

Development of J48 Algorithm-Based Application in Predicting Teacher's Techno-Pedagogical Competence

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Abstract

Education 4.0 in the Philippines encourages the use of advanced technologies in facilitating the educational ecosystem where teachers are required to be competent in information and communications technology (ICT). On the contrary, the established instrument in assessing the pedagogical ICT competence in the Philippines is still a manual process showing a gap between the actual and the ideal in terms of education 4.0 requirement. In this paper, it is empirical to develop a model and implement this model in actual system development where the software learns through time based on the data collected from the system users in predicting the pedagogical ICT competence of the teachers. This study was conducted in a Philippine state university, where the total enumeration of the respondents was taken. The use of Knowledge Discovery in Databases was utilized to develop a model using J48 algorithm, evaluated through 10-cross-fold validation, and used to develop an application that predicts the pedagogical ICT competence of the teacher using R programming. The result showed a significant improvement and efficiency in predicting the pedagogical ICT competence of the teachers.

Keywords: data mining, software development, predictive analytics, decision tree model, pedagogical competence

1. Introduction

21st century skills for teachers refer to the core competencies such as collaboration, digital literacy, critical thinking, and problem-solving needed in teaching students to thrive in today's world. Generally, the goal of education is to aid society's progress creating an educational ecosystem where lifelong learning exists. The philosophy of learning throughout life is everything but modern since ancient civilizations have emphasized the need to learn from the cradle to the grave (Medel-Añonuevo *et al.*, 2001). In this

context, lifelong learning has changed and become a guiding and organizing principle of education reforms. Many types of research were conducted to shed light on the skills of teachers. A survey conducted by Tican and Deniz (2019) discovered that pre-service teachers are ready for using 21st century skills and teacher skills specifically on their techno-pedagogical skills, yet, they were not capable of making acceptable use of learner and teacher skills during their practicum teaching. The need for the techno-pedagogical skills of teachers has an impact on classroom teaching such as developing instructional strategies and materials for active learning and information and communications technology (ICT)-based teaching and learning, adapting the type of learners we have today, which can address teacher learning and practice (Yue, 2019). Therefore, if these are the kind of teacher graduates that universities are producing, techno-pedagogical skills for teachers must be delivered and practiced to develop mastery and innovativeness in using technologies for classroom teaching.

On the contrary, combining technologies and pedagogy has become a daunting task (Jung, 2005) due to a lack of right teaching materials and the capacity to practice due to inadequate technologies to use. Many teachers reported that they had not received adequate training to prepare them to use technology effectively in teaching and learning; however, in that respect, several efforts had been induced to answer this problem such as training to use technology as tools for enhancing teaching and learning (Jung, 2005). Rastogi and Malhotra (2013) emphasized that in order to integrate ICT more effectively in the educational ecosystem, it may be worth understanding the teacher's present level of ICT skills and their attitudes related to the ICT-pedagogy integration syndrome to improve their ICT skills and thereby, making the teaching-learning and development process more effective. As cited by McGarr and McDonagh (2019) from the previous works (Krumsvik, 2008, 2014; Pettersson, 2018), teachers also need high levels of digital competence, and there is general agreement that within teacher education it has added complexities. This is because digital competence is now an essential element of teacher education across the globe (Yusop, 2015; Instefjord and Munthe, 2016; Gudmundsdottir and Hatlevik, 2018; McGarr and McDonagh, 2019). The importance of digital competence in the changing world of teaching and learning is experienced by many. Many have seen problems with the capacity of the teachers to use ICT in teaching unveiling the techno-pedagogical skills which are required in the 21st century skills for teachers.

Real-time teachers' techno-pedagogical competence remains unexplored. Hence, this paper developed a model applying the J48 algorithm and applied this model in creating a computerized assessment in predicting teachers' techno-pedagogical competence because it takes a substantial impact on the educational ecosystem for the 21st century learners.

2. Methodology

This study utilized an interactive and iterative process called Knowledge Discovery in Database (KDD) of Piatetsky-Shapiro *et al.* (1996) in developing and implementing the model as shown in Figure 1 and Agile – Systems Development Life Cycle (SDLC) as shown in Figure 4. A combination of the incremental and iterative process with the rapid delivery of developing software products is called Agile SDLC (Leau *et al.*, 2012; Stoica *et al.*, 2013; Learn SDLC, 2019). The combination of the two procedures such as KDD and Agile SDLC would result in the development of application software in predicting teacher's pedagogical ICT competence.

