RESEARCH ARTICLE

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Analyses of Diverse Agricultural Worker Data with Explainable Artificial Intelligence: XAI based on SHAP, LIME, and LightGBM

Shinji Kawakura, Masayuki Hirafuji, Seishi Ninomiya, and Ryosuke Shibasaki

ABSTRACT

We use recent explainable artificial intelligence (XAI) based on SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and Light Gradient Boosting Machine (LightGBM) 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. However, existing methods and systems are not sufficient for in-depth analysis of human motion. Thus, we have also developed wearable sensing systems (WS) 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-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, Explainable Artificial Intelligence, SHapley Additive Explanations, Local Interpretable Model-agnostic Explanations, Light Gradient Boosting Machine.

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S. Kawakura*
Research Center for Artificial Photosynthesis (ReCAP) at Osaka City University/Osaka City, Osaka, Japan.
(e-mail: s.kawakura@gmail.com)

M. Hirafuji
Graduate School of Agricultural and Life Sciences at The University of Tokyo/Bunkyo-ku, Tokyo, Japan.
(e-mail: hirafuji@g.ecc.u-tokyo.ac.jp)

S. Ninomiya
Graduate School of Agricultural and Life Sciences at The University of Tokyo/ Bunkyo-ku, Tokyo, Japan.
(e-mail: snino@isas.a.u-tokyo.ac.jp)

R. Shibasaki
Center for Spatial Information Science (CSIS), The University of Tokyo, Meguro-ku, Tokyo, Japan, and Department of Socio-Cultural and Socio-Physical Environmental Studies, The University of Tokyo/Kashiwa-shi, Chiba, Japan.
(e-mail: shiba@csis.u-tokyo.ac.jp)

Corresponding Author

I. Introduction

Over several years, we have been developing various body-sensing systems to address challenges and drive innovation in the agricultural (agri-) field. Key aims include improved training, knowledge sharing/preservation, and security. However, existing methods and systems are not sufficient for in-depth analysis of human motion. In addition, they are often complicated and expensive. Where possible, we aim for low-cost and automatic solutions.

To this end, we have been developing wearable sensing systems (WS) that can capture real-time three-axis acceleration and angular velocity data related to agri-worker motion in different environments, such as fields, meadows, and gardens.

Fujii *et al.* [1] noted emerging problems concerning the critical shortage of young, beginner (novice) agri-workers and challenges in sharing knowledge and traditional farming approaches to experienced and inexperienced workers. At the same time, the field of agricultural informatics is expanding and advancing [1]–[10]. Such advancements often correlate with increased complexity of methodologies and systems.

The existing literature does not cover concrete user suggestions for improving physical motions in agricultural work, especially for beginners and inexperienced agri-workers. Therefore, our research aims to support such agri-workers (and their daily activities) by applying electronic technologies, understanding of human dynamics, and statistical methods to provide workers with concrete feedback in a variety of formats, such as oral, visual, data, and written formats.

In the future, we expect the increasing integration of several sensing techniques and existing large-size farming machinery, the latest IT services (such as cloud services), sensor devices, and other tools. There are efficiency and knowledge-sharing benefits for users and industry when an integrated approach or tool becomes ubiquitous in the field.

With this in mind, we have been building integrated systems to enhance productivity, accuracy, and quality by recording and sharing traditional skills and approaches via

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extracting and analyzing diverse agri-worker motion data.

For in-depth analysis, we apply recent explainable artificial intelligence (XAI) methods based on SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and Light Gradient Boosting Machine (LightGBM) [11]–[34]. Based on the results, we aim to identify indicators related to agri-skills and safety.

We highlight two key considerations of using XAI as follows:

1) The matching of dataset backgrounds, features, and tendencies

Generally, background knowledge is essential to meaningfully analyze data and interpret key outputs. This is also true for the outputs of artificial intelligence (AI). We can only gain insight when we attach meaning to the data. However, in the absence of background knowledge, understanding the charecteristics in the datasets is important for interpreting results from an XAI-based system.

