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A Brighter Future with Tropical Innovation in the Application of Industry 4.0

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Editors • Rudy Agung Nugroho, Veliyana Londong Allo, Meiliyani Siringoringo, Surya Prangga, Wahidah, Rahmiati Munir and Irfan Ashari Hiyahara

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Study of features importance level identification of machine learning classification model in sub-populations for food insecurity

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Endang Yuliani, Bagus Sartono, Hari Wijayanto, et al.

Study of Features Importance Level Identification of Machine Learning Classification Model in Sub-Populations for Food Insecurity

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Abstract. To explain a complicated machine-learning model, data scientists work a lot with identifying the importance of predictor features of the model. Shapley Additive Explanation (SHAP) and Permutation Feature Importance (PFI) are popular methods useful to measure the feature-importance levels. This research examines the utilization of both techniques to reveal the contribution of predictors in a model to classify the food-insecurity status of Indonesian households. Food insecurity is a condition in which a person does not have protected access to safe and nutritious food in sufficient quantities for normal growth and development and active and healthy life. Instead of identifying significant predictors for a population in general, the study is interested in identifying each sub-population: urban and rural areas in West Java Province. A random forest algorithm was implemented to generate a model using both complete data and separate data. A follow-up analysis was then conducted by applying SHAP for both types of data and PFI for separate data. In general, the two approaches using SHAP resulted in quite similar feature importance levels. Meanwhile, the results of SHAP and PFI are relatively different.

INTRODUCTION

Big data is a term for data that is large, has a fast growth rate, and usually consists mainly of unstructured data. Therefore, machine learning techniques are needed in the big data analysis process. This technique produces predictive models with excellent accuracy [1]. In addition, this technique can capture linear patterns to provide additional information that generally fails to be captured by the classical linear model approach [2] and produce more satisfactory predictions. One of the most widely used supervised machine learning prediction models is a classification tree-based model. One of these models is a random forest which can produce better accuracy performance than some other algorithms because it is a development of the ensemble tree method whose formation is a combination of several classification trees [3].

Popular interpretation methods used are PFI based on classification tree [3] and SHAP [4]. These two interpreters have different algorithms for calculating the feature importance. SHAP places more emphasis on the attribution of features and provides local information or information from an individual. SHAP can describe the effect of each predictor to obtain an individual's guess. Meanwhile, PFI is based on the importance score derived from the error rate of the original model. A feature that does not contribute to the performance of a model, then changing the data structure will have no significant effect. However, a significant feature will significantly affect the model's performance if the data structure is changed. These two methods produce the level of feature importance, which can be a solution in interpreting the black-box model that is useful for the government in making policies and determining the direction of development. One of the focuses of world development, including Indonesia, is food insecurity. Food insecurity is when a person does not have protected access to safe and nutritious food in sufficient quantities for average growth

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and development and active and healthy life [5]. Food insecurity is the second purposes of the Sustainable Development Goals (SDGs) of 17 other purposes that the government has agreed.

According to the March 2020 Susenas data, as many as 21.6% of households are food insecure, of which 26.48% are in rural areas and 18.91% in urban areas. Rural and urban area are sub-populations that have different characteristics. So it is possible to have different levels of feature importance. Complete data and separate data approaches are used to identify the importance of features in the sub-populations. [6] found that the variables that affect food insecurity are having low levels of education, less social capital, weak social networks, low household income, and being unemployed. [7] found that households with younger, less-educated household heads were more likely to suffer food insecurity.

Based on the problems above, we need a method to interpret the black box model (random forest), namely SHAP and Permutation Feature Importance. Furthermore, the complete data and separate data approaches are expected to provide additional insight into the interpretation of sub-populations.