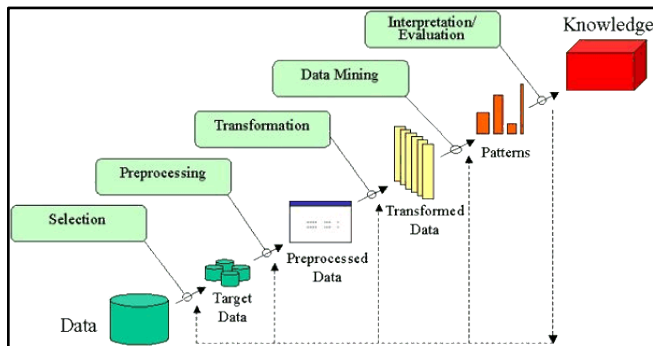


Figure 1. Knowledge Discovery in Database (KDD) (Fayyad *et al.*, 1996)

Respondents of this study were teachers with permanent and temporary status of a state university, comprising 126; they were asked to answer the survey questionnaire. However, only 97 respondents participated because most of them were on study and personal leave, and summer vacation. The utilization of the 97 datasets was performed in developing the initial model in predicting pedagogical ICT competence as the basis of developing application software for this purpose. Moreover, the instrument used in this study was adapted from the National ICT Competency Standards (NICS) for Teachers. The instrument

has two parts, such as the profile of the respondents and the level of computing relative to pedagogical ICT indicators. The instrument was validated with a Cronbach's alpha of 0.884 or 88.4% reliability, where the general rule is to attain 0.70 and above of the Cronbach's alpha to be good to best (Cronbach's Alpha, n.d.; Bland, 1997; Gliem and Gliem, 2003). An evaluated instrument using a tool is an integral part of research because it shows the reliability of data and the result of the study. Failure to test the validity and reliability of an instrument would result in unreliable outcomes.

2.1 Knowledge Discovery in Database (KDD) Process

2.1.1 Data Selection and Preprocessing

The gathered data were encoded in Microsoft Excel and were coded based on the type variable, namely categorical and continuous variables. Data cleaning was performed to improve data integrity and reliability of results. In the selection and preprocessing of the dataset, it is a must that data cleaning should be taken into consideration as it is the process of detecting and removing corrupt or inaccurate data from the datasets (Fayyad *et al.*, 1996; Zhang *et al.*, 2003). Therefore, incomplete information that may affect the result was removed.

2.1.2 Data Transformation

Before the application of a data mining algorithm, the dataset was transformed into readable and acceptable information for the task. Table 1 shows the data dictionary of the different variables that were transformed into class, and some remained as continuous variables. The standards were adapted from the NICS for Teachers.

2.1.3 Data Mining Algorithm Application

The J48 Algorithm

A tree-like graph decision support tool showing their potential effect and outcomes known as a model of decisions is called a decision tree (Brid, 2018). Decision tree (Figure 2) is one of the most powerful approaches in knowledge discovery and data mining to discover useful patterns (Bhargava *et al.*, 2013).

Table 1. Data dictionary

Variable	Definition	Values
Personal Profile		
Age	Continues (Num)	Continues
Sex	Class (Num)	1-Male 0-Female
Highest Educational Attainment	Class (Num)	1-Bachelors' Degree 2-with Masters' Degree Unit 3-Masters Degree 4-with Doctoral Degree Unit 5-Doctoral Degree
Length of Service Seminars	Continues (Num) Class (Num)	Continues 1-Yes 0-No
Training	Class (Num)	1-Yes 0-No
Pedagogical Indicators		
Standard1	Class (Num)	1-Digital Illiterate
Standard2		2-Basic
Standard3		3-Proficient
Standard4		4-Advanced
Standard5		5-Expert
Standard6		
Pedagogical ICT Competence	Class (Text)	Digital Illiterate Basic Proficient Advanced Expert

