Method for Hyperparameter Tuning of Image Classification with PyCaret

Kohei Arai[1], Jin Shimazoe[2], Mariko Oda[3]
Information Science Dept., Saga University, Saga City, Japan[1]
Applied AI Laboratory, Kurume Institute Technology, Kurume City, Fukuoka, Japan[1, 2, 3]

***Abstract*—A method for hyperparameter tuning of image classification with PyCaret is proposed. The application example compares 14 classification methods and confirms that Extra Trees Classifier has the best performance among them, AUC=0.978, Recall=0.879, Precision=0.969, F1=0.912, Time=0.609 bottom. The Extra Trees Classifier produces a large number of decision trees, similar to the random forest algorithm, but with random sampling of each tree and no permutation. This creates a dataset for each tree containing unique samples, and from the ensemble set of features a certain number of features are also randomly selected for each tree. The most important and unique property of the Extra Trees Classifier is that the feature split values are chosen randomly. Instead of using Gini or entropy to split the data to compute locally optimal values, the algorithm randomly selects split values. This makes the tree diverse and uncorrelated. i.e. the diversity of each tree. Therefore, it is considered that the classification performance is better than other classification methods. Parameter tuning of Extra Trees Classifier was performed, and training performance, test performance, ROC curve, accuracy rate characteristics, etc. were evaluated.**

Keywords*—*PyCaret; extra trees classifier; AUC; gini; entropy; feature split; ROC curve

I. Introduction

Most machine learning problems require many hyperparameter tunings. Unfortunately, it is not possible to provide specific tuning rules for all models but may converge very slowly for another model. Finding the best set of hyperparameters for your dataset requires experimentation. Some rules of thumb, here is the training loss, which should decrease abruptly at first, then more slowly and steadily until the slope of the curve reaches or approaches zero, and if the training loss does not converge, wait for more epochs of training.

If the training loss decreases too slowly, increase the learning rate. Note that setting the learning rate too high can prevent the training loss from converging. Decrease the learning rate if the training loss varies a lot (that is, if the training loss jumps around). Increasing the number of epochs or batch size while decreasing the learning rate is often a good combination. Setting the batch size to a very small batch number can lead to instability. First, try increasing the batch size value. Then reduce the batch size until you see a drop. For real datasets consisting of a very large number of samples, the entire dataset may not fit in memory. In such cases, the batch size should be reduced so that the batch fits in memory. For the optimization of these hyperparameters, hyperopt, gpyopt, AutoML, PyCaret, Optuna, etc. are proposed as black-box optimization methods, automating trial-and-error on hyperparameters and automatically finding the optimal solution. Similarly, a method for training and white boxing DL, BDT, random forest and mind maps based on GNN is proposed [1]. In particular, Optuna uses an algorithm called TPE (Tree-structured Parzen Estimator), which is a new technique among Bayesian optimization, and parallel processing is possible, and by saving the results in a database, it is possible to resume in the middle. Depending on the definition of the objective function and the validity of the importance of the parameters, hyperparameters that do not necessarily match the evaluation criteria may appear. Usually, it is desirable to introduce such cases, and propose a method to intentionally change the hyperparameters of Optuna and PyCaret and select parameters with less loss by trial and error. It, however, PyCaret only uses hyperparameters obtained by random grid search, and does not intentionally change hyperparameters in this paper.

As a comparative study on classification methods with PyCaret and its application to textile fluctuations of classifications, we propose a comparative study of classification methods by PyCaret and its application to the classification evaluation of textile pattern deviations. Many classification methods have been applied to the classification evaluation of textiles, but trial and error are necessary to determine the optimum method, which requires not a little time. The method proposed in this paper finds the optimal method using PyCaret, and is a method for finding the optimal method easily in a relatively short time without repeating trial and error. As one application of this method, an example of applying it to classification of Kurume Kasuri patterns is shown. This is just one application example, and the proposed method can be widely applied to other classifications.

