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Adaptations of Explainable Artificial Intelligence (XAI) to Agricultural Data Models with ELI5, PDPbox, and Skater using Diverse Agricultural Worker Data

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ABSTRACT

We use explainable artificial intelligence (XAI) based on Explain Like I'm 5 (ELI5), Partial Dependency Plot box (PDPbox), and Skater to analyze diverse physical agricultural (agri-) worker datasets. We have developed various promising body-sensing systems to enhance agri-technical advancement, training and worker development, and security. This includes wearable sensing systems (WSSs) that can capture real-time three-axis acceleration and angular velocity data related to agri-worker motion by analyzing human dynamics and statistics in different agri-environments, such as fields, meadows, and gardens. After investigating the obtained time-series data using a novel program written in Python, we discuss our findings and recommendations with real agri-workers and managers. In this study, we use XAI and visualization to analyze diverse data of experienced and inexperienced agri-workers to develop an applied method for agri-directors to train agri-workers.

Keywords: agricultural worker data, ELI5, explainable artificial intelligence, PDPbox, skater.

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I. Introduction

Over several years, we have developed diverse body-sensing systems to address challenges in enhancing physical, agricultural (agri-) technical advancement, knowledge sharing and teaching, and security.

In this study, we first obtain basic data about farmers and data on body acceleration. Then, we conduct a broad explanation of multiple explainable artificial intelligence (XAI) libraries. XAI is a particular approach within data science to articulate how an AI reaches its conclusions. The user may adopt this explanation in some cases. In doing so, it is essential that we grasp how to use it.

Thus, in this study, we use sample data with key techniques in the XAI library to understand the behavior of complex AI models. Specifically, we explore Explain Like I'm 5 (ELI5), Partial Dependency Plot box (PDPbox), and Skater.

We use ELI5 to quantitatively indicate feature quantities and to what extent a feature is emphasized by PermutationImportance and discuss the results.

We apply PDPboxes to execute a partial dependence plot (individual condition expectation). We present and discuss changes in the predicted output for feature quantities and various feature combinations.

We base our Skater-based computations on using TreeSurrogate. We process and indicate the internal judgment of the AI model via conditional branching of the decision tree and discuss the results.

II. Method

A. *Method*

In this study, we combine our past achievements with recent XAI-based analysis methodologies. We shaped our study's approach in light of our results [1]–[16]. We designed system constructs to measure and analyze acceleration and

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angular velocity data using general human dynamics and statistical approaches [17]–[27].

To test and obtain outdoor data, subjects wore specially designed integrated structures with original wearable systems (WWSs) (Fig. 1) [19]. Each trial had 30 swings (digging up) with a traditional Japanese hoe, and each subject performed three trials successively on the same day to create sampled datasets per subject (Fig. 2).

For each subject, we captured diverse information as presented in Table I. This included two specific scales, the Visual Analogue Scale (VAS) and the Borg Rating of Perceived Exertion (RPE) scale, to measure worker fatigue and feelings against the strength of a task. The RPE measures perceived exertion in sports and particularly in exercise testing.

We selected fifteen subjects, whose characteristics are summarized in Table II.

After basic trials in outdoor fields, we defined indicators concerning vertical acceleration and direction: 1) maximum value, 2) minimum value, 3) standard deviation (SD), and 4) direct current (DC) component concerning subjects' hoe (hand) and waist [20].

In particular, we note that the SD and DC component are meaningful values for discriminating subjects' physical and motion characteristics.

Fig. 1. A subject equipped with measuring modules and knapsack with laptop PC connecting to various modules.

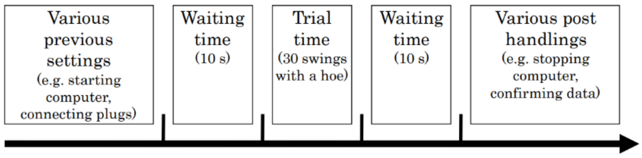

Fig. 2. Timeline of the outdoor trials.