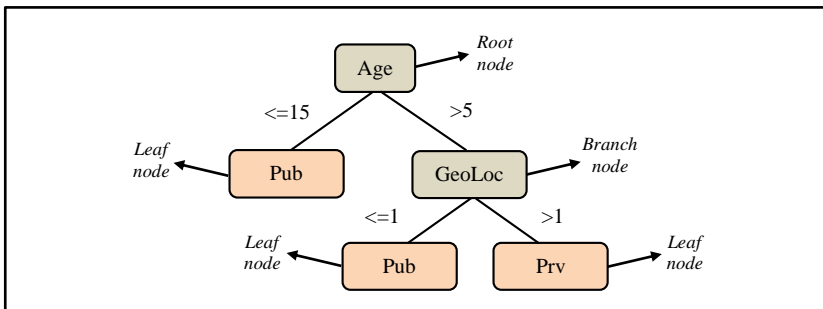


Figure 2. A decision tree example

The decision tree process includes selecting an attribute for the root node; making a branch for each possible attribute value; splitting occurrences into subsets – one for each branch ranging from the node; repeating recursively for each branch, using only occurrences that reach the branch; and stopping if all occurrences have the same class.

In this paper, the J48 algorithm was utilized to generate the initial model in predicting the pedagogical ICT competence of the teacher. J48 algorithm is a Java version of the C4.5 algorithm (Quinlan, 1996, 2014). The study utilized J48 algorithm as it is one of the best machine learning algorithms to examine the data categorically and continuously. It used in classifying medical data with high acceptability in performance and accuracy compared with other decision trees.

J48 in Action

Splitting Criteria

Entropy is a probabilistic measure of impurity (Heylighen and Joslyn, 2001). To compute the probabilistic impurity of the tree, Equation 1 was utilized, where p is the value of the predictor variable divided by the sum of all predictor variables.

$$entropy(p_1, p_2, \dots, p_n) = -p_1 \log p_1 - p_2 \log p_2 \dots - p_n \log p_n \quad (1)$$

or

$$H(X) = - \sum_x p(x) \log p(x)$$

Information is a measure of the reduction of uncertainty or impurity. To determine the best attribute for a specific node in the tree, information gain (IG) was used. The split of attributes in the dataset is based on the decrease of IG. Decision tree is based on finding the highest IG (Jain, 2017). To calculate this, Equation 2 was performed.

$$IG(S, A) = Entropy(S) - Entropy(A) \quad (2)$$

Gain ratio (GR) is an alteration of the information gain that reduces its bias on highly branching features. It also solved the drawback of IG. GR tends to prefer unbalanced splits in which one partition is much smaller than the other. Therefore, the information gain ratio is a ratio of IG and the intrinsic information. Intrinsic information (Equation 3) represents the potential information generated by splitting the dataset into v partitions. So, the feature with the maximum gain ratio (Equation 4) is selected as the splitting feature.

$$IntrinsicInfo(D) = - \sum_{j=1}^v \frac{|D_j|}{D} \cdot \log_2 \left(\frac{|D_j|}{D} \right) \quad (3)$$

$$GainRatio(S, A) = \frac{Gain(S, A)}{IntrinsicInfo(S, A)} \quad (4)$$

Attribute Type and Pruning Strategy

J48 handles categorical, numerical, and text value. Error based pruning was used. The purpose of pruning is for the removal of nodes that do not provide additional information.

Validation/ Interpretation/ Evaluation

The following are the variable definitions: TP – true positive, TN – true negative, FP – false positive, FN – false negative, TPR – true positive rate, FPR – false positive rate, SN – sensitivity, and PR – precision rate.

TPR is the number of correct positive predictions divided by the total number of positives, also known as SN (Equation 5). The best sensitivity is 1.0, whereas the worst is 0.0 (More, 2017). Calculated using Equation 6, TPR is the probability that an actual positive will test positive.

$$SN = \frac{TP}{TP + FP} \quad (5)$$

$$TPR = \frac{TP}{TP} + FN \quad (6)$$

FPR is the number of incorrect positive predictions divided by the total number of negatives. The best false positive rate is 0.0 and the worst is 1.0 (More, 2017). FPR was calculated through using Equation 7.

$$FPR = \frac{FP}{TN + FP} \quad (7)$$

PR is the number of correct positive predictions divided by the total number of positive predictions (Equation 8). It is also called positive predictive value (PPV) (Saito and Rehmsmeier, 2015). The best precision is 1.0 and the worst is 0.0 (More, 2017).

$$PREC = \frac{TP}{TP + FP} \quad (8)$$

Area under the receiver operating characteristics (AUC-ROC Area) (Figure 3) is the essential evaluation metrics for checking any classification model's

performance. ROC is a probability curve, and AUC represents the degree or measure of separability. It indicates how much model is capable of distinguishing between classes. The best ROC is 1.0 and the worst is 0.0.