LITERATURE REVIEW

Food Insecurity Experience Scale

FAO launched the Voices of Hungry project in 2013 to develop a methodology for measuring the severity of food insecurity, namely Food Insecurity Experience Scale (FIES). FIES measures the severity of food insecurity at the household or individual level, whose value depends on yes/no answers to 8 questions regarding respondents' access to adequate food [8]. In 2017 Indonesia used FIES for the first time in the National Socio-Economic Survey (Susenas) questionnaire for the household level. The experience of global food insecurity begins with a feeling of worry about not having enough food. In conditions that do not improve, adjustments will be made to the quality of nutrition and types of food. This condition indicates a state of mild food insecurity. However, the ongoing food insecurity situation causes respondents to skip meals and have food portions that are not following what is needed. This condition indicates a moderate food insecurity situation. The worst condition is when hungry but have no food and even experience not eating all day. This condition suggests a state of severe food insecurity.

Random Forest

The Random Forest (RF) algorithm is the development of the Classification and Regression Tree (CART) method by applying the bootstrap aggregating (bagging) and random feature selection [3]. The RF algorithm is an algorithm that is suitable for classifying big data, and in the RF algorithm, there is no pruning of features as in the decision tree algorithm. The RF method combines many trees, unlike a single tree which only consists of one tree to make classification and class predictions. In RF, tree formation is done by training sample data. The way to take data samples is using Sampling with replacement. The selection of features used for split is taken randomly. Classification is run after all trees are formed. The determination of the classification in this RF is taken based on the votes from each tree, and the majority votes are the winners.

The following is a algorithm for constructing a Random Forest on a data set consisting of n observations and p predictor features [3][9]:

1. Perform random sampling of size n with recovery on the data cluster. This stage is the bootstrap stage.
2. Using the bootstrap example, the tree is constructed until it reaches its maximum size (without pruning). Then, arrange a tree based on these data, but in each separation process, randomly select $m \ll p$ predictor features and do the best separation. This stage is the stage of random feature selection.
3. Repeat steps 1 and 2 k times to form a forest consisting of k trees.
4. Perform a composite estimate based on k trees. For the classification case, a majority vote is used, which is the category or class that appears most often due to predictions from k classification trees.

Classification Model Evaluation

The classification resulting from a method is expected to classify all data correctly, but it is undeniable that the performance of a system cannot be 100% accurate and correct. Generally, the measurement of the performance of the classification model performs using a confusion matrix, namely cross-tabulation between the response feature data included in the prediction and observation classes [10]. For example, for cases with two classes, the cross-tabulation formed is as follows:

TABLE 1. Confusion matrix

Actual	**Predicted**	
	Positive	**Negative**
Positive	True Postive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TN)

The performance of a classification model can be measured through three values, namely accuracy, F1-Score, and AUC. Accuracy is the percentage of the model that is correct in making predictions. The F1-score is a comparison of the average precision with weighted recall. The AUC value measures discriminatory performance by estimating the output probability from a randomly selected sample. The AUC value is 0-1, the greater the AUC value, the stronger the classification used.

Permutation Feature Importance (PFI)

Permutation Importance is an algorithm to obtain information on the feature importance by permutating (rearranging data sets) the features used in training prediction models. The permutation feature importance measurement was introduced by [3] for random forest algorithm. Then, [11] proposed an agnostic model version of feature importance called the reliance model. The inputs determining feature importance are trained to model f, matrix variable X, response vector y, error size $L(y, f)$. Thus, the Permutation Feature Importance Algorithm is :

1. Estimate the original model error $e^{orig} = L\big(y, f(X)\big)$
2. For each feature $j = 1, \dots, p$ do:
   - Generate feature matrix X^{perm} by permuting feature j in the data X. his breaks the association between feature j and true outcome y.
   - Estimate error $e^{perm} = L\big(Y, f(X^{perm})\big)$ based on the predictions of the permuted data.
   - Calculate permutation feature importance $FI^j = \frac{e^{perm}}{e^{orig}}$ Alternatively, the difference can be used: $FI^j = e^{perm} - e^{orig}$
   - Sort features by descending FI

If a feature does not contribute much to the performance of a model, then changing the arrangement of the data will have no significant effect. On the other hand, a feature that has a significant contribution will significantly affect the model's performance if the data structure is changed.