2) Understanding which factors can be influenced

We should not simply analyze and explain factual data with XAI. To appropriately apply XAI, it is essential to understand the dataset. For example, critical questions include who gathered the dataset? and what is the purpose of the dataset?

II. Method

A. Method

We reviewed literature on industrial goods, patents, and academic papers. We also discussed our findings with agri-informatics researchers, actual workers, and farmland managers.

Based on what we learned, in this study, we combine our past achievements with recent XAI-based analysis methodologies. In light of recent XAI-trends, we describe five fundamental points concerning the evaluation of an XAI's outputs:

1) Description fidelity: An index for evaluating the extent to which the XAI for explaining complex AI models can reproduce the original AI model.

2) Reliability of the description: An index c that evaluates the level of reliability of the explanation given by the XAI from the perspective of the person receiving the explanation.

3) Satisfaction with description: An index to assess the extent to which the XAI is able to provide explanations that lead to user satisfaction.

4) Mental model: A representation of how the explanation given by the XAI affects the recipient psychologically. An index is used for evaluation.

5) Affinity for real systems and the real world: An index to evaluate the usefulness of the XAI in relation to AI in real systems.

LightGBM is a model in which a large number of decision trees are connected in series. It is fast and highly accurate and has become increasing powerful in recent years. Owing to these characteristics and its applicability for predictive models with table data, we adopt it in this study.

From our literature review, we identified a gap in considerations of such problems. We shaped our approach in light of our results [4].

We designed system constructs to measure and analyze acceleration and angular velocity data using general human dynamics and statistics approaches [5]–[10].

After designing the system, we selected and applied some existing techniques and modules. We then performed indoor operational testing to evaluate the utility and suitability of the proposed system. During testing, subjects wore specially designed integrated structures with original WSs (Fig. 1 and 2) [35]–[36].

We categorized common agricultural tasks and selected one involving a semi-crouching position, i.e., digging with a hoe, because it is repetitive and requires full-body movement.

Based on observations and discussions with key stakeholders, we set that every trial had 30 swings (digging up), and every subject performed three trials successively on the same day (Fig. 3).

We selected fifteen subjects (Table I) and gathered experienced (careered) and inexperienced workers without any known serious mental or physical limitations or special characteristics. This latter criterion was developed based on preliminary discussions with key stakeholders and observations of basic time-series data. It covered not having any serious diseases, remarkable habits, or specific careers (especially in sports and martial arts). The standard deviation (SD) values were higher for experienced workers than for inexperienced workers across all indices.

In contrast to the literature, we aimed to capture and combine a broad scope of relevant information about agri-worker features. Thus, we considered and selected major items (indicators) from statistics, human dynamics, and exercise physiology, as shown in Table II.

Some indicators, such as fitness habits, smoking habits, and backache, were developed and are used by the Japan Association of Industrial Health and other health organizations and are considered reliable.

We also chose 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 VAS uses a psychometric response scale as used in questionnaires to measure subjective characteristics or attitudes. Respondents specify their level of agreement with a statement by indicating a position along a continuous line between two endpoints. This continuous (or analogue) aspect of the scale differentiates it from discrete scales.

The RPE measures perceived exertion in sports and particularly in exercise testing. In medicine, this scale is used to document a patient's exertion during a test, and sports coaches use the scale to assess the intensity of training and competition. The original scale rated exertion on a scale of 6 to 20.

Fig. 1. Microcomputers with various devices, store-bought sensing modules, and original vest-shaped and belt-shaped WSs.

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Fig. 2. A subject equipped with measuring modules and knapsack with laptop PC connecting to various modules.

After basic trials in outdoor fields, we defined some major indicators related to 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 [4]. Since these trials are preliminary, we selected major indices according to previous studies, such as Bao (2003) and other researchers. In particular, the SD and DC component are useful values for discriminating subjects and tasks. We also calculated and used large-sized a correlation matrix and performed an analysis of principal components because these are considered comprehensive methods to categorize and identify key data components.