The application example compares 14 classification methods and confirms that Extra Trees Classifier has the best performance among them, AUC=0.978, Recall=0.879, Precision=0.969, F1=0.912, Time=0.609 bottom. The Extra Trees Classifier produces a large number of decision trees, similar to the random forest algorithm, but with random sampling of each tree and no permutation. This creates a dataset for each tree containing unique samples, and from the ensemble set of features a certain number of features are also randomly selected for each tree. The most important and unique property of the Extra Trees Classifier is that the feature split values are chosen randomly. Instead of using Gini or entropy to split the data to compute locally optimal values, the algorithm randomly selects split values. This makes the tree diverse and uncorrelated i.e. the diversity of each tree. Therefore, it is considered that the classification performance is better than other classification methods. Parameter tuning of Extra Trees Classifier was performed, and training performance, test performance, ROC curve, accuracy rate characteristics, etc. were evaluated.

In the following section, some of the related research works are described together with a research background, followed by the comparative study conducted. Then, some of the simulation studies are described, followed by a conclusion with some discussions.

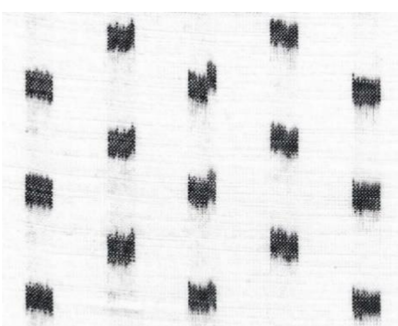
II. Related Research Works and Research Background

A. Research Background

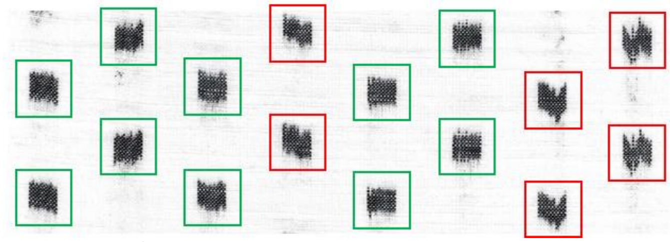
Image classification is required for textile pattern discrimination in this concern. Patterns are boring and uninteresting because they are regular, but moderately irregular patterns feel comfortable. For instance, Kurume Kasuri of textile patterns are moderately irregular so that we feel these patterns are comfortable. It is understandable that the moderately irregular patterns contain 1/f fluctuations. However, a pattern with too much irregularity gives an unpleasant feeling to the person who sees it. Therefore, it is thought that there is a boundary between pleasant irregularities and unpleasant irregularities. The purpose of this paper is to discriminate between both. In order to find the best discrimination performance of classification method, 14 of classification methods are compared these accuracies and their other performances.

B. Examples of Pleasant and Unpleasant Irregularity of Kurume Kasuri

One of the typical Kurume Kasuri of textile patterns is shown in Fig.1 (a). Also, examples of the regular (green) and the moderately irregular patterns (red) are shown in Fig. 1 (b), respectively. As shown in Fig. 1 (b), it is obvious that the regular patterns make a good impression while the irregular patterns make a bad impression. The cause of these irregular patterns is the lack of control over the warp tension of the Kurume Kasuri automatic loom. If the pattern is too comfortable, it will exceed the allowable limit and become an unpleasant pattern. It is too difficult to control the warp tension. It is important to evaluate the quality of woven Kurume Kasuri and determine whether it is good or bad to send it to the market.



(a) Typical Kurume Kasuri of textile pattern



(b) Examples of the regular (green) and the moderately irregular patterns (red)

Fig. 1. Typical kurume kasuri textile pattern and example of the regular and the moderately irregular patterns.

C. Related Research Works

Method for 1/f fluctuation component extraction from images and its application to improve Kurume Kasuri quality estimation is proposed [2]. In this paper, it is shown that Kurume Kasuri textile pattern quality depends on 1/f component. On the other hand, classification by re-estimating statistical parameters based on auto-regressive model is proposed [3]. Similarly, multi-temporal texture analysis in TM classification is proposed [4] together with Maximum Likelihood (MLH) TM classification taking into account pixel-to-pixel correlation [5]. Meanwhile, a supervised TM classification with a purification of training samples is proposed [6]. Also, TM classification using local spectral variability is proposed [7]. Furthermore, a classification method with spatial spectral variability is proposed [8].