Shapley Value

The Shapley value created by Lloyd Shapley (1953) is an in-game method of determining the rewards to a player "fairly" by considering the player's contribution to the accumulated value. The player is referred to as the predictor, while the rewards is the estimated value. Thus, all possible combinations of players or predictor must be evaluated with and without the jth predictor to calculate Shapley's value. If M is the number of players, $S \subseteq \mathcal{M} = \{1, \dots, M\}$ is a subset consisting of S players and assumed a characteristic function or a contribution function $v(S)$ which can map a subset of players to a number, then the Shapley Value for the jth player is:

$$\varphi_j(v) = \sum_{S \subseteq \mathcal{M} \setminus \{j\}} \frac{|S|!\,(M - |S| - 1)}{M!} \big(v(S \cup \{j\}) - v(S)\big) \tag{1}$$

Shapley Additive Explanation

SHAP is an interpretation method for individual predictions based on the optimal game theory of Shapley Values [12]. SHAP aims to explain the prediction of an individual x by calculating the contribution of each feature. The SHAP interpretation formula is:

$$g(z') = \emptyset_0 + \sum_{j=1}^{M} \emptyset_j z'_j \quad (2)$$

Where g is the interpretation model, $z' \in \{0,1\}^M$ is the (simplified) coalition vector, M is the maximum coalition size, and $\emptyset_j \in \mathbb{R}$ is the Shapley value. The value of $g(z')$ is calculated for all observations, so the size of the Feature Importance is the sum of all observations:

$$I_J = \sum_{i=1}^{n} \left|\emptyset_j^{(i)}\right| \quad (3)$$

One type of SHAP is treeSHAP which is used for machine learning based on classification trees, such as random forest.

MATERIALS AND METHODS

Source of Data

The data from the National Socio-Economic Survey (Susenas) Kor 2020 (March) of West Java Province, including 24,769 sample households. The level of food insecurity is a response variable in this study. These predictors are presented in Table 2 below:

TABLE 2. Research predictors

Features Name	Measurement Scale	Features Name	Measurement Scale
Education of Household Head	Ordinal	Grantee of Health Insurance National Program	Nominal
Vulnerable Household Head	Nominal	Grantee of Health Insurance Local Program	Nominal
Number of Family Members Having Saving Account	Ratio	Grantee of Scholarship Social Program	Nominal
Number of Family Members Illiterate	Ratio	Roof Types	Nominal
Main Income From the Transferee	Nominal	Floor Types	Nominal
Ownership of Land	Nominal	Wall Types	Nominal
Internet Access	Nominal	House Size	Ratio
Access to Outpatient Treatment	Nominal	Electricity	Nominal
Grantee of Non Cash Social Assistance	Nominal	Types of Cooking Fuel	Nominal
Grantee of Hopeful Family Program	Nominal	Drinking Water Source	Nominal
Grantee of Prosperous Family Program	Nominal	Decent Drinking Water	Nominal
Grantee of Social Assistance From Local Goverment	Nominal	Decent Sanitation	Nominal

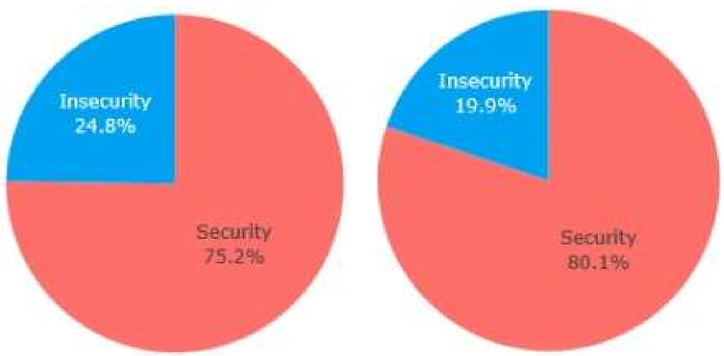
Procedure of Analysis

There are three step of analysis carried out in this study. First step is the data pre-processing, then the model formation, and the model interpretation. The analysis and processing data is using Python software.