B. Theory

A In this study, we utilize XAI-based methodologies and explore what is happening behind the algorithms. While other studies have applied this approach to training methodologies, ours is the first to use it in agri-research, although there have been other agri-research studies undertaken into training methodologies.

TABLE I: ITEMS IN SURVEY SHEET

Category	Index	Range of score (point)
Basic information	Name, affiliation, occupation, stature, weight, pre-existing disease	These depend on content
Low back pain (LBP)	Experience of LBP	No experience of LBP (0), Experience LBP in the past (1), Currently experiencing LBP (2)
	Frequency in the present workplace	No (0), Sometimes (1), Frequently (2)
	Frequency in past workplace(s)	No (0), Yes (1)
Daily successive fatigue	Frequency of continuing fatigue from the previous day	No (0), Rarely (1), Sometimes (2), Always (3)
Drinking and smoking habits	Alcohol consumption	No (0), A few times a month or a year (1), Every day or a few times a week (2)
	Tobacco consumption	Non-smoker (0), Past smoker (1), Smoker (2)
Sport habits	During spare time	No (0) Yes (1)
	In the past	No (0), A little in the past (1), Regularly in the past (2)
Feeling of fatigue in this trial	Indicators in VAS and Borg RPE scale tests, and oral, general questions	VAS (0 to 100), RPE (6 to 20), and open-ended question
Usability of the systems	Load of the systems and the tasks, load of the work posture fatigue of muscles	Five-grade evaluation (0 to 5), and open-ended question

TABLE II: SUBJECTS' DATA

Index	Experienced N=7			Inexperienced, novice N=8		
	Range	Ave	S.D.	Range	Ave	S.D.
Age (year)	31 to 74	62.52	14.2	23 to 34	5.6	3.58
Experience (year)	2 to 60	34	18.1	0	0	0
Stature (cm)	155 to 173	164	5.5	170 to 180	174	3.2
Weight (kg)	55 to 85	70	8.9	58 to 78	67	7.5

TABLE III: BASIC DATA AFTER ONE SET OF TRIALS

Index	Experienced			Inexperienced		
	Range	Average	SD	Range	Average	SD
VAS	0 to 68.1	28.2	24.6	0 to 73.6	26.8	23.3
RPE	9 to 12	10.1	1.17	12 to 13	12.1	0.35
Experience of LBP	0 to 1	0.38	0.48	0 to 1	0.57	0.49
Frequency of LBP in the present workplace	0 to 1	0.50	0.50	0 to 1	0.29	0.45
Frequency of LBP in the past workplace	0	0	0	0 to 1	0.14	0.35
Frequency of continuing fatigue from the previous day	0 to 2	1.25	0.83	1 to 2	1.86	0.35
Alcohol consumption	0 to 2	1	0.87	0 to 2	1	0.53
Tobacco consumption	0 to 2	0.63	0.70	0 to 1	0.14	0.35
Sports habit during spare time	0 to 1	0.38	0.48	0 to 1	0.86	0.35
Sports habit in the past	0 to 1	0.38	0.48	1 to 2	1.57	0.49

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C. Phase 1:

1) ELI5, PermutationImportance

We input a fitted predictive model *m* and a tabular dataset (training or validation) *D*. Then, we compute the reference score *S* of the model *m* on dataset *D* (for example, the accuracy for a classifier or the R^2 for a regressor).

Furthermore, for each feature *j* (column *D*), for each repetition *K* in 1 to *K*, we randomly shuffle column *j* of dataset *D* to generate a corrupted version of the data named $D2_{k,j}$. Then, we compute the score $S_{k,j}$ of model *m* on the $D2_{k,j}$.

In PermutationImportance for ELI5, importance i_j for feature f_j is calculated as:

$$i_j = S - \frac{1}{K}\sum_{k=1}^{K} S_{k,j} \tag{1}$$

where
i is the importance variable;
j is the feature amount (quantity);
S is the original predicted score value;
K is the total number of records in the data;
k indicates the kth data record;
$S_{k,j}$ is predicted score value of the data *k* after shuffling feature amount *j*.