An inversion for emissivity-temperature separation with ASTER data is proposed [9]. TM classification using local spectral variability is also proposed [10]. On the other hand, application of inversion theory for image analysis and classification is proposed [11]. Meanwhile, polarimetric SAR image classification with maximum curvature of the trajectory in eigen space domain on the polarization signature is proposed [12]. Moreover, a hybrid supervised classification method for multi-dimensional images using color and textural features are proposed [13].

Human gait gender classification using 3D discrete wavelet transformation feature extraction is proposed [14]. Meanwhile, polarimetric SAR image classification with high frequency component derived from wavelet multi resolution analysis: MRA is proposed [15]. On the other hand, a comparative study of polarimetric SAR classification methods including proposed method with maximum curvature of trajectory of backscattering cross section in ellipticity and orientation angle space is proposed [16]. Human gait gender classification using 2D discrete wavelet transforms energy is proposed [17]. Also, human gait gender classification in spatial and temporal reasoning is proposed [18]. Comparative study on discrimination methods for identifying dangerous red tide species based on wavelet utilized classification methods is conducted [19].

Multi spectral image classification method with selection of independent spectral features through correlation analysis is proposed [20]. On the other hand, image retrieval and classification method based on Euclidian distance between normalized features including wavelet descriptor is also proposed [21].

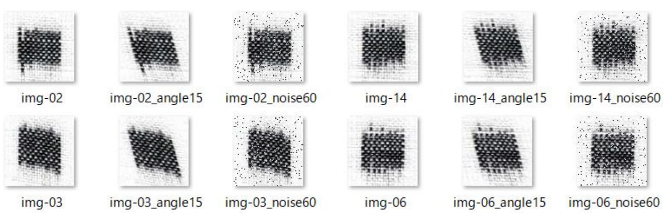
Gender classification method based on gait energy motion derived from silhouettes through wavelet analysis of human gait moving pictures is proposed [22]. Similarly, human gait skeleton model acquired with single side video camera and its application and implementation for gender classification is proposed [23] together with human gait skeleton model acquired with single side video camera and its application and implementation for gender classification [24]. Gender classification method based on gait energy motion derived from silhouette through wavelet analysis of human gait moving pictures is proposed [25].

Image classification considering probability density function based on simplified beta distribution is proposed [26]. Also, Maximum Likelihood (MLH) classification based on classified result of boundary mixed pixels for high spatial resolution of satellite images is proposed [27]. Meanwhile, context classification based on mixing ratio estimation by means of inversion theory is proposed [28]. On the other hand, optimum spatial resolution of satellite-based optical sensors for maximizing classification performance is discussed [29]. Combined non-parametric and parametric classification method depending on normality of PDF of training samples is proposed [30].

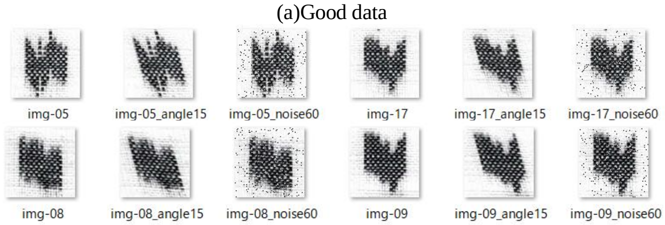
III. Experiment

A. Data used

180 of training samples and 30 of test samples are used. A small portion of the data used as a good data is shown in Fig. 2(a) while those for a bad data are shown in Fig. 2(b), respectively. There are 24 images in total, including two good and bad training data and two good and bad test data, including data augmentation (noise, skew).



(a)Good data



(b)Bad data

Fig. 2. A portion of good and bad data used.