1. Data Pre-processing
   a. Data preparation
      At this step, several things are carried out, namely: aggregation of the individual to household-level data, discarding observations containing missing values, "Not Answering" codes and "Don't Know"codes for the eight FIES questions, and categorization of food insecurity consisting of "Vulnerable" and "not".
   b. Data exploration
2. Model formation
   a. Complete data
      First, dividing training data (70%) and testing data (30%), then balancing training data with SMOTE technique, and doing modeling using random forest algorithm.
   b. Separate data
      For each area, divide the training data (70%) and test data (30%), then balance the training data using the SMOTE technique and modeling using the random forest algorithm.
3. Model Interpretation
   Interpretation for the separated data using Permutation Feature Importance (PFI), while SHAP is applied to complete and separate data.

RESULT AND DISCUSSION

Of the 25091 sample households in the March 2020 SUSENAS of West Java province, as many as 322 households stated they did not know (code 8) or refused to answer (code 9) at least one of the 8 FIES questions so that only 24769 households will be analyzed in this study.



(a) (b)

FIGURE 1. (a) Comparison of response variable classes in rural areas. (b) Comparison of response variable classes in urban areas

The comparison of food security and food insecurity households based on area status is shown in Fig. 1(a) and 1(b). In rural areas, the number of food security is 6631 households (75.2%), while food insecurity is 2182 households (24.8%). In urban areas, number of food security is 12787 households (80.1%), while food insecurity is 3169 households (19.9%). The random forest algorithm is used in classification modeling by carrying out a 10-fold cross-validation process to obtain stable model performance by looking at the optimal hyperparameter values. The hyperparameters used are ntree (the number of trees formed), mtry (the number of predictor), and the criterion (gini or entropy). The optimal hyperparameters are shown in Table 3.

TABLE 3. Optimal hyperparameters

Hyperparameter	Models		
	Rural	Urban	Complete
ntree	152	181	265
mtry	5	5	5
criterion	gini	gini	entropy

The comparison of the goodness of the random forest algorithm for the three models is shown in Table 4. The metrics we use to evaluate the model are AUC, accuracy, and F1-Score. Accuracy is used to determine the percentage of households correctly predicted to be food insecure and not food insecure from all households. In addition, accuracy is used because the dataset has a very close (symmetric) number of false negative and false positive data. The F1-score is used to find the optimal combination of precision and recall. The data in this study were unbalanced and focused on sensitivity and specificity, so the AUC was appropriate to evaluate the model.

TABLE 4. Model goodness measure

Models	AUC	Accuracy	F1-Score
Rural	83.3%	74.87%	75.5%
Urban	87.68%	79.40%	80.1%
Complete	85.71%	77.69%	78.0%

Feature Importance for Rural Area

Figure 2 represent feature importance for rural areas using PFI. Based on the PFI method, the predictors that characterize food insecurity in rural areas are house size, education of household head, number of family members having a saving account, decent sanitation, and floor types. The feature above is the most influential, and the lower the influence decreases.

