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The Implementation of Restricted Boltzmann Machine in Choosing a Specialization for Informatics Students

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ABSTRACT

Choosing a specialization was not an easy task for some students, especially for those who lacked confidence in their skill and ability. Specialization in tertiary education became the benchmark and key to success for students' future careers. This study was conducted to provide the learning outcomes record, which showed the specialization classification for the Informatics students by using the data from the students of 2013-2015 who had graduated. The total data was 319 students. The classification method used for this study was the Restricted Boltzmann Machine (RBM). However, the data showed imbalanced class distribution because the number of each field differed greatly. Therefore, SMOTE was added to classify the imbalanced class. The accuracy obtained from the combination of RBM and SMOTE was 70% with a 0.4 mean squared error.

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1. INTRODUCTION

In tertiary education, choosing a specialization is important for the student's learning process. It aims to guide the students to focus more on developing their skills and interest [1]. For students, the appropriate specialization will help them during the learning process and also in finishing the final project to graduate on time. In educational psychology studies, interest and talent also play an important role in academic achievement [2].

Universities should optimally utilize their facilities, students and lecturers, infrastructures, and data [3]. Data can be processed and used as a means to solve some problems, like choosing a specialization for students. In choosing a specialization, the data that can be used are the academic records and the specialization chosen by the students who had graduated. By using these data, students can see the grade graphic and consider the suitable specialization for them. In choosing a specialization, there are several factors to be considered. The internal factor is the factor from within the individual, while the external factor is the factor from outside of the individual [4].

Some students still have difficulties in determining the right choice. It becaused they did not fully recognize their skill and ability in certain fields. In contrast, students who have good grades and a fixed mindset will find it easy to choose their specialization. The right specialization also affects the study program accreditation. Therefore, stakeholders should evaluate such difficulties to help the students graduate on time.

In regard to overcoming the difficulty in choosing a specialization, several studies have been conducted to help solve this problem. In a study [5], choosing a major in SMAN 16 Semarang was implementing a k-nearest neighbor by classifying the data based on the scores in the report card, test scores, major of interest, counselor recommendation, and the chosen major. In another study [6], the forward selection was applied in Support Vector Machine and Naïve Bayes classifier with kernel density estimation for major classification in senior high school. The other study [7] applied fuzzy Naïve Bayes in choosing a specialization for Informatics Students of Universitas Islam Lamongan based on their names, hobbies, favorite subject, GPA, and field of interest. Invariant Moment and Restricted Boltzmann Machine [8] were also implemented to recognize handwriting by using the signatures from 10 correspondents with 150 data. Restricted Boltzmann Machine (RBM) was also employed for classification problems by creating new types in the organizational structure [9].

RBM is an established category of machine learning models that have had a significant impact on the advancement of deep learning [10]. In the previous study, RBM was used to implement a recommendation system. Lee [11] compared several methods for MovieLens 100K data. The methods compared were User-Based CF, Item-Based CF, SVD, Biased-SVD, RBM, Autoencoder, Stacked Autoencoder, and Neural Network. The result showed that RBM had the highest accuracy score, i.e. 0.953. Salakhutdinoy et al. [12] used RBM in a CD which resulted in a 6% higher score than the standard baseline predictor system of Netflix. RBM made a good performance for classification.

This study aimed to signify the performance of RBM on data classification in choosing a specialization for Informatics students of UMM. In a study [13], RBM was used to predict the graduation delay based on students' characteristics and performance. The result showed that the prediction made by Boltzmann Machine was 75% higher compared to SVM and Gaussian Processes. The prediction was not only based on the student's characteristics but also on inappropriate specialization. The dataset used in this study was 319 Informatics students, class of 2013-2015,

The contribution of this study was the implementation of the RBM method to predict the graduation delay based on the student's chosen specialization. In addition, this study also compared RBM to naïve bayes, naïve bayes to SMOTE, and RBM to SMOTE by using confusion matrix. The accuracy obtained was used to assess the performance of the method. Concerning the students' difficulty in choosing a specialization and the utilization of data, classification needs to be conducted to provide consideration in choosing a specialization using deep learning [[12]] by implementing Restricted Boltzmann Machine. This study aimed to signify the performance of RBM on data classification in choosing a specialization for Informatics students of UMM. In addition, this study also aimed to help the stakeholders to produce competent students who have expertise in accordance with their field.

2. METHOD

2.1. Specialization

Specialization is a medium to facilitate a person with the skill for a certain occupation. It affects their daily activities and also in making important decisions for their lives [11]. In the Informatics department of UMM, there are three specializations, namely Software Engineering, Network, and Smart Game. These specializations are expected to produce qualified and competent alumni in certain fields.