B. Classfication Methods for Comparison

There are the following methods for comparing classification performance of the good or bad categories,

Extra Trees Classifier

Logistic Regression

Ridge Classifier

Random Forest Classifier

Light Gradient Boosting Machine

Ada Boost Classifier

SVM - Linear Kernel

Gradient Boosting Classifier

K Neighbors Classifier

Naive Bayes

Linear Discriminant Analysis

Decision Tree Classifier

Quadratic Discriminant Analysis

Dummy Classifier

These are typical and widely used classification methods. Therefore, details of explanation of the method are not necessary.

C. Evaluated Performances

The following typical and widely used classification performances are evaluated for comparison,

Accuracy

AUC

Recall

Precision

F1 score

Kappa value

MCC

TT (Sec)

These are typical and widely used classification performances. Therefore, it seems that details of explanation of the performances are not necessary.

D. Evaluation Results

Evaluation results are summarized in Table I. Cells shaded yellow have the best performance. Almost all the classification performances of the Extra Trees Classifier show the best performance except “Recall”. Total time required for learning and classification is also not so bad either. Extra Trees are similar to Random Forests. The points to construct multiple trees are the same, but one of the features (Gini coefficient, entropy) at which the node (leaf) of the tree is divided is randomly selected.

In the decision tree, when dividing the feature axis, the feature that maximizes the gain based on the feature amount (Gini coefficient, entropy), etc., and the threshold for the division are selected. Extra-Trees randomly select them. Prepare multiple random trees and bag them in the same way as Random Forest.

TABLE I. CLASSIFICATION PERFORMANCE EVALUATED

Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
Extra Trees Classifier	0.9176	0.9783	0.8786	0.9689	0.9122	0.8354	0.8522	0.6090
Logistic Regression	0.9110	0.9737	0.8679	0.9607	0.9078	0.8224	0.8317	1.0200
Ridge Classifier	0.9105	0.0000	0.8786	0.9532	0.9091	0.8206	0.8319	0.5470
Random Forest Classifier	0.8390	0.9417	0.8232	0.8842	0.8359	0.6783	0.6981	0.6020
Light Gradient Boosting Machine	0.8138	0.9084	0.8393	0.8253	0.8210	0.6260	0.6475	0.5670
Ada Boost Classifier	0.8133	0.8434	0.8018	0.8381	0.8105	0.6277	0.6430	0.5950
SVM - Linear Kernel	0.8067	0.0000	0.8143	0.8368	0.8045	0.6136	0.6432	0.5430
Gradient Boosting Classifier	0.7924	0.9156	0.8107	0.8040	0.7955	0.5832	0.5991	0.5700
K Neighbors Classifier	0.7910	0.9162	0.7018	0.8530	0.7510	0.5842	0.6015	0.9240
Naive Bayes	0.7438	0.7821	0.7304	0.7696	0.7460	0.4872	0.4924	0.5760
Linear Discriminant Analysis	0.7219	0.8245	0.6589	0.7731	0.6906	0.4447	0.4655	0.5730
Decision Tree Classifier	0.7157	0.7143	0.7714	0.7064	0.7271	0.4298	0.4471	0.5630
Quadratic Discriminant Analysis	0.5229	0.5205	0.5839	0.5260	0.5512	0.0406	0.0366	0.5730
Dummy Classifier	0.5133	0.5000	1.0000	0.5133	0.6783	0.0000	0.0000	0.5670

TABLE II. PARAMETERS FOR EXTRA TREES LEARNING PROCESSES

Parameters	
bootstrap	False
ccp_alpha	0.0
class_weight	{}
criterion	gini
max_depth	7
max_features	sqrt
max_leaf_nodes	None
max_samples	None
min_impurity_decrease	0.001
min_samples_leaf	5
min_samples_split	2
min_weight_fraction_leaf	0.0
n_estimators	110
n_jobs	-1
oob_score	False
random_state	123
verbose	0
warm_start	False

```
Pipeline(memory=FastMemory(location=C:¥Users¥shima¥AppData¥Local¥Temp¥joblib),
         steps=[('numerical_imputer',
                 TransformerWrapper(exclude=None,
                                    include=['pixel_1', 'pixel_2', 'pixel_3',
                                             'pixel_4', 'pixel_5', 'pixel_6',
                                             'pixel_7', 'pixel_8', 'pixel_9',
                                             'pixel_10', 'pixel_11', 'pixel_12',
                                             'pixel_13', 'pixel_14', 'pixel_15',
                                             'pixel_16', 'pixel_17', 'pixel_18',
                                             'pixel_19', 'pi...
                 ExtraTreesClassifier(bootstrap=False, ccp_alpha=0.0,
                                      class_weight={}, criterion='gini',
                                      max_depth=7, max_features='sqrt',
                                      max_leaf_nodes=None, max_samples=None,
                                      min_impurity_decrease=0.001,
                                      min_samples_leaf=5, min_samples_split=2,
                                      min_weight_fraction_leaf=0.0,
                                      n_estimators=110, n_jobs=-1,
                                      oob_score=False, random_state=123,
                                      verbose=0, warm_start=False))],
         verbose=False)
```