D. Phase 2:

1) PDPbox

For partial dependency plots (PDP), one or two features indicate the marginal effect on the prediction results of the machine learning model. PDPs can express whether the relationship between input and output is linear, monotonic, or more complex.

For instance, if we apply it to a linear regression model, the PDP always shows a linear relationship:

$$f_{x_s}(x_s) = E_{x_c}\left[f(x_s, x_c)\right] = \int f(x_s, x_c) \tag{2}$$

where
x_S is a feature amount that plots the data concerning the partial dependence function
x_C represents the other feature amounts for the machine learning model f.

Typically, a set *S* contains one or two feature amounts. The feature amount in *S* is the target value of the effect on the prediction. We construct the *feature space x* by combining the *feature vectors* x_s and x_c. Partial dependence works by marginalizing the output from the machine learning model focusing on the distribution of feature amounts in a set *C*. We can utilize the function to describe the relationship between the feature amounts in set *S* and the prediction result, as well as interactions between feature amounts. By marginalizing other features, we obtain a function that depends only on the feature amounts in the set *S*.

We calculate the partial function $f_{x_s}(x_s)$ as the average of the training data. This is sometimes referred to as the Monte Carlo method:

$$f_{x_s}(x_s) = \frac{1}{n}\sum_{i=1}^{n} f\left(x_s, x_c^{(i)}\right) \tag{3}$$

The partial dependence function indicates the average marginal effect on the prediction for the value given to the feature *S*.

The PDP assumption is that feature amounts in *C* are not correlated with features in *S*. If this assumption does not hold, then the average calculated for the PDP will contain data points that are highly unlikely, if not impossible.

Hereinafter, we describe a classification calculation in which a machine learning model outputs a probability value. In this case, the PDP displays the probability of a particular class where different values are given to the feature amounts of S. Note that PDP is a global method here, i.e., this method considers all instances.

Then, we provide a statement concerning the global relationship between feature amounts and prediction results.

For categorical feature amounts, we can easily compute partial dependence. We force all instances of each category into the same category. This enables us to calculate PDPs.

E. Phase 3:

1) Skater, Tree Surrogate

Here, we discuss interpretable models with Tree Surrogates using Skater. There are various ways to interpret machine learning models such as with features, dependence plots, and even Local Interpretable Model-agnostic Explanations (LIME).

However, we cannot build an approximation or a surrogate model that is more interpretable from a very complex black box model, such as an Extreme Gradient Boost (XGBoost) model with hundreds of decision trees.

Thus, we present the novel idea of using TreeSurrogate as a means of explaining a model's learned decision policies:

$$\mathrm{EPE}(x) = \left(f(x) - f(x)\right)^2 + \mathrm{var}(x) \tag{4}$$

where
$f(x)$ is the true function;
$f(x)$ is the prediction function – (a);
var(*x*) is the prediction variance – (b).

The combination of (a) and (b) is called a surrogate model.

F. Program

1) Phase 1: ELI5, PermutationImportance

ELI5 is compatible with a variety of AI algorithms. Furthermore, it can be used even for models that do not have functions such as visualization of feature importance, which is valuable. It can also calculate PermutationImportance for individual prediction results. Thus, it is also a tool for making a choice of local explanations.

Using ELI5, we can visualize the importance of the feature amount that the AI model uses to determine classifications, and then can output a broad explanation and a local explanation for the classification model and the regression model, respectively.

For this phase, we scrutinize the internal parameters of the model for a broad description. Then, we focus on what types of feature classifiers and regressors are designated as important from a broad perspective. Next, data is computed regarding what the program is processing.

For local explanations, we provide output for individual programmatic predictions on the factors of the model's predictions.

In some cases, it is possible to tune various elements such as parameters for the output result. Thus, we change the parameters for calculating feature importance.

We then give an output explanation of how we value features inside the AI model. We execute the process using the parameter *gain*. Thus, we confirm the contribution of the feature amount to the aspect of discrimination accuracy.

