and machine learning algorithms. We conduct experiments on four datasets: fset_mean, fset_std, fset_dist, and fset_bones_mean. Four feature selection methods and six machine learning models can form 24 combinations. To fairly evaluate the models, we use the mean value ± standard deviation (Mean ± SD) to assess the validity of the classification predictions.

First, we classify the dataset and calculate the performance of the 24 combinations in the four datasets: fset_mean, fset_std, fset_dist, and fset_bones_mean, as shown in Table 2. It can be intuitively seen that regardless of the feature selection methods and machine learning models used, the accuracy for the fset_mean and fset_bones_mean datasets is very high, reaching over 95%. In contrast, the fset_dist dataset, which extracts positional variations, shows a 6% lower accuracy compared to the former two datasets. The standard deviation-based dataset, fset_std, performs the worst, with only about 72% accuracy. Additionally, from the standard deviation calculated in the table, it can be seen that the fset_mean and fset_bones_mean datasets have good stability, with a small fluctuation range in accuracy and other indicators. On the other hand, the fset_dist and fset_std datasets perform poorly with wide fluctuations in their results. Therefore, their usage in practical applications should be carefully considered.

Next, we calculate the classification results based on the six machine learning models. We evaluate the performance of these models across all datasets and feature selection methods, as shown in Table 3. Firstly, the LR and KNN models, which are based on single classifiers, show the most average performance, with mean values of 80% and 85%, respectively. These results are significantly less effective than those of the tree-based machine learning models, all of which predicted results of over 90%. Additionally, the prediction results of both the LR and KNN models exhibited larger fluctuations compared to the tree-based models, indicating less stability. Among the four tree-based machine learning models, the ET model achieve the best prediction results and the lowest volatilities. Therefore, in practical applications, we should prioritize tree-based machine learning models, especially the ET model, due to its better robustness.

In order to observe which feature selection method is superior, we test the performance results of all datasets and machine learning models based on the four feature selection methods. As shown in Table 4 and Figure 2, both visualize the superiority of our proposed novel DML-based approach for feature selection. The traditional feature selection methods, PCA, SFM, and VAR, achieve an average accuracy that does not exceed 90% in any of the six subsequent machine learning model predictions, with PCA being the closest to this figure. SFM and VAR only reached 87% and 85%, respectively. In contrast, the DML method has a prediction accuracy of more than 90%. Among them, PCA and DML have similar effects. However, during the calculation process, PCA compresses all variables to generate new ones. These new variables retain most of the original information, but their interpretability is poor. However, with DML method, we can still explore the impact of these variables on the outcome after selecting variables using causal machine learning, maintaining the interpretability of machine learning. Figure 2 shows that the overall performance of SFM and VAR is quite poor, with SFM exhibiting a wider range of fluctuations. To better visualize the performance effect of feature selection under each dataset and each machine learning model, we conduct a deeper analysis.

We divide the results into performance based on feature selection and classification metrics under the dataset, as shown in Table 5. Similar to the results in Table 2, we can see that all machine learning models achieve better results with the fset_mean and fset_bones_mean datasets, which contain features more aligned with the research topic of gesture recognition. We can also observe that the DML method achieves the best classification results with both the fset_mean and fset_bones_mean datasets. Specifically, in the fset_bones_mean dataset, its 97.014% accuracy is 0.5% higher