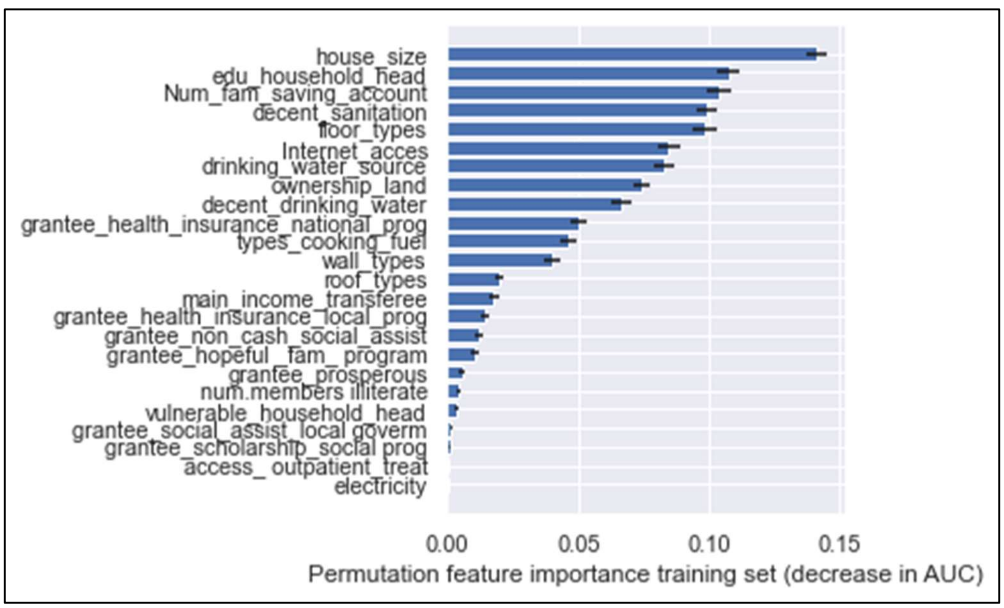
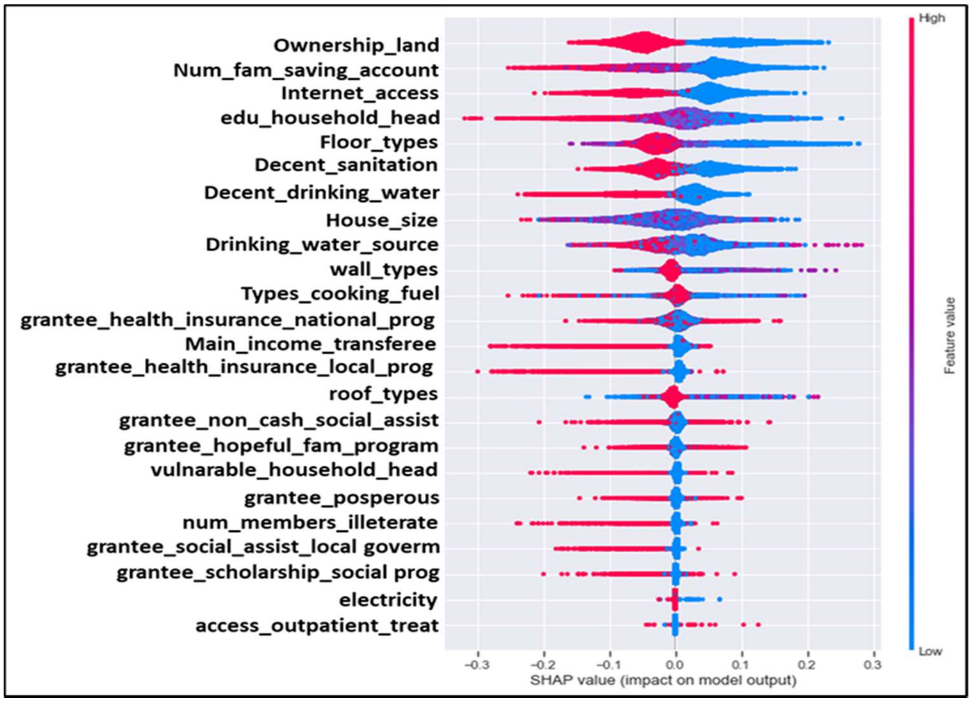
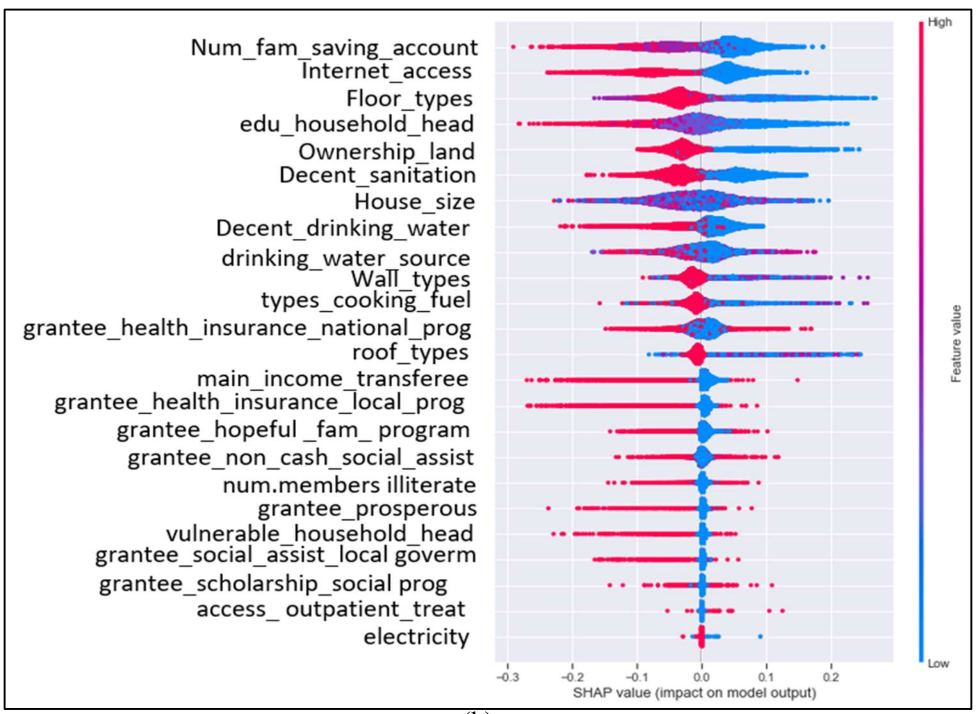