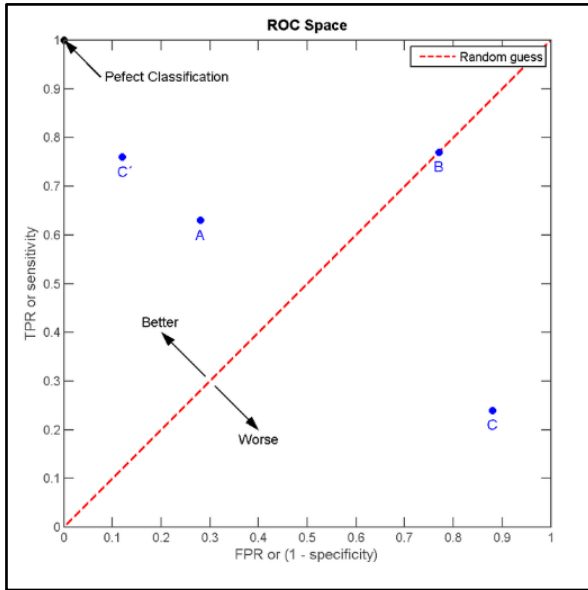


Figure 3. AUC-ROC space

Precision-recall curve (PRC) can provide the viewer with an accurate prediction of future classification performance because it evaluates the fraction of true positives among positive predictions (Saito and Rehmsmeier, 2015). PRC is more useful if you are only interested in the behavior of the classifier in one class. The best PRC is 1.0 and the worst is 0.0.

Kappa statistics, also known as kappa coefficient (K) (Equation 9), measures pairwise agreement among a set of coders or raters making category judgments, correcting for expected chance agreement.

$$K = \frac{P(A) - P(E)}{1 - P(E)} \tag{9}$$

Where $P(A)$ is the fraction of times that the raters agree and $P(E)$ is the proportion of times that we would expect them to agree by chance, calculated along the lines of the intuitive argument presented above (Carletta, 1996). The interrater reliability test is frequently used like the Kappa statistics. The

importance of rater reliability is to show the level to which the data collected in the study are correct illustrations of the variables measured (McHugh, 2012). In this paper, Table 2 was utilized to determine the interrater reliability. By following the table, the kappa statistics should be at least .60 and above with a level of agreement among the respondents in a particular question is moderate to almost perfect agreement and established strong rater reliability among the respondents and reliable results.

Table 2. Kappa coefficient table (McHugh, 2012)

Value of Kappa	Level of Agreement	% of Reliable Data
0-.20	None	0-4%
.21-.39	Minimal	4-15%
.40-.59	Weak	15-35%
.60-.79	Moderate	35-63%
.80-.90	Strong	64-81%
Above .90	Almost Perfect	82-100%

Confusion matrix is a table used to illustrate the performance of a classification model (Markham, 2014).

2.2 Agile Systems Development Life Cycle Process

In the planning phase, systems requirements were performed after the generation of the initial model. Also, the generated model was explicitly studied on the different variables where the users input their information for data analysis and prediction.

Software designs were performed in the designing phase, where the study implemented the requirements in the system. It utilized flex-dashboard and shiny libraries to design the application.

In the building phase, R programming was the core programming language in this project where this programming language in building the application was utilized. It combined the output generated in the planning phase and in the designing phase, where it harmonized the actual model and the logic needed in predicting teacher’s pedagogical ICT competence.

Several techniques were implemented in testing phase. First, the model was tested and evaluated, as stated in the previous discussion utilizing TP and FP rate, PR, PRC, ROC, and confusion matrix.

Alpha and beta testing was conducted reviewing phase as part of reviewing processing where it needed to satisfy the user's feedback adapting the International Organization for Standardization (ISO) 9126 concept to generate quality software. The evaluators of the developed software were three information technology (IT) professionals working in the industry, 10 IT and 20 non-IT faculty members in the university.

The process (Figure 4) was recursively performed until the evaluation results were highly acceptable and compliant.