Fig. 3. Finalized parameters of the extra trees classifier.

Bagging is short for bootstrap aggregating. As the name suggests, the training data used for each learner is obtained by bootstrap sampling, and the learned learner is used for prediction and the final ensemble is performed.

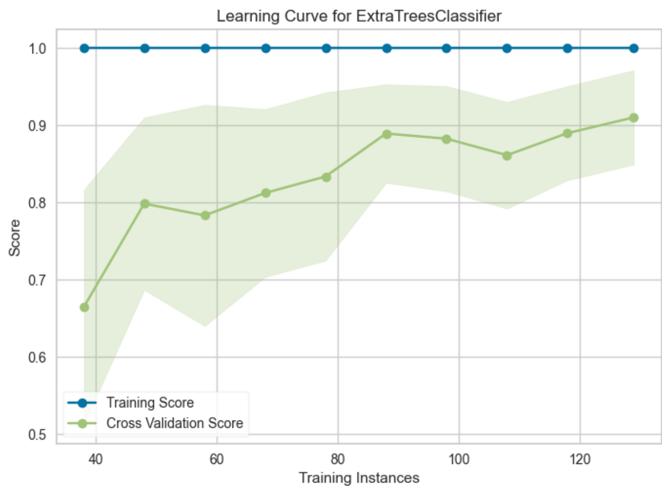
Bootstrap sampling is a method of resampling by randomly extracting some data from the population while allowing overlaps when there is data to be used as a population.

Ensemble learning in machine learning is a method of generating a single learning model by fusing multiple models (learners). A feature of Extra-Trees learning is that each tree is trained without bootstrap sampling, that is, without resampling by randomly extracting some data from the population while allowing for duplication. Use all data. Let it learn from all the data. Table II shows the parameters for Extra Trees learning processes. After the above mentioned hyperparameter tuning, the Extra Trees Classifier is finalized as shown in Fig. 3. Accuracy was specified as an optimization metric. Accuracy improved after 100 trials, but there is no guarantee that the parameters are optimal because they are optimized by random grid search.

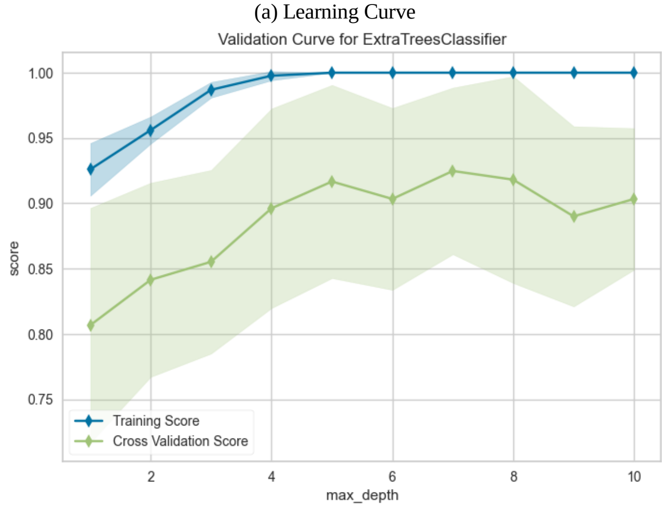
Because it is simple, processing speed is very high, and the classification accuracy is better than Random Forest, a representative machine learning library for Python. The Extra Trees Classifier when using scikit-learn looks like this: When you think of machine learning, you might think of using complex formulas or something that seems difficult, but with scikit-learn you can try out machine learning very easily.