2) *Phase 2: PDPbox*

From Phase 1, we can understand the overlapping feature amounts, however that is not sufficient for an adequate explanation. Thus, in this phase, we verify what kind of change occurs in the prediction result due to changes in the feature amount. Here, we use a PDPbox library that outputs a PDP. A PDPbox outputs changes in the prediction of the model caused by any variable, such as a PDP or Individual Conditional Expectation (ICE).

We show the output data using a Python-language program (scikit learn), which allows us to use operators and biaxial graphs. We also address supervised learning algorithms that are compatible with them.

The PDP and ICE outputs of the PDPbox correspond only to a combination of one and two variables. We provide both PDP and ICE outputs.

Here, we show (a) the graph of the impact of a single feature, and (b) the graph of the influence of the interaction of two features.

We can specify a PDP in the program and draw a two-axis graph within the range of standard deviation. We also specify ICE and draw plots of results for each individual dataset in a two-axis graph.

3) *Phase 3: Skater, TreeSurrogate*

We use Skater, a big-picture explanatory technique, to understand the prediction judgment process, and thereby generate a surrogate model of the decision tree.

Here, we review the internal structure of the surrogate model and describe how the AI model grasps the rules of judgment. Fundamentally, Skater is a framework for interpreting various AI models. Skater's explanatory functions include:

1) Functions for providing broad pictures: PartialDependence, FeatureImportance;
2) Functions for providing local pictures: LimeTabularExplainer, DeepInterpreter;
3) Functions for providing both broad and local pictures: Bayesian Rule List Classifier (BRLC), TreeSurrogate.

We can also use Skater to implement other algorithms, such as LIME, and improve the ability to interpret the model by various approaches.

In the current study, we focus on applying TreeSurrogate. We first use decision trees that have learned the prediction results of the target model. We then approximate the tendency of judgment and explain the output by AI. The model to be described is one that performs learning discrimination of supervised AI. There is no dependency on the analysis target. Thus, we can apply it to various algorithms.

For Skater, our general procedure is to generate a functional description base, an interpretation, and a local model, InMemoryModel. We combine these to explain the output of AI.

We generate InMemoryModels by inputting a set of predictive functions and data samples for the model to be explained.

We use Skater to generate decision-tree surrogate models for pre-trained light gradient boosting machine (LightGBM) models.

III. Result

We performed the necessary operating verifications concerning each function of the aforementioned system factors and essential experimental results concerning WSs.

Generally, it is known that the output differs to some extent depending on the calculation method of PermutationImportance (Fig. 3–8). We found this to be the case in our study as well.

For Fig. 3 and Fig. 4, we want to consider the feature amounts that we place importance on from the perspective of the accuracy of the classification of outputs. To this end, we used gain, which is able to emphasize desired features such as "Weight", "SD of hoe (1st trial)", etc.

We also used splits for the same purpose, however it could not fairly indicate an important feature quantity in the judgment. However, both gain and splits can be useful for recognizing what decisions are being made within AI.

Here, we output the importance of the calculated feature only with LightGBM and we compare this with the output of ELI5. In the LightGBM model, the importance of the feature amounts is calculated based on the sharpness and gain of the decomposition. We can confirm them.

Hereafter, we describe the data shown in Fig. 6.

This is the calculation of PermutationImportance that actually performs the process of sorting data. This calculation includes a random component.

For ELI5, the initial setting requires executing the calculation five times. This data was produced accordingly. We present the mean value of PermutationImportance. From this data, we confirmed that the trend of PermutationImportance is similar for the training and validation data. In other words, it can be seen that the trend of the verification data is close to the trend of the training data.

In this way, PermutationImportance can be used for deep analysis and understanding. Furthermore, future AI model improvements may be based on this technique.

IV. Discussion

In this study, we succeeded in visualizing to some extent the importance of the feature amount (quantity) used for the analysis with ELI5. As described, ELI5 supports a variety of algorithms. However, the accuracy and stability of this may be further improved as this is a new technical field.