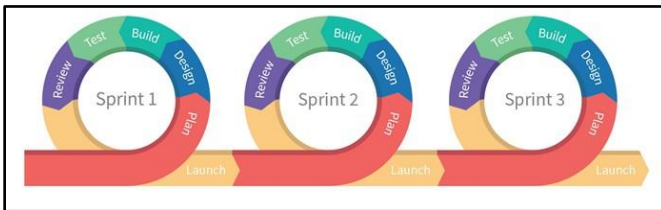


Figure 4. Agile methodology (Gulam, 2016)

2.3 Data Mining Software and Programming Language

PHP ML – hypertext preprocessor (PHP) is a server-side scripting language used for web-based applications where users input data or information for data analysis. While ML stands for machine learning, in this paper, a machine learning library for PHP programming was utilized for normalization and computations as an input in developing a model that learns based on the previous or historical data. MySQL is a relational database management system used to create databases and tables for the application. It is used to store, retrieved, show, and alter information for future use.

R programming is a programming language used for statistical computations, and data analysis and graphical representation. Google utilized the R programming language, and it is an integral part of the analytics that Google does, such as Google Flu Trends projects and Google Analytics. In this paper, R was used to generate a model and this model was implemented using the shiny library and flex dashboard for designing the application.

RStudio is a cross-platform integrated development environment (IDE) for the R statistical language. The study utilized RStudio in developing the application faster and easier using the R core libraries.

3. Results and Discussion

Figure 5 shows the generated J48 tree model grounded on the data collected about the pedagogical ICT competence of the teachers. Based on the J48 model, a pseudocode algorithm (Figure 6) was proposed showing the rules in predicting the pedagogical ICT competence of the teacher. Through this model, the assessment of the teacher’s skills in teaching using ICT technologies would be easy and fast compared with the traditional assessments.

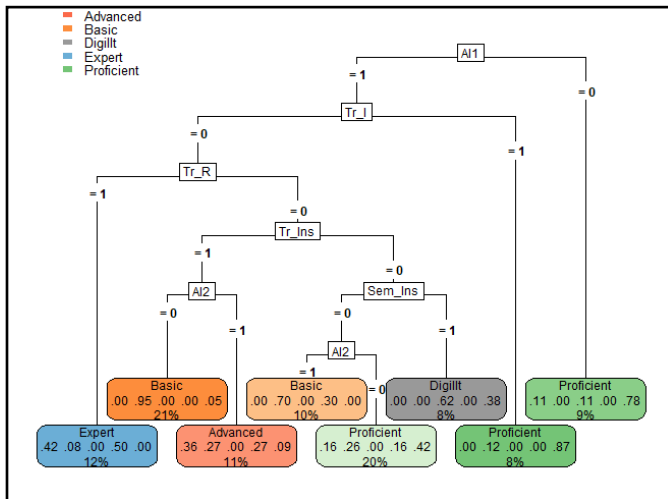


Figure 5. J48 Decision tree model for techno-pedagogical competence

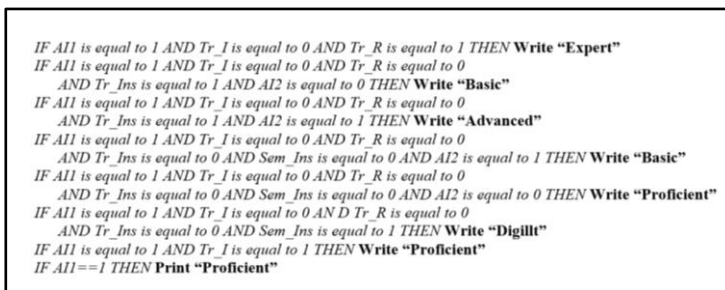


Figure 6. The proposed pseudocode algorithm

The generated J48 model summary on pedagogical ICT competence is shown in Table 3. In this table, there were 89.69 and 10.31% correctly classified and incorrectly classified instances, respectively. The agreement of the rater was

measured through the kappa coefficient with a value of 0.86 with an interpretation of strong reliability (Viera and Garrett, 2005). Strong reliability means that the raters have substantial agreement on their choice or answers made in the instrument to have a collective experience, knowledge, and competence on the issue that was evaluated.