TABLE I: 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

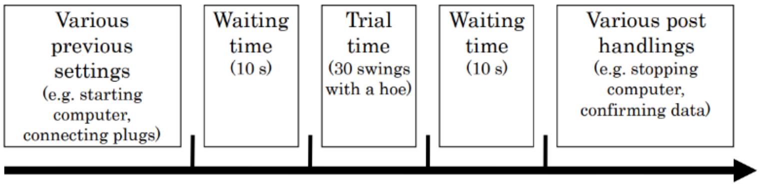

Fig. 3. Timeline of the outdoor trials.

TABLE II. ITEMS IN SURVEY SHEET

Category	Index	Range of score (point)
Basic information	Name, affiliation, occupation, stature, weight, pre-existing disease	These depend on contents
Low back pain (LBP)	Experience of Low back pain	No experience of LBP (0), Experience LBP in the past (1), Now having LBP (2)
	Frequency in the present workplace	No (0), Sometimes (1), Frequently (2)
	Frequency in the past workplace	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 habit	Alcohol consumption	No (0), A few times a month or a year (1), Everyday or a few times a week (2)
	Tobacco consumption	Non-smoker (0), Past smoker (1), Smoker (2)
Sport habit	During spare time	No (0) Yes (1)
	In the past	Non (0), A little in the past (1), Regularly in the past (2)
This trials' feeling of fatigue	Indicators in VAS (Visual Analogue Scale) and RPE (Borg RPE Scale) test, and oral, general question	VAS (0～100), RPE (6～20), 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 (0～5), and open-ended question

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

B. Theory

In this study, we utilize XAI-based methodologies and explore what is happening behind the algorithms. Although some studies have applied this to training methodologies, it has not previously been used in agri-research.

1) SHAP is a technique for explaining individual predictions. It is based on the SHapley value in game theory. The goal of SHAP is to calculate and present the contribution of each feature to the prediction to help explain the prediction.

SHAP uses cooperative game theory to calculate the SHapley values. The instance feature value behaves as part of the cooperating players. The SHapley value indicates the way that the reward can be distributed fairly among the feature values, where the reward is a predicted value. In the case of general matrix datasets, each player has a distinct feature value. In other cases, the players can be a set of feature values.

For an example that describes an image, the pixels are grouped as super-pixels and the prediction is distributed among those groups.

One of the innovations of SHAP is that the SHapley value is expressed as the sum of the effects of the feature quantities, such as in a linear model. The point, feature links LIME and SHapley values. SHAP provides the following explanation model, g:

$$g(x') = \phi_0 + \sum_{j=1}^{M} \phi_j \tag{1}$$

where is a federated vector, M is the maximum size of the federated vector, and $z' \in \{0,1\}^M$ is the feature attribute for feature j and the SHapley value.

To calculate the SHapley values, we simulate the existence of only some feature quantities and assume that the others are absent. The united linear model's representation is a technique for computing ϕ. For the concerned instance x, the federated vector x' is a vector whose elements are all 1. That is, all features can exist for the vector.

2) The Local Surrogate Model is an interruptive LIME model used to describe individual predictions of black-box machine-learning models. With a surrogate model, we try to approximate the prediction underlying the black-box model. The use of a local rather than global surrogate model allows LIME to explain individual predictions.

First, before considering the training data, we discuss the black-box model that returns a predicted value when data is entered. We can examine this black box as many times as we want.

The aim is to understand why the machine-learning model returns certain predicted data. When the perturbation is added to the input data of a machine-learning model, LIME examines what changes occur in the predicted data.

LIME replaces the feature values in the sample and creates a new resulting dataset, which helps to predict the black-box model outputs. Additionally, LIME learns an interpretable model based on this new dataset. The model is weighted by its proximity to the sampled or related instance.