The learning curve of the Extra Trees Classifier is shown in Fig. 4(a) while the validation curve is shown in Fig. 4(b), respectively.

N-fold cross validation with shuffle and stratification (for classification tasks). Different hyperparameters for each algorithm were checked during the training. For binary classification the Area Under ROC Curve (AUC) metric was used. Table III shows the results of the n-fold cross validation while Fig. 5 shows the AUC.



(a) Learning Curve



(b)Validation Curve

Fig. 4. Learning and validation curves of the extra trees classification.

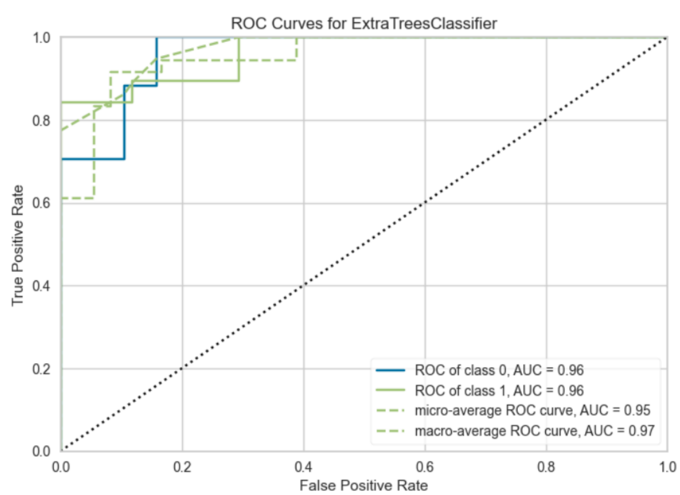


Fig. 5. Evaluated AUC.

TABLE III. THE RESULTS FROM THE N-FOLD CROSS VALIDATION

Fold	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	0.9333	0.9821	1.0000	0.8889	0.9412	0.8649	0.8729
1	0.9333	0.9107	0.8750	1.0000	0.9333	0.8673	0.8750
2	0.8000	0.9464	0.6250	1.0000	0.7692	0.6087	0.6614
3	0.8667	0.9643	1.0000	0.8000	0.8889	0.7273	0.7559
4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5	0.8571	1.0000	0.7143	1.0000	0.8333	0.7143	0.7454
6	0.9286	0.9796	0.8571	1.0000	0.9231	0.8571	0.8660
7	0.8571	1.000	0.7143	1.0000	0.8333	0.7143	0.7454
8	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
9	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Mean	0.9176	0.9783	0.8786	0.9689	0.9122	0.8354	0.8522
Std	0.0669	0.0285	0.1387	0.0653	0.0761	0.1327	0.1163

Also, confusion matrix of the Extra Trees Classifier is shown in Fig. 6. In the Fig. 6, the number of “Good” samples is 17 while the number of “Bad" samples is 19. Of the 180 training data, 20% are used as validation data, so there are 36 validation data. Of the 36 cards, 17 are 0: good and 19 are 1: bad. All good answers were correct (17 0), and three bad answers were incorrect (3 16). It is such a confusion matrix.

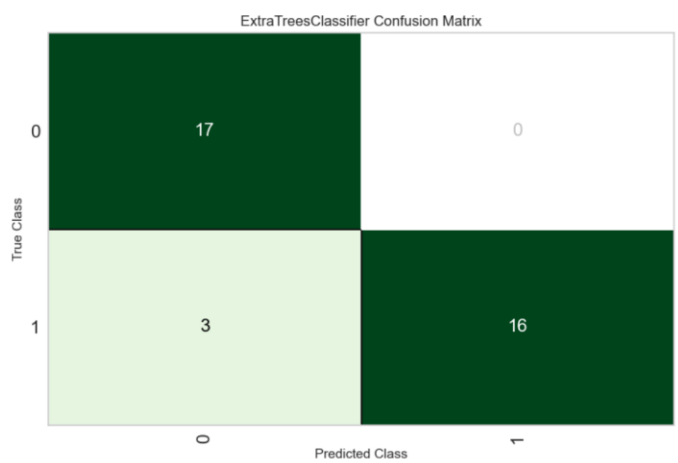


Fig. 6. Confusion matrix of the extra trees classifier.