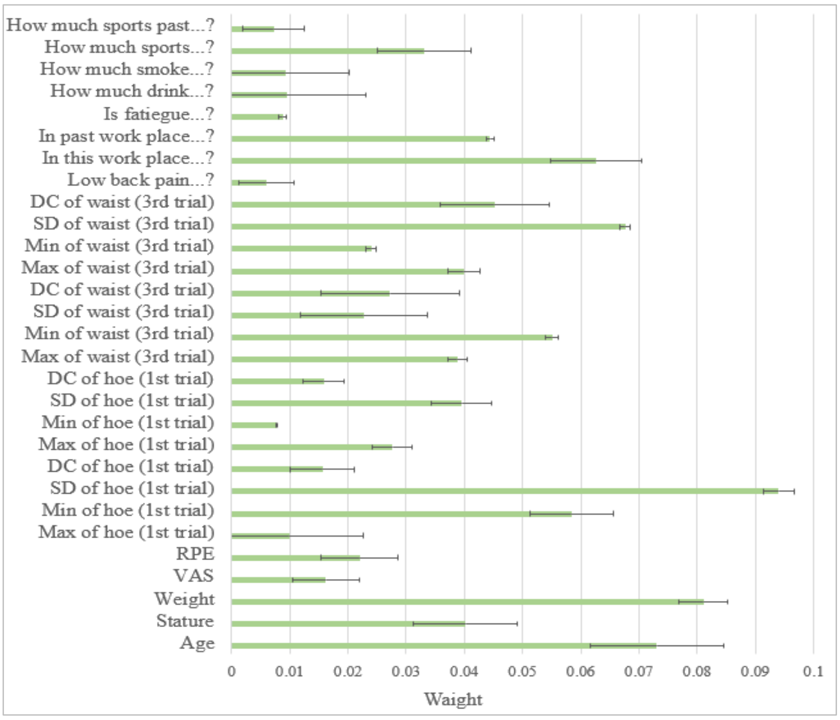

Fig. 3. Bar graph of importance values versus years of experience for the LightGBM model (gain parameter).

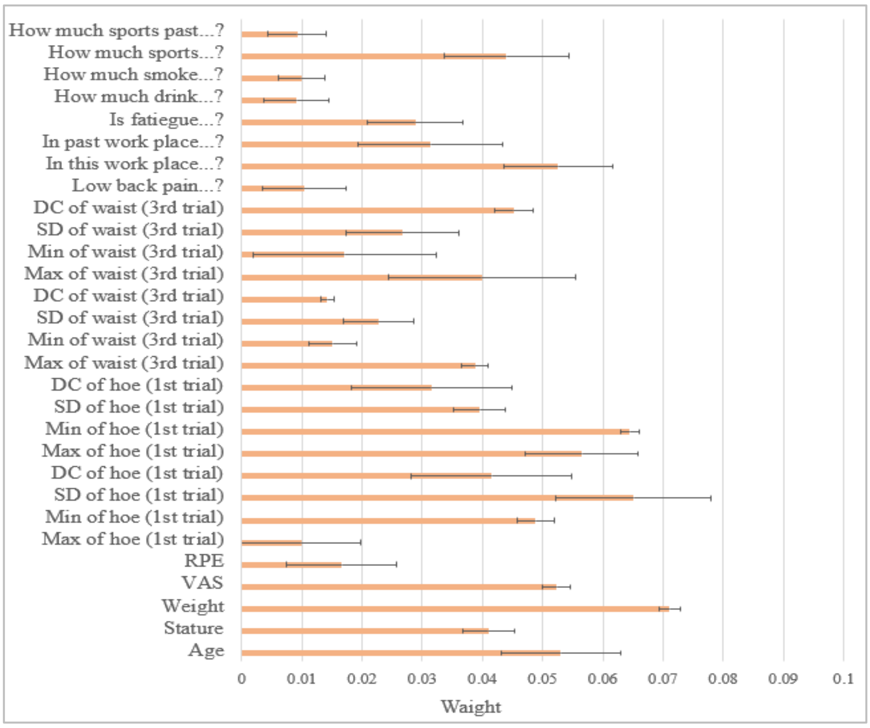

Fig. 4. Bar graph of importance values versus years of experience for the LightGBM model (splits parameter).