2.2. Data Collection

In Figure 1, the data were collected from the Informatics students of 2013-2015 and retrieved with permission from the Informatics department office. The total data obtained for this study was 319 data. The data were divided into three specializations, namely Software Engineering, Network, and Smart Game. The parameter in choosing the specialization was based on the student's scores for each subject in 5 semesters.

The scores were obtained from the subjects the students had in 5 semesters, namely Structured Programming, Introduction to Information Technology, Informatics Logic, Human Computer Interaction, Computer Organization and Architecture, Java's Object-oriented Programming, Introduction to Topology, Algorithms and Data Structures, Computer Graphics I, Database Design, Data Communication, Multimedia Design and Application, Microcontroller, Web Programming, Information Systems, Operating System, Computer Network, Computer Graphics II, the student's interest, and length of study.

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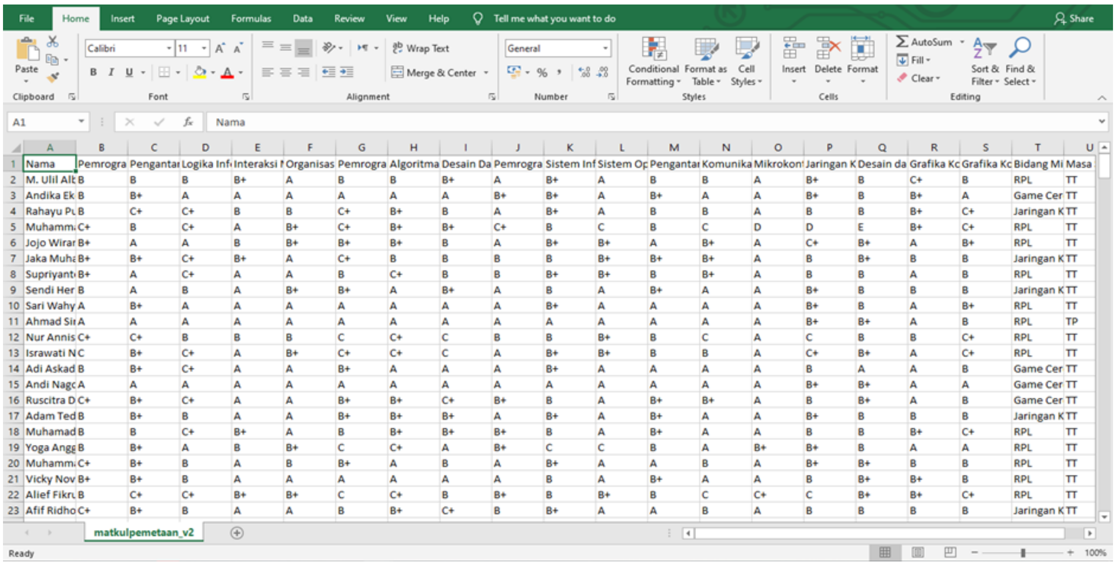