Various options are available for interpretable models, including Lasso and decision trees. Locally, the trained model approximates the predictive data of the machine-learning model; however, globally, it is not a good approximation. This type of accuracy is known as local fidelity. Mathematically, we express a local surrogate model with interpretable constraints as follows:

$$\text{explanation}(x) = \arg\min_{g \in G} L(f, g, \pi_x) + \Omega(g) \tag{2}$$

The explanatory model, for instance, x is a model g that minimizes losses such as the sum of squared errors. This is the loss L, which represents the extent to which the predictions of the original model f can be explained. The term $\Omega(g)$ indicates the complexity of this model and should be a smaller feature quantity. G is a possible explanation, such as all possible linear regression models. The proximity measure πx defines the size of the neighborhood used to account for instance x.

However, LIME actually only optimizes the loss function. Through the process, we select the maximum number of features that the linear regression model uses, which is an indication of its complexity. Therefore, we need to determine its complexity. The local surrogate model is learned as follows. First, we select the instance where we desire to explain the black-box prediction. We obtain the predictions concerning the black boxes for new data points by perturbing the datasets. We then weight the new sample datasets according to their proximity to the instance of interest. In other words, we learn weighted, interpretable models on datasets created with intentionally added variations. We can then explain the predictions with interpretable local models.

3) The LightGBM framework supports diverse algorithms (e.g., GBT, GBDT, GBRT, GBM, MART).

LightGBM shares many advantages with eXtreme Gradient Boost (XGBoost), including sparse optimization, parallel training, multiple loss functions, regularization, bagging, and early stopping. For major differences between the two lies in the construction of trees, LightGBM does not grow a tree level-wise as most other implementations do. Instead, it grows trees' leaf-wise; it chooses the leaf it believes will yield the largest decrease in loss.

C. Program

We describe each phase of the program as follows.

Phase 1:

1. Construct Python-language-based environment necessary for this trial.
2. Install Required Libraries for XAI (e.g., LightGBM library).
3. Select and install key analysis packages, such as: numpy, pandas, matplotlib, scikit-learn, seaborn, etc.
4. Execute the basic mandatory processing of the target data (e.g., formatting).
5. Read XAI-based systems.
6. Check the size, format, etc. of the data in the output of the program in text format. At that time, if there is an error, return to step 4.
7. Display the data in the system for visual confirmation.
8. Perform statistical processing using pandas and seaborn functions, such as processing correlation variables between datasets and calculating categorical variables.

9. Check for missing data or other problems with the dataset.

10. Display map data for correlation coefficients between diverse variables.

11. Calculate, display, and check correlation coefficients between specific variables.

Phase 2:

1. Preprocess the table datasets for learning XAI models.
2. Import libraries.
3. Set fundamental, necessary variables and functions.
4. Execute feature quantity calculations.
5. Execute other tasks.
6. Learn and output the model file.
7. Use the model file after deep learning and check the data for accuracy. If the accuracy seems inappropriate, repeat the check and then return to step 1.

Phase 3:

1. Analyze the discriminant result when the predicted data is inputted to the trained model using LIME. Then, the basis of that judgment will be expelled. We discuss this further later in the paper.
2. Make necessary preparations to use LIME in advance (e.g., import LIME's fundamental libraries, prepare classes for explanation).
3. Perform arithmetic processing for local explanations.
4. Prepare the following LIME outputs: (1) visualization of various bar data, (2) acquisition in matplotlib format, and (3) acquisition of numerical data and shaping in the order of the original feature values.
5. Visually confirm the validity of the output explanatory data.
6. For other explanatory data, perform steps 1-5.

Phase 4:

1. Perform Phase 3 steps while varying the kernel width and check how much the contribution of the variable changes depending on the kernel width. (Kernel width is a weighting variable for adjusting the weight of random dummy data generated inside LIME; it indicates the degree of local explanation.)
2. Generally, for such an analysis, the description results vary depending on the parameters. Furthermore, there is no quantitative index for judging which explanation is appropriate for LIME. Therefore, parameter setting should ensure the analyst and the user of the service can discharge explanatory data that they are satisfied with.