FIGURE 2. Feature importance using PFI in rural areas



(a)



(b)

FIGURE 3. (a) SHAP summary plot for complete data in rural areas, (b) SHAP summary plot for separate data in rural areas

Figure 3 represents the importance of using SHAP for complete and separate data. It can be seen that for these two approaches, the top five features are the same, namely ownership of land, the number of family members having a saving account, internet access, education of household head, and floor types. The x-axis is the SHAP value, and the y-axis is the variables listed in rank order. The predictor with the top order means that it has the most significant contribution to the prediction. The blue color indicates a low variable value, the closer to red the higher the variable value. The dots on the SHAP summary plot represent households (individuals).

The first feature importance in complete data is ownership of land. If the household owns land assets, then the value of Shapley gets smaller. It means that the probability of households being categorized as food insecure is getting smaller. On the other hand, if the household does not own land assets, the value of Shapley will increase. It means that the possibility of households entering the food insecurity category is higher.

The first feature importance in separate data is the number of family members having a saving account. In this predictor, if more household members have savings accounts, the Shapley value will be lower. It means that the more household members who have savings accounts, the lower the probability of a household being categorized as food insecure. On the other hand, if fewer household members have savings accounts, then the value of Shapley will be higher. It means that the probability of a household being categorized as food insecure is higher. The next most feature important is internet access. If the value of the internet access for each household is higher, then the Shapley value will be smaller. It means that the probability of a household being categorized as food insecure is getting smaller. Conversely, if the value on the internet access for each household is lower, then the Shapley value will be greater. It means that the probability of a household being categorized as food insecurity is higher.

The interesting in here is the grantee of health insurance national program. If households receive assistance from this program, then Shapley's value will be even greater. It means that the opportunity for households to be categorized as food insecure is getting bigger. On the other hand, if households do not receive assistance from this program, then Shapley's value will decrease. This means that the opportunity for a household to enter the food insecurity category is getting smaller. It becomes two opposite sides.