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	Nama	Pemrogra	Pengantar	Logika Inf	Interaksi I	Organisas	Pemrogra	Algoritma	Desain Da	Pemrogra	Sistem Inf	Sistem Op	Pengantar	Komunika	Mikrokon	Jaringan K	Desain da	Grafika Kc	Grafika Kc	Bidang Mi	Masa
2	M. Ulil Alt	B	B	B	B+	A	B	B	B+	A	B+	A	B	B	A	B+	B	C+	B	RPL	TT
3	Andika Ek	B	B+	A	A	A	A	A	A	B+	B+	A	B+	A	A	B+	B	B+	A	Game Cer	TT
4	Rahayu Pu	B	C+	C+	B	B	C+	B+	B	A	B+	A	B	B	A	B	B	B+	C+	Jaringan K	TT
5	Muhamm	C+	B	C+	A	B+	C+	B+	B+	C+	B	C	B	C	D	D	E	B+	C+	RPL	TT
6	Jojo Wirar	B+	A	A	B	B+	B+	B+	B	A	B+	B+	A	B+	A	C+	B+	A	B+	RPL	TT
7	Jaka Muha	B+	B+	C+	B+	A	C+	B	B	B	B	B+	B+	B+	A	B	B+	B	B	Jaringan K	TT
8	Supriyant	B+	A	C+	A	A	B	C+	B	B	B+	B+	B	B+	A	B	B	A	B	RPL	TT
9	Sendi Her	B	A	B	A	B+	B+	A	B+	A	B	A	B+	A	A	B+	B	B	B	Jaringan K	TT
10	Sari Wahy	A	B+	A	A	A	A	A	A	A	B+	A	A	A	A	B+	B	A	B+	RPL	TT
11	Ahmad Sir	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B+	B+	A	B	RPL	TP
12	Nur Annis	C+	C+	B	B	B	C	C+	C	B	B	B+	B	C	A	C	B	B	C+	RPL	TT
13	Israwati N	C	B+	C+	A	B+	C+	C+	C	A	B+	B+	B	B	A	C+	B+	A	C+	RPL	TT
14	Adi Askad	B	B+	C+	A	A	B+	A	A	A	B+	A	A	A	A	B	A	A	B	Game Cer	TT
15	Andi Nagc	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B+	B+	A	A	Game Cer	TT
16	Ruscitra D	C+	B+	C+	A	A	B+	B+	C+	B+	B	A	B+	B+	A	B	B+	A	B	Game Cer	TT
17	Adam Ted	B	B+	B	A	A	B+	B+	B+	A	B+	A	B+	A	A	B+	B	B	B	Jaringan K	TT
18	Muhamad	B	B	C+	B+	A	B	B+	B+	B+	B	A	B+	A	A	B	B	B+	C+	RPL	TT
19	Yoga Angg	B	B+	A	B	B+	C	C+	A	B+	C	C	B	A	B+	B+	B	A	A	RPL	TT
20	Muhamm	C+	B+	B	A	B	B+	A	B	A	B+	A	A	B	A	B+	B+	B	B	RPL	TT
21	Vicky Nov	B+	B+	B	A	A	A	A	A	A	B	A	B+	A	A	B	B+	B+	B	RPL	TT
22	Alief Fikru	B	C+	C+	B+	B+	C	C+	B	B+	B	B+	B	C	C+	C	B+	B+	C+	RPL	TT
23	Afif Ridho	C+	B+	B	A	A	B	B+	C+	B	B+	A	A	B	A	B	B	B	B	Jaringan K	TT

Figure 1. Data Collection

2.3. *Data Preprocessing*

Data preprocessing was the initial step before inputting the dataset into the model. This step aimed to clean the data, fill in the missing value, and resolve the inconsistent and noisy data. The followings were the steps in data preprocessing.

Data cleaning, this step aims to clean the noisy data, resolve the noisy and inconsistent data, and handle outliers. Data integration, this step was conducted to combine the data from several databases or data storage. This step aimed to reduce and prevent redundancy and inconsistency.

Data reduction, this step was conducted to reduce the data volume without affecting the integrity of the original data. Data transformation, in this step, the data modified under the required outcomes to produce more efficient results. Normalization was implemented in this step by modifying the attribute data into a scale or a range of 0.0 to 1.0. The last stage was data splitting. In this stage, the data were divided into data training and testing, 80% and 20%, respectively.

2.4. *Restricted Boltzman Machine*

In 2006, Hinton et al. offered an effective method for deep learning named Deep Believe Network. In DBN, Restricted Boltzmann Machine was implemented to train the network weights layer by layer. The RBM is an energy-based model, which is also a type of Markov Random Field (MRF)[12]. RBM consists of hidden layer and visible layer. Hidden neurons represent the feature vector for pattern recognition. The number of hidden neurons plays an important role in classification [9]. The architecture of RBM was presented and explained in Figure 2 and Equation 1.

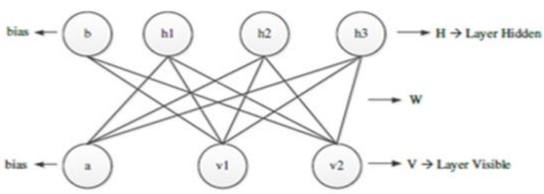

Figure 2. RBM Architecture

$$E(V,H) = -\sum_{i} a_i V_i - \sum_{j} b_j H_j - \sum_{i,j} V_i H_j W_{i,j} \quad (1)$$

This algorithm can be implemented in high dimensional data such as images and text, and also in classification, texture modeling, motion modeling, information retrieval, and recognition. Besides being used for classification in several studies [12][14], it has also been used for recommendation system such as movie recommendations based on user rating preference [15] and predicting drug side effects [16]. It can also be used for clustering, as seen in a study about speaker clustering and tracking tasks in TV [17]. Based on the previous studies related to the implementation of RBM, it can be said that this algorithm can be implemented in various problems on supervised and unsupervised learning algorithms.