III. Results

After performing the necessary verifications of the operation of each function of the system, we determined that the model's performance seems appropriate only for actions not containing "moving over" (such as walking or cycling, which are untargeted in this study). The kernel width was set as follows by default:

$$(\textit{Number of Explanatory variables})^{1/2} \times 0.75 = \textit{Kernel width} \quad (3)$$

Thus, in this trial, its value was set as $30^{1/2} \times 0.75 \fallingdotseq 4.18$. Therefore, we decided to use a set of three values centered near the kernel width: 1.0, 4.0, and 8.0. For LimeTabularExplainer, it generates slightly different dummy data every time, that's why we output datasets and present both the average and Standard Deviation (SD).

(i) In Fig. 4, we show the results for the probability of prediction. We output a bar graph from the LIME analyses concerning basic information from subjects' survey sheets and vertical acceleration of the hoe.

Specifically, the system predicted that the probability of identifying an experienced subject is 0.48 and the probability of identifying an inexperienced subject is 0.52. We also present the SDs.

(ii) The results in Fig. 5–7 are for kernel widths 1, 4, and 8, respectively. Using LIME, we can show the reason for the judgment based on the AI model.

The contribution of each variable varied greatly depending on the kernel width. When the kernel width was rather narrow at 1.0, the system's ability to describe was significantly degraded.

According to this, the characteristics of the figures are similar to those of Fig. 6. Fig. 6 and 7 present diverse features. Therefore, the above can be said to have succeeded in visualizing the judgment basis of XAI.

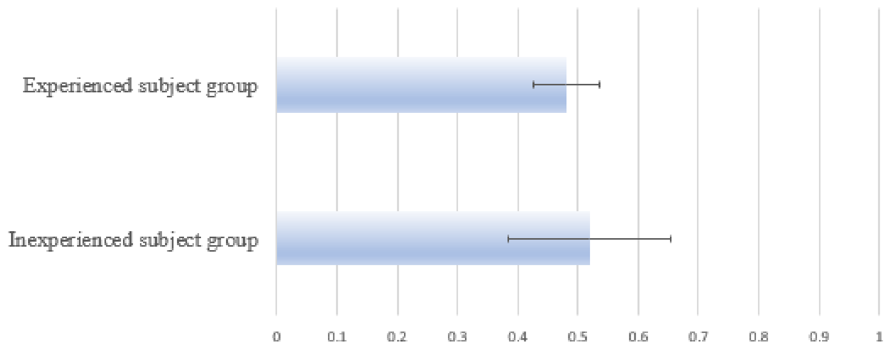

Fig. 4. Probability of prediction: Bar graph from LIME analyses concerning various data from subjects' survey sheets and hoe vertical acceleration.