Feature Importance for Urban Area

Figure 4 represent feature importance for urban areas using PFI. Based on the PFI method, the features that characterize food insecurity in urban areas are house size, education of household head, number of family members having a saving account, ownership of land, and drinking water source.

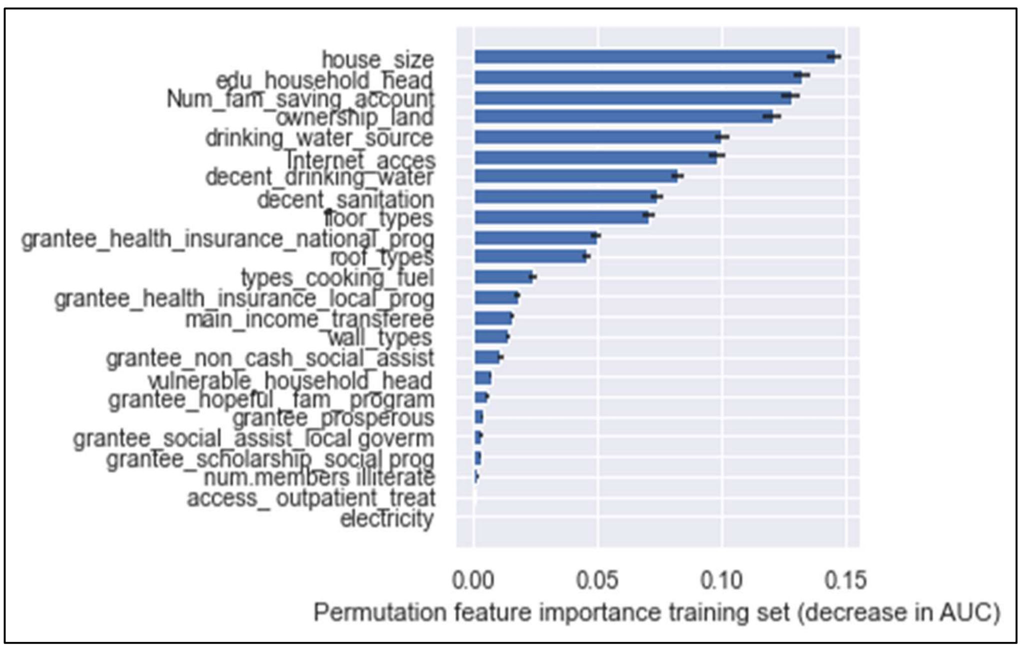
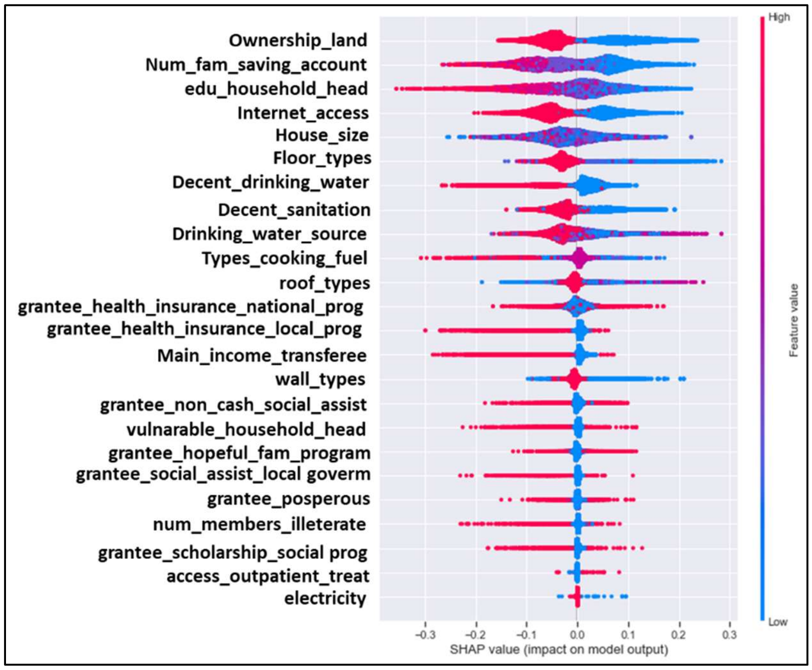
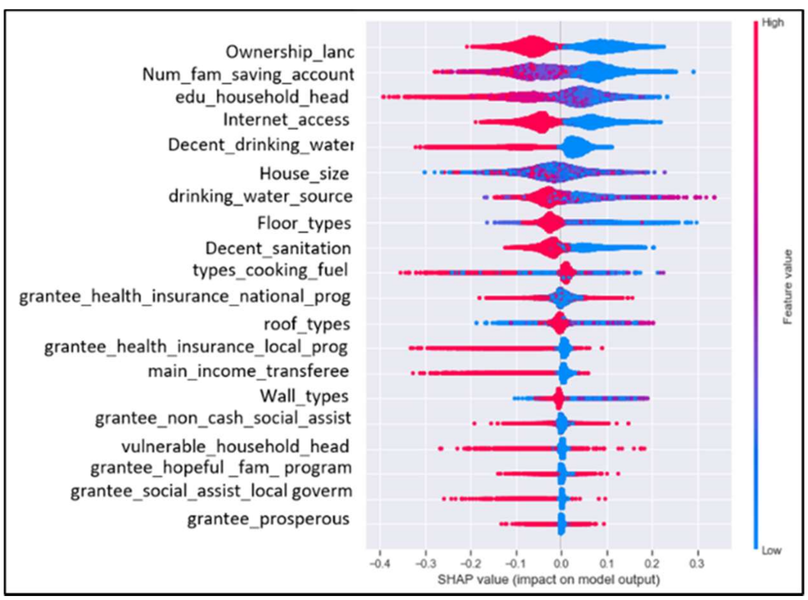