Table 3. ICT competence in pedagogy model summary

Correctly classified instances	87	89.69%
Incorrectly classified instances	10	10.31%
Kappa statistic	0.86	
Total number of instances	97	

Table 4 shows the detailed accuracy by class. The model had a probability of 92.3% of being right and only 2.4% probability of being wrong for advanced users. While for basic users, the model showed a probability of 91.7% of being right every time as a positive and only 4.9% probability of being wrong. Also, for digital illiterate users, a probability of 83.3% of being right and 1.1% of being wrong every time as a positive. Among the expert users, the model showed a 93.3% probability of being right and 2.4% of being wrong. Lastly 85.2% probability of being right and 2.9% probability of being wrong were found for proficient users. In determining the accuracy rate per class, this study applied the ROC. The concept of ROC is that the closer the ROC curve to one, the higher accuracy the class is detected. The table shows that in terms of detecting advanced users, the ROC curve was 99.5% accurate, and basic users had 97.6% accuracy. Also, ROC curves were 99.3, 99, and 97.1% accurate for digital illiterate, expert, and proficient users, respectively. Finally, the overall accuracy in detecting the type of user’s competence classification had a weighted average of 98%, interpreted as high accuracy rating.

Table 4. Detailed accuracy by class

TP Rate	FP Rate	Precision	ROC Area	PRC Area	Class
0.923	0.024	0.857	0.995	0.952	Advanced
0.917	0.049	0.917	0.976	0.948	Basic
0.833	0.011	0.833	0.993	0.819	Digillt
0.933	0.024	0.875	0.990	0.932	Expert
0.852	0.029	0.920	0.971	0.912	Proficient
0.897	0.034	0.898	0.980	0.928	Weighted Avg.

To visualize the classification of the data in detecting pedagogical ICT competence, this study utilized the confusion matrix as shown in Table 5. The explanation in obtaining the misclassification was presented in the preceding section where all that results found at the top of the true positive rate are called

the FP rate and those below the true positive rate are called the FN rate. Both FP and FN are the misclassifications.

The confusion matrix explains that 12 users were correctly classified as advanced, one as digitally illiterate, and one as proficient resulting in two misclassification. Also, 33 users were correctly classified as basic users and one as expert resulting in one misclassification. While for digitally illiterate users, there were five correctly classified and one as proficient, resulting in one misclassification. Moreover, 14 users were correctly classified as expert, one as advanced, and another one as basic resulting in two misclassification. Finally, 23 users were correctly classified as proficient and two as basic resulting in two misclassification.

Table 5. Confusion matrix

Advanced	Basic	Digillt	Expert	Proficient	← classified as
12	0	0	1	0	Advanced
0	33	0	1	2	Basic
1	0	5	0	0	Digillt
0	1	0	14	0	Expert
1	2	1	0	23	Proficient

Pedagogical ICT Competence Predictor System

Figure 7 illustrates a form where the teacher inputs data and takes a short survey to determine his or her pedagogical ICT competence. The user is asked according to the pruned tree, as shown in the right pane such as age, sex, highest educational attainment, training and seminars attended, and internet connectivity. Also, the figure shows a J48 decision tree model for pedagogy. This decision tree model was based on the previous data present in the database. This model is now the basis of predicting the pedagogical ICT competence of the teacher. The decision tree model is a boxplot of pedagogy and age based on the previous data. The purpose of this boxplot is to illustrate descriptively the data found in the database that was utilized in generating the decision tree model.

After the user provides information, the testing and evaluation of the data follow. The application would then provide its probability value whether the user is classified as digitally illiterate, basic, proficient, advanced, or expert. In this case, the user, as shown in Figure 8, had the probability value of 0.125 as basic and 0.875 as proficient. Therefore, the user was predicted to be an expert as its pedagogical ICT competence.