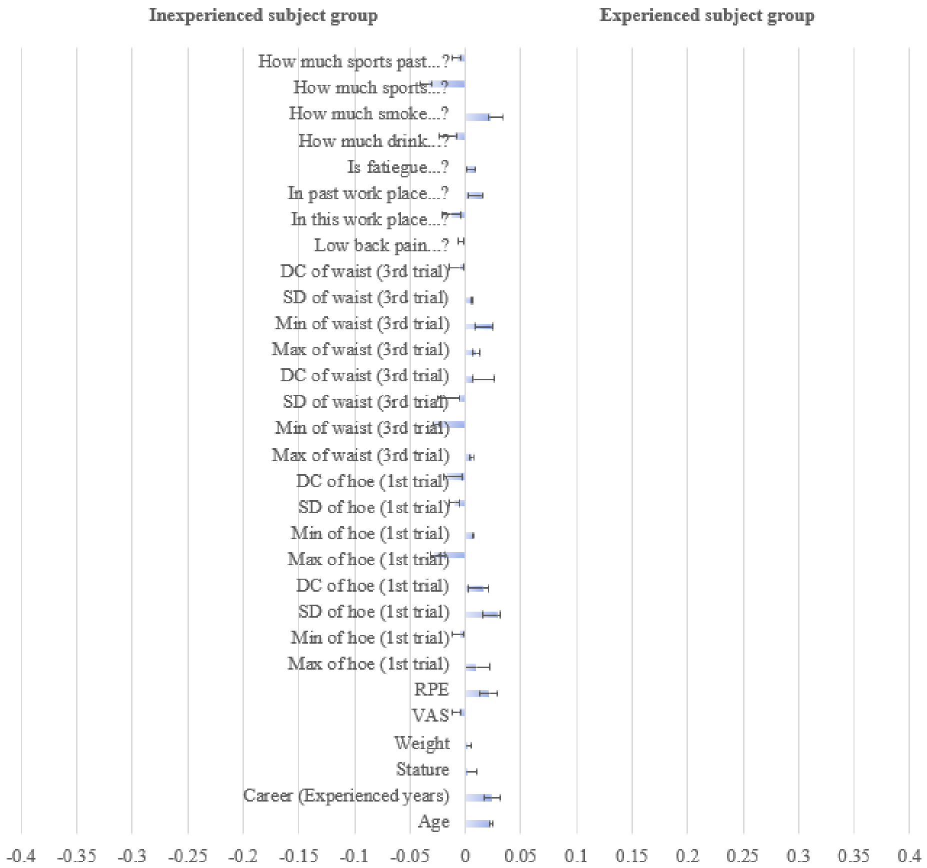

Fig. 5. Contribution ratios of variable data from LIME analyses concerning basic information and hoe vertical acceleration. Width of kernel: 1.0.

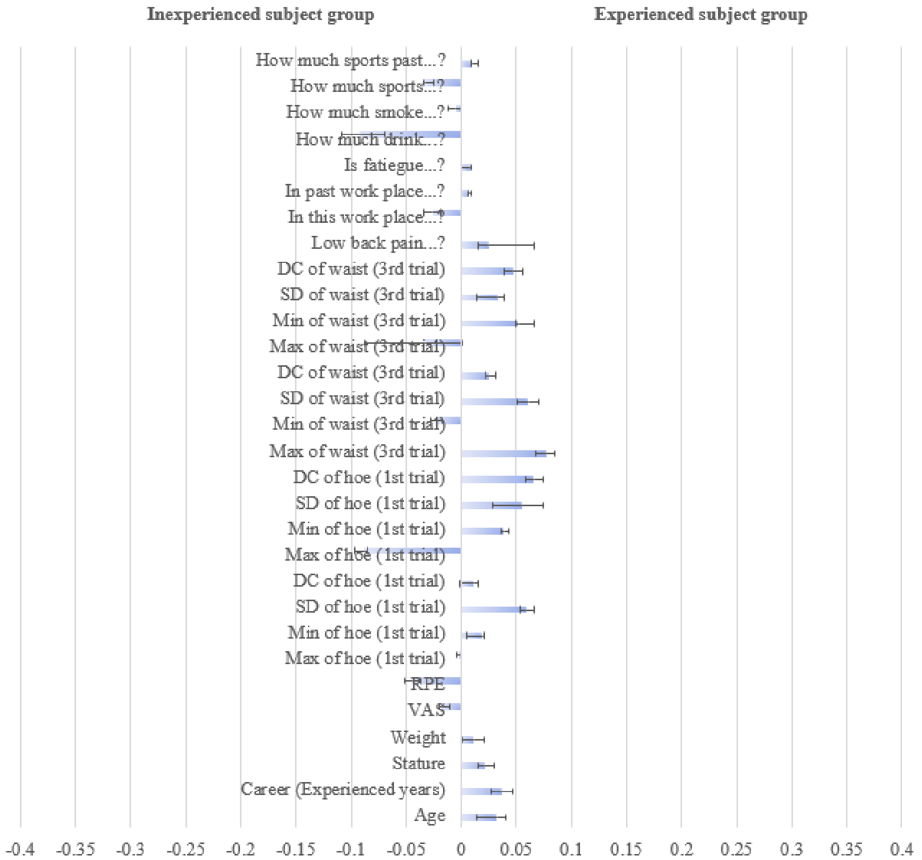

Fig. 6. Contribution ratios of variable data from LIME analyses concerning basic information and hoe vertical acceleration. Width of kernel: 4.0.