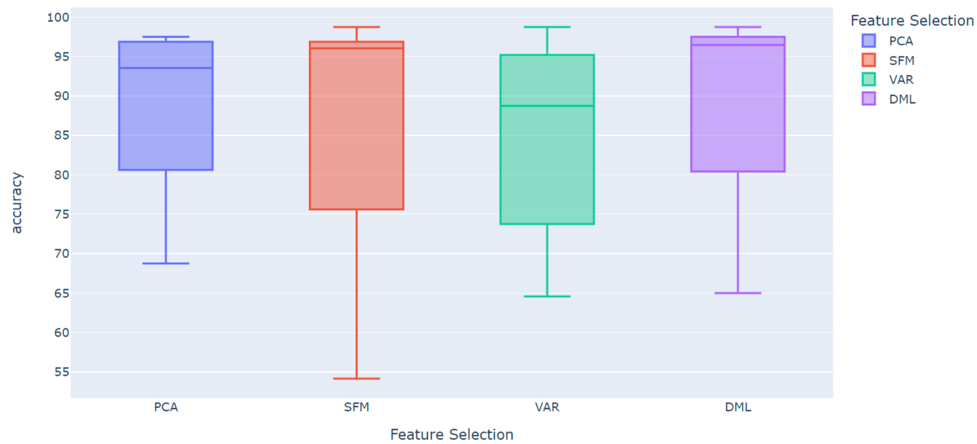


Figure 2: Comparisons of Accuracy based on Feature Selection Methods

Table 4: Average Classification Results for different Feature Selection Methods

Feature Selection	accuracy	precision	recall	f1 score
PCA	89.705 ± 8.623	90.216 ± 8.375	89.705 ± 8.623	89.651 ± 8.637
SFM	87.413 ± 13.548	87.803 ± 13.361	87.413 ± 13.548	87.361 ± 13.578
VAR	85.243 ± 11.586	86.140 ± 11.006	85.243 ± 11.586	85.264 ± 11.521
DML	90.035 ± 10.289	90.624 ± 9.853	90.035 ± 10.289	90.049 ± 10.293

Table 5: Average Classification Results for different Feature Selection Methods and Dataset

Feature Selection	Dataset	accuracy	prcision	recall	f1 score
PCA	fset_mean	96.250 ± 1.577	96.490 ± 1.357	96.250 ± 1.577	96.218 ± 1.586
	fset_std	76.389 ± 3.622	77.147 ± 3.490	76.389 ± 3.622	76.319 ± 3.619
	fset_dist	90.833 ± 5.023	91.509 ± 4.672	90.833 ± 5.023	90.760 ± 5.026
	fset_bones_mean	95.347 ± 1.823	95.720 ± 1.613	95.347 ± 1.823	95.308 ± 1.850
SFM	fset_mean	95.833 ± 2.690	96.093 ± 2.559	95.833 ± 2.690	95.817 ± 2.697
	fset_std	66.875 ± 8.897	67.506±8.920	66.875±8.897	66.824±9.001
	fset_dist	92.014 ± 7.190	92.410 ± 6.970	92.014 ± 7.190	92.000 ± 7.165
	fset_bones_mean	94.931 ± 5.066	95.201 ± 4.771	94.931 ± 5.066	94.805 ± 5.255
VAR	fset_mean	92.014 ± 5.327	92.916 ± 4.235	92.014 ± 5.327	91.996 ± 5.278
	fset_std	69.653 ± 3.371	71.123 ± 3.665	69.653 ± 3.371	69.756 ± 3.192
	fset_dist	82.847 ± 8.500	83.777 ± 7.742	82.847 ± 8.500	82.854 ± 8.462
	fset_bones_mean	96.458 ± 2.135	96.742 ± 1.954	96.458 ± 2.135	96.450 ± 2.133
DML	fset_mean	96.389 ± 2.729	96.716 ± 2.391	96.389 ± 2.729	96.401 ± 2.717
	fset_std	75.694 ± 5.732	77.035 ± 5.473	75.694 ± 5.732	75.778 ± 5.891
	fset_dist	91.042 ± 9.093	91.453 ± 9.056	91.042 ± 9.093	91.009 ± 9.142
	fset_bones_mean	97.014 ± 2.171	97.291 ± 1.926	97.014 ± 2.171	97.009 ± 2.182

than the second-ranked VAR method. In the fset_std and fset_dist datasets, DML also achieved the second position, with performance not much different from the corresponding first-ranked feature selection method. Therefore, from a comprehensive perspective, the new DML method has a more obvious advantage in feature selection.