IV. Conclusion

A method for hyperparameter tuning of image classification with PyCaret is proposed. The application example compares 14 classification methods and confirms that Extra Trees Classifier has the best performance among them, AUC=0.978, Recall=0.879, Precision=0.969, F1=0.912, Time=0.609 bottom. The Extra Trees Classifier produces a large number of decision trees, similar to the random forest algorithm, but with random sampling of each tree and no permutation.

This creates a dataset for each tree containing unique samples, and from the ensemble set of features a certain number of features are also randomly selected for each tree. The most important and unique property of the Extra Trees Classifier is that the feature split values are chosen randomly. Instead of using Gini or entropy to split the data to compute locally optimal values, the algorithm randomly selects split values.

This makes the tree diverse and uncorrelated, i.e. the diversity of each tree. Therefore, it is considered that the classification performance is better than other classification methods. Parameter tuning of Extra Trees Classifier was performed, and training performance, test performance, ROC curve, accuracy rate characteristics, etc. were evaluated.

Future Research Works

Further investigations are required to identify alternative prediction methods that may lead to more accurate results.

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AUTHORS' PROFILE

Kohei Arai, He received BS, MS and PhD degrees in 1972, 1974 and 1982, respectively. He was with The Institute for Industrial Science and Technology of the University of Tokyo from April 1974 to December 1978 also was with National Space Development Agency of Japan from January, 1979 to March, 1990. During from 1985 to 1987, he was with Canada Centre for Remote Sensing as a Post-Doctoral Fellow of National Science and Engineering Research Council of Canada. He moved to Saga University as a Professor in Department of Information Science on April 1990. He was a councilor for the Aeronautics and Space related to the Technology Committee of the Ministry of Science and Technology during from 1998 to 2000. He was a councilor of Saga University for 2002 and 2003. He also was an executive councilor for the Remote Sensing Society of Japan for 2003 to 2005. He is a Science Council of Japan Special Member since 2012. He is an Adjunct Professor of University of Arizona, USA since 1998. He also is Vice Chairman of the Science Commission "A" of ICSU/COSPAR during 2008 and 2020 then he is now award committee member of ICSU/COSPAR. He is now Visiting Professor of Nishi-Kyushu University since 2021, and is Visiting Professor of Kurume Institute of Technology (Applied AI Laboratory) since 2021. He wrote 87 books and published 700 journal papers as well as 570 conference papers. He received 66 of awards including ICSU/COSPAR Vikram Sarabhai Medal in 2016, and Science award of Ministry of Mister of Education of Japan in 2015. He is now Editor-in-Chief of IJACSA and IJISA. http://teagis.ip.is.saga-u.ac.jp/index.html

Jin Shimazoe, He received BE degree in 2022. He also received the IEICE Kyushu Section Excellence Award. He is currently working on research that uses image processing and image recognition in Master's Program at Kurume Institute of Technology.

Mariko Oda, She graduated from the Faculty of Engineering, Saga University in 1992, and completed her master's and doctoral studies at the Graduate School of Engineering, Saga University in 1994 and 2012, respectively. She received Ph.D (Engineering) from Saga University in 2012. She also received the IPSJ Kyushu Section Newcomer Incentive Award. In 1994, she became an assistant professor at the department of engineering in Kurume Institute of Technology; in 2001, a lecturer; from 2012 to 2014, an associate professor at the same institute; from 2014, an associate professor at Hagoromo university of International studies; from 2017 to 2020, a professor at the Department of Media studies, Hagoromo university of International studies. In 2020, she was appointed Deputy Director and Professor of the Applied of AI Research Institute at Kurume Institute of Technology. She has been in this position up to the present. She is currently working on applied AI research in the fields of education.