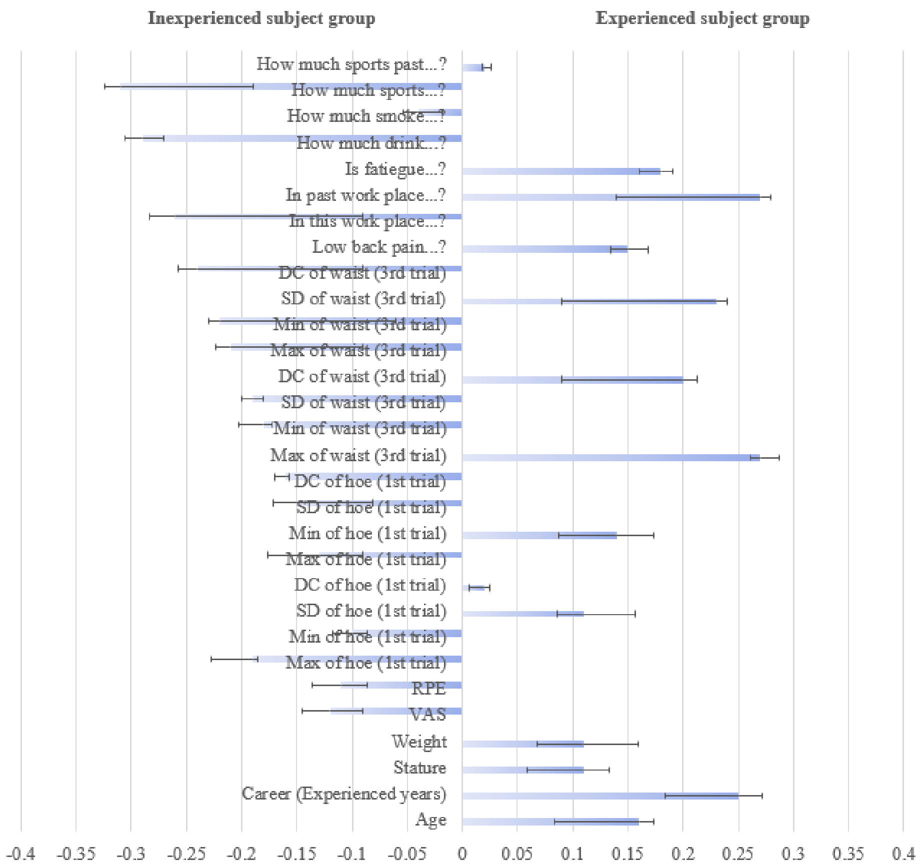

Fig. 7. Contribution ratios of variable data from LIME analyses concerning basic information and hoe vertical acceleration .Width of kernel: 8.0.

IV. Discussion

As shown in Fig. 4, the probability of prediction of the experienced subject group is 0.04 higher than that of the inexperienced subject group, which is very similar to the proportions presented in Table I.

As shown in Figs. 5–7, “Age”, “Career (experienced year)”, “SD of hoe (1st trial)”, and other variables were closer to the experienced subject group. In other words, these factors are explanatory for the experienced subjects group.

Interestingly, subjects’ “DC of hoe (1st trial)” and “How much sports past…?” hardly affected to the contribution ratios.

Of course, we should consider the subjects’ physical (muscle) strength, stature, and weight. For this analysis, there were a variety of other problems. These may be solved by increasing the number and variety of subjects, or by homogenizing their stature and weight to the extent possible.