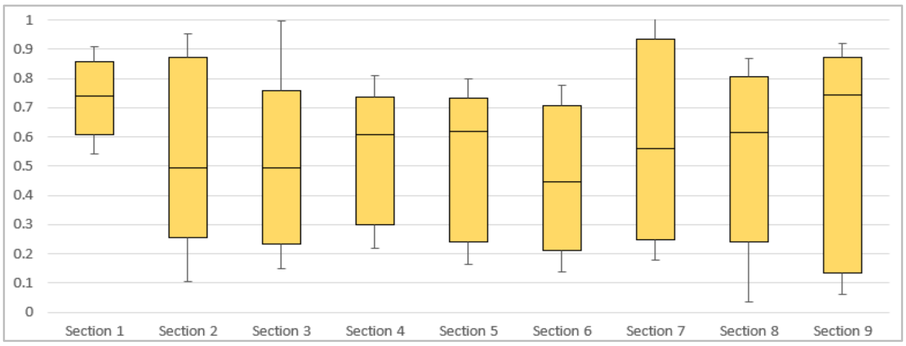

Fig. 5. Actual predictions for years of experience utilizing the LightGBM model.

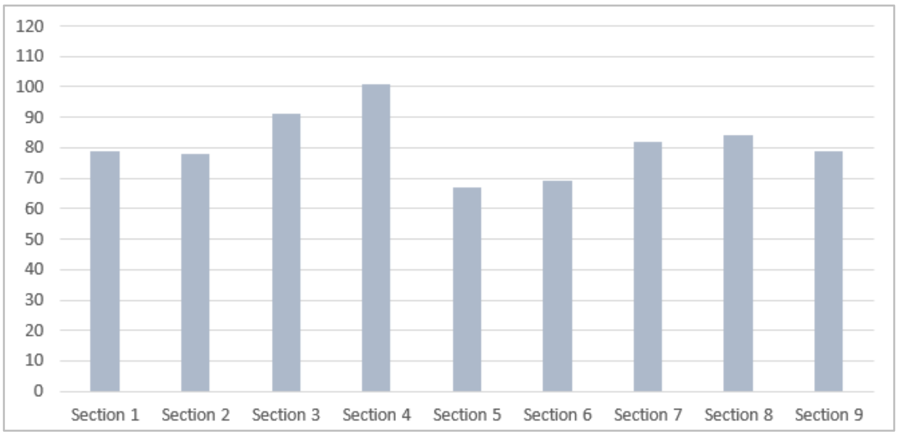

Fig. 6. Actual predictions for years of experience utilizing the LightGBM model.

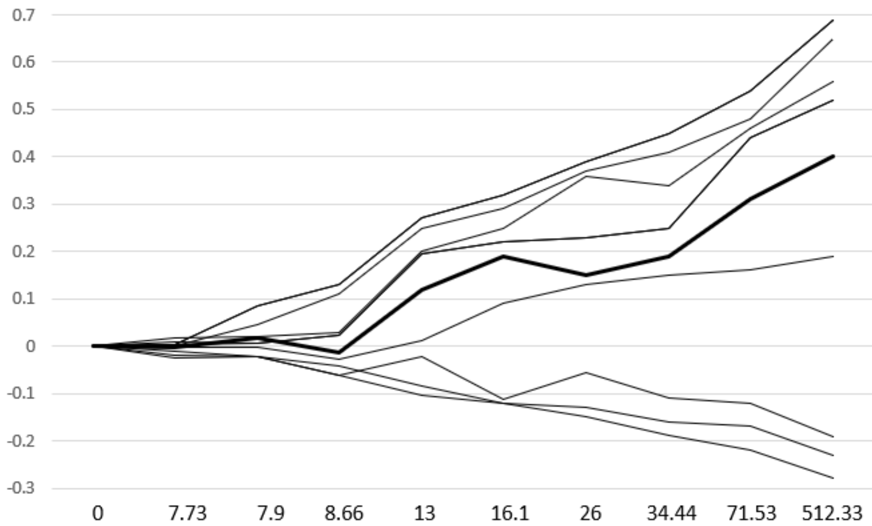

Fig. 7. Line graph of output data of PDP (ICE) for years of experience.