Finally, we divide the results into the performance of classification metrics based on feature selection and machine learning models, as shown in Table 6 and Figure 3. From these, we can clearly see that the classification effect based on SFM and VAR methods is the most general. None of the classification indexes based on SFM and LR, KNN models exceeded 90%. In the VAR method, the classification index of all machine learning models ranged only between 78-86%. Not only does the underlying data impact the model, but the choice of feature selection method is also crucial. Among them, PCA and DML methods have comparable

Figure 3: Comparisons of Accuracy based on Feature Selection Methods and Machine Learning Models

Table 6: Average Classification Results for different Feature Selection Methods and Machine Learning Models

Feature Selection	Machine Learning	accuracy	prcision	recall	f1 score
PCA	LR	86.146 ± 6.849	87.232 ± 6.471	86.146 ± 6.849	86.126 ± 6.806
	KNN	87.708 ± 11.568	88.405 ± 11.109	87.708 ± 11.568	87.662 ± 11.563
	RF	90.521 ± 7.775	90.888 ± 7.543	90.521 ± 7.775	90.476 ± 7.828
	ET	91.458 ± 6.552	91.915 ± 6.344	91.458 ± 6.552	91.380 ± 6.518
	Hist-GB	91.146 ± 8.516	91.371 ± 8.539	91.146 ± 8.516	91.091 ± 8.565
	LightGBM	91.250 ± 8.042	91.487 ± 8.187	91.250 ± 8.042	91.173 ± 8.125
SFM	LR	76.250 ± 13.598	76.771 ± 13.956	76.250 ± 13.598	76.018 ± 13.699
	KNN	83.854 ± 17.044	84.472 ± 16.597	83.854 ± 17.044	83.791 ± 16.974
	RF	90.625 ± 11.202	91.060 ± 10.802	90.625 ± 11.202	90.605 ± 11.219
	ET	91.562 ± 10.807	91.939 ± 10.426	91.562 ± 10.807	91.584 ± 10.750
	Hist-GB	91.250 ± 9.633	91.461 ± 9.588	91.250 ± 9.633	91.248 ± 9.622
	LightGBM	90.938 ± 9.941	91.112 ± 9.939	90.938 ± 9.941	90.923 ± 9.940
VAR	LR	78.437 ± 10.028	80.772 ± 9.412	78.437 ± 10.028	78.445 ± 10.026
	KNN	85.000 ± 11.141	85.833 ± 10.842	85.000 ± 11.141	84.950 ± 11.080
	RF	86.458 ± 12.578	87.160 ± 12.059	86.458 ± 12.578	86.554 ± 12.432
	ET	89.479 ± 10.633	89.906 ± 10.347	89.479 ± 10.633	89.475 ± 10.648
	Hist-GB	85.833 ± 11.641	86.412 ± 11.160	85.833 ± 11.641	85.879 ± 11.529
	LightGBM	86.250 ± 10.337	86.755 ± 9.955	86.250 ± 10.337	86.282 ± 10.241
DML	LR	81.667 ± 9.829	82.429 ± 9.996	81.667 ± 9.829	81.662 ± 9.833
	KNN	86.458 ± 13.099	87.387 ± 12.324	86.458 ± 13.099	86.367 ± 13.229
	RF	93.125 ± 8.114	93.545 ± 7.726	93.125 ± 8.114	93.180 ± 8.002
	ET	94.062 ± 7.403	94.405 ± 7.017	94.062 ± 7.403	94.084 ± 7.376
	Hist-GB	92.812 ± 7.674	93.259 ± 7.300	92.812 ± 7.674	92.856 ± 7.612
	LightGBM	92.083 ± 8.181	92.718 ± 7.526	92.083 ± 8.181	92.147 ± 8.083

performance. For LR and KNN models, the performance under PCA-based methods is better than DML. This may be because PCA can linearly compress high-dimensional variables, reducing the pressure on single-model machine learning models to classify accurately when facing high-dimensional data. The tree-based machine learning models under the DML method outperform all other methods. In addition to the strong fitting ability of tree-based machine learning models, DML plays a role in selecting the variables that are more important to the results by indicating their significance while seeking the causal relationship between the independent and dependent variables. This makes the use of DML for variable selection more advantageous.

4 Conclusions

In this research, a new feature selection method DML is introduced for gesture recognition. The DML method in causal inference is used to select the dependent variable in gesture recognition more effectively, and six machine learning algorithms are employed to achieve better classification results. The best classification results are obtained on the fset_mean and fset_bones_mean datasets. In summary, this research uses gesture recognition examples to confirm the practical value of DML in feature selection and provides a new perspective for feature selection in many fields. In future research, we can further expand the research samples or explore different topics. For example, we can add more styles of gestures to the dataset or validate the feature selection more effectively with the help of additional models in causal inference, such as linear DML, sparse linear DML, and causal forest DML.

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