V. Conclusion and Future Tasks

We verified the fundamental operations concerning each function of the XAI using SHAP, LIME, and Light GBM systems and tested the proposed system. After reviewing past similar results related to human dynamics and primary-components-based analyses, our achievements seemed appropriate to some extent. First, we presented several basic steps of the aforementioned styles of systems and methods by examining real agri-work sites, with particular consideration for the fusion of agricultural informatics, statistics, and human dynamics. Second, we obtained promising non-specific three-axis acceleration and angular velocity time-series data for agri-motions. Finally, we executed and presented (1) the probability of the prediction, and (2) the contribution ratio of variable datasets.

In future work, we should add a greater variety of worker information into these statistical data. Furthermore, other recent methodologies of human dynamics and visual data analysis (e.g., higher mathematics) should be tested and incorporated, as appropriate. Using these results and many sets of experimental evidence, we plan to launch practical supporting projects for workers.

From the perspective of global agricultural dynamics, we have plans to launch to other countries. Although these trials have been challenging, they will provide significant benefit to workers in agricultural industries.

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Shinji Kawakura Place of birth: Toyama Pref., Japan. Date of birth: July 14, 1978. Ph.D. in Environmentology, University of Tokyo, 2015, Bunkyo-ku, Tokyo, Japan. B.A. in Control System Engineering, Tokyo Institute of Technology, 2003, Meguro-ku, Tokyo, Japan. M.A. in Human-Factor Engineering, Tokyo Institute of Technology, 2005, Meguro-ku, Tokyo, Japan.

Career: Systems engineering, research for private companies. Development and verification of sensing systems for outdoor agricultural workers.

Dr. Kawakura, Research Center for Artificial Photosynthesis (ReCAP) at Osaka City University/Osaka City, Osaka, Japan. IEEE senior member, Hong Kong Chemical, Biological & Environmental Engineering Society (HKCBEES) senior member.

Masayuki Hirafuji Place of birth: Kawasaki-shi, Kanagawa Pref. Japan. Date of birth: Oct. 29, 1956. Dr. in Agriculture, the University of Tokyo, 1983, Bunkyo-ku, Tokyo, Japan. B.A in Agriculture, the University of Tokyo, 1981, Bunkyo-ku, Tokyo, Japan. M.A. in Agriculture, the University of Tokyo, 1979, Bunkyo-ku, Tokyo, Japan.

Career: National Agriculture and Food Research Organization (NARO), The University of Tokyo.

Dr. Hirafuji, Project Professor at Field Phenomics Research Laboratory, Bunkyo-ku, Tokyo, Japan.

Seishi Ninomiya Place of birth: Tokyo, Japan. He is currently a Project Professor with the Graduate School of Agricultural and Life Science, The University of Tokyo, and a Visiting Professor with the Plant Phenomics Research Center, Nanjing Agricultural University, Nanjing, China. His research interests include agro-informatics, statistics, breeding science, and plant phenomics.

Dr. Ninomiya, Project Professor at Graduate School of Agricultural and Life Science, The University of Tokyo, and a Visiting Professor, Bunkyo-ku, Tokyo, Japan.

Ryosuke Shibasaki Place of birth: Fukuoka. Pref. Japan. Date of birth: March 1, 1958. Dr. in Engineering, the University of Tokyo, 1987, Bunkyo-ku, Tokyo, Japan. B.A in Engineering, the University of Tokyo, 1980, Bunkyo-ku, Tokyo, Japan. M.A. in Engineering, the University of Tokyo, 1982, Bunkyo-ku, Tokyo, Japan.

Career: Professor at the Center for Spatial Information Science, University of Tokyo.

Dr. Shibasaki, Center for Spatial Information Science (CSIS), The University of Tokyo, Bunkyo-ku, Tokyo, Japan, and Department of Socio-Cultural and Socio-Physical Environmental Studies, The University of Tokyo/Kashiwa-shi, Chiba, Japan.