FIGURE 4. Feature importance using PFI urban areas



(a)



(b)

FIGURE 5. (a) SHAP summary plot for complete data in urban areas, (b) SHAP summary plot for separate data in urban areas

Figure 5 represents the importance of using SHAP for complete and separate data. It can be seen that for these two approaches, the top four features are the same, namely ownership of land, number family members having saving account, education of household head, and internet access. Based on the SHAP summary plot, the first feature importance is ownership of land. If the household owns land assets, then the value of Shapley gets smaller. It means that the probability of households being categorized as food insecure is getting smaller. On the other hand, if the household does not own land assets, the value of Shapley will increase. It means that the possibility of households entering the food insecurity category is higher. The next most feature importance for separate data in urban is the number of family members having a saving account. In this predictor, if more household members have savings accounts, the Shapley value will be lower. It means that the more household members who have savings accounts, the lower the probability of a household being categorized as food insecure. On the other hand, if fewer household members have savings accounts, then the value of Shapley will be higher. It means that the probability of a household being categorized as food insecure is higher.

The next most feature importance is education level of the household head. The higher the education of the head of the household, the lower Shapley's score will be. It means that the higher the education of the head of the household, the lower the probability of a household being categorized as food insecure. On the other hand, the lower the education level of the household head, the higher Shapley's score will be. This means that the possibility of households entering the food insecurity category is higher.

CONCLUSION

In general, the two approaches using SHAP resulted in a quite similar feature importance levels. Meanwhile, SHAP and PFI are relatively different. In rural areas, the features of the education of household head, number of family members having saving account, and floor types are features importance in the three models in the top five. In urban areas, the features of the education of household head, number of family members having a saving account, and ownership of land feature importance in the three models in the top five. The computational process takes a long time, especially for the SHAP method. We recommend using complete data in analyzing the level of features importance. This study only uses the random forest algorithm, which is an ensemble tree method. Therefore, it is necessary to compare with other methods that are not tree-based. The SHAP method can be applied to models not based on a classification tree using the KernelSHAP.

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