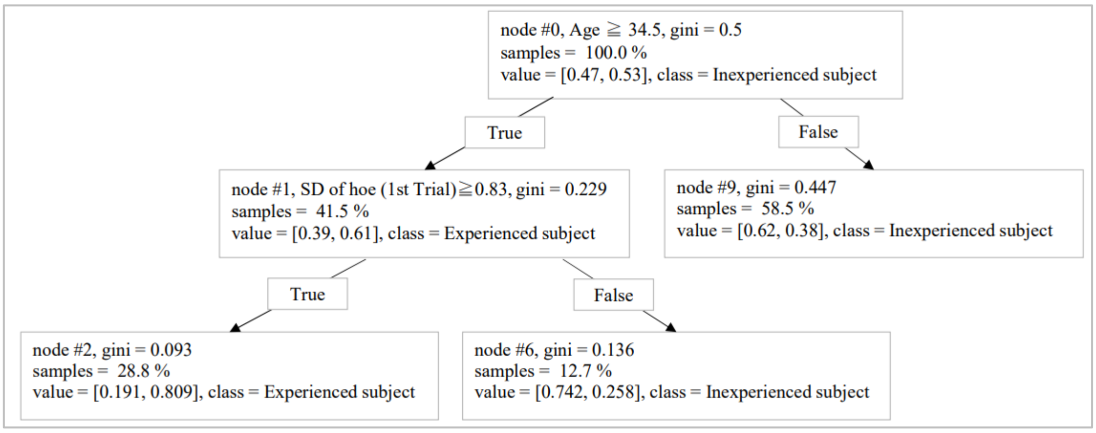

Fig. 8. Block chart formed by a decision-tree generated from surrogate-model-based analyses using Skater. (Accuracy of surrogate-model=0.85)

By changing the parameters for calculating FeatureImportance, we were able to confirm the importance of the feature amount and related changes within the AI models.

Additionally, we were able to visually confirm feature quantities and how they impact discrimination accuracy from the execution result for the parameter gain. We confirmed the technique can handle models that do not have a visualization function for importance.

Using PDPbox (Fig. 7), we visually confirmed that the predicted probability of PDP for feature “Subjects’ years of experience” changes as years of experience. increases. We also presented ICE in plotted data under the conditions of individual data.

We also showed the effect of changes of the feature amount on the resulting data in two types of planar graphs, InformationPlots and PDPs. Furthermore, we were able to identify changes in characteristics that occur only under certain conditions using only some data. Regarding the target data of this study, PDPbox is an effective tool for practically observing the relationship between the AI model and the feature amount in detail.

V. Conclusion and Future Tasks

We verified the fundamental operations of explainable artificial intelligence (XAI) techniques (ELI5, PDPbox, and Skater) by utilizing our diverse, pre-obtained agricultural (agri-) worker data from WSs and questionnaires.

First, we developed several basic steps of the aforementioned XAI-based systems and methods, especially with consideration for the fusion of agri-informatics, statistics, and human dynamics. Second, we obtained, checked, and discussed various promising XAI data.

In future, other recent methodologies of human dynamics and data analysis (e.g., higher mathematics) should be incorporated. Further exploration of "skill tradition" and agri-worker daily tasks would be very useful.

We also believe that the overall results and outcomes demonstrate that the measure of precision for diagnosing agri-critical situations (e.g., heavy diseases, injuries) can be improved. From the perspective of global agricultural dynamics, we have some plans to launch to other countries.

These trials have certainly been challenging so far; however, they will comprehensively contribute to agri-industries and workers.

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