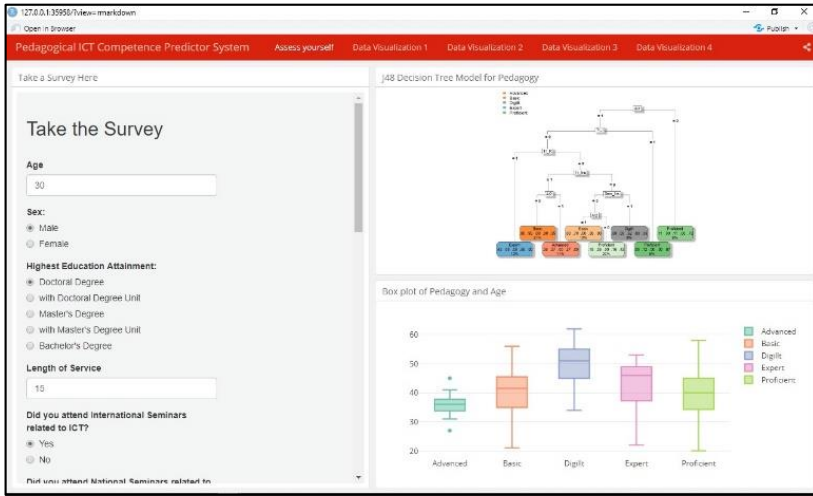


Figure 7. Survey form for predicting techno-pedagogical competence

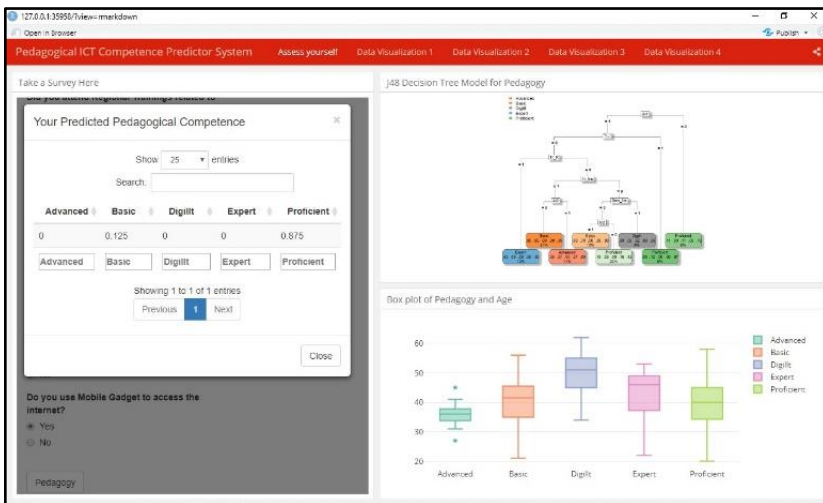


Figure 8. Predicted probability modal form

The application also illustrates the description of the data graphically (Figures 9 and 10). The graphs below are shown to better understand the data in the database through time. The system also shows descriptive statistics in illustrating the information found in the database. These illustrations give important information in designing appropriate action relative to the trainings and other capability buildings appropriate for the users of the system. Bar graphs are shown to show the highest educational attainments of the teachers,

scatter plot showing linear regressions about service and pedagogy, and linear regression for the length of service and age.



Figure 9. Data visualization 1

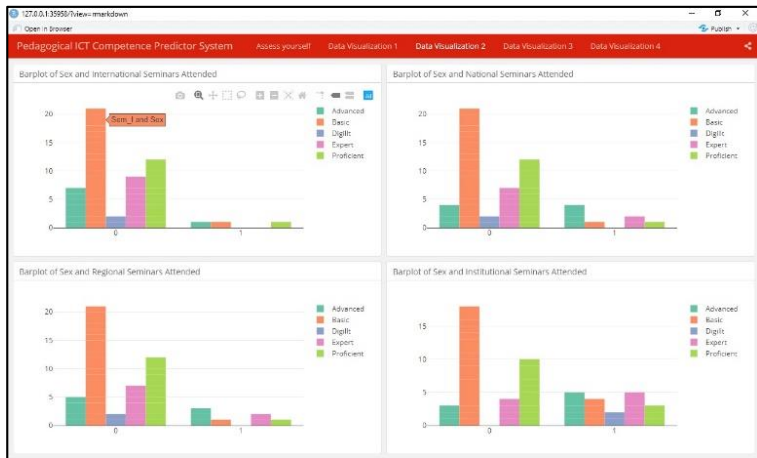


Figure 10. Data visualization 2

4. Conclusion

Data accuracy is essential in model and system development. This study has shown a significant result in class detection. The J48-based model in predicting teachers' techno-pedagogical competence was utilized and helped

the development of real-time detection software that would assist the teachers and policymakers in augmenting the skills of the teachers in using ICT-based technologies in teaching and scholarship. Furthermore, there are other variables relative to the use of ICT in teaching and learning that may be incorporated to enhance the model and the system to have a universal model, which is applicable to any educator in adapting to the changing world of teaching and learning.

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