2.5. Rbm Network Scheme

Figure 3 describes the first step in training RBM with multiple inputs. The inputs were multiplied by the weights and then added to the bias, the result was then passed through the sigmoid activation function, and the output determined whether the hidden nodes should be activated or not. The weights will be a matrix with the number of input nodes as the number of rows and the number of hidden nodes as the number of columns. The first hidden node will receive the vector multiplication of the inputs multiplied by the first column of weights before the appropriate bias is added. In choosing a specialization, the value of x used is the grade of each course as the input to obtain the sample values from the distributed training. In RBM training, visible nodes and hidden nodes are not connected to the other visible nodes or other hidden nodes. To train RBM, samples from the training set were used as the input for RBM via visible neurons, and then it went back and forth between visible and hidden neurons. This training aimed to learn the connection weights in visible or hidden neuron and the activation bias of neurons to help RBM reconstructs the input data during the phase where the visible neuron samples were from the hidden neuron. Sampling between the hidden and was controlled by the learning rate. In the sklearn Bernoulli RBM library, the function used is the sigmoid activation function which is already in the library by default.

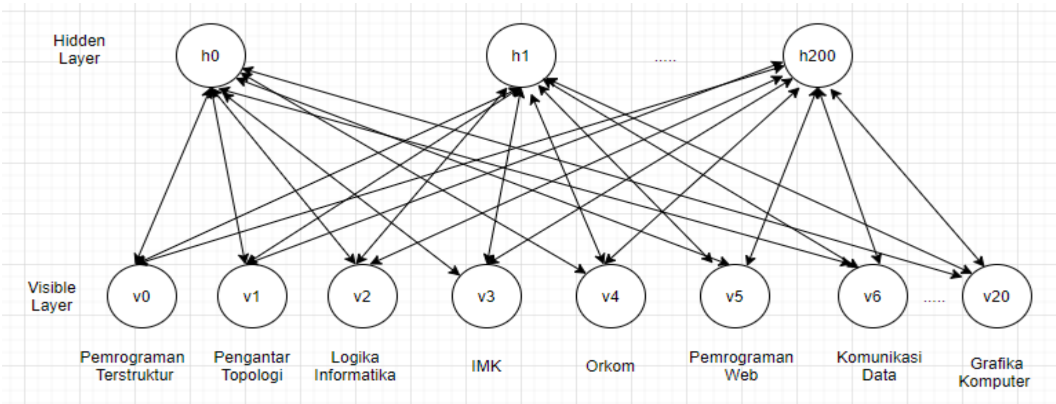

Figure 3. RBM Architecture

2.6. Implementation Design and Algorithm Testing

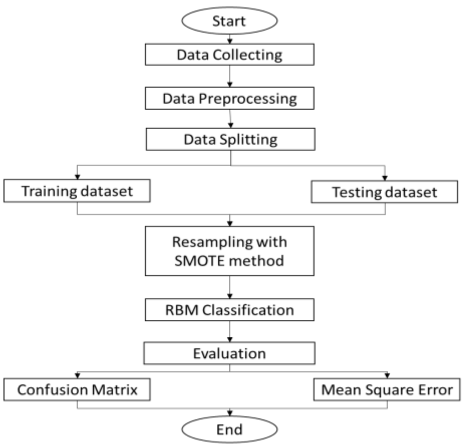

Figure 4. Algorithm Implementation and Testing Scheme

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2.7. Random Oversampling

Class imbalance in a dataset is a problem in machine learning. It occurs because the minority class is far less than the majority class. Imbalance data will cause low prediction accuracy in the minority class [18]. This condition can also affect the quality of the data in classification performance. Data imbalance can be overcome by using resampling technique to balance the original data by adjusting the number of samples from different classes. There are three categories in resampling, namely oversampling, under-sampling, and hybrid. Oversampling is a technique where the minority class is duplicated in order to balance the number of the majority class. One of the popular techniques in the oversampling is Synthetic Minority Oversampling Technique. Initially, SMOTE did not improve the classification performance because the duplication of the given data might increase the minority pattern. However, the results in [19] showed that using SMOTE had significant effect on classification problem.

2.8. Measurement of Model Accuracy

The classification model was evaluated by using confusion matrix and mean squared error. The prediction results of the model can be seen in the confusion matrix table [20] by comparing the actual data and the predicted data, so that the number of wrong and accurate predictions can be seen as well as the classification results for each class. The classification results were evaluated by using mean squared error [21]. If the accuracy results are considered good, then the classification process is complete; but if the results are not good, an analysis of the data will be carried out by finding the cause and conducting other evaluations.

Table 1. Confusion Matrix

		Actual	
		Yes	No
Prediction	Yes	TP	FP
	No	FN	TN

The followings are the description of Table 1:
a. TP (True Positive) → Total data with positive true value and positive predictive value
b. FP (False Positive) → Total data with negative true value and positive predicted value
c. FN (False Negative) → Total data with positive true value and negative predictive value
d. TN (True Negative) → Total data with negative true value and negative predictive value

The followings are Equation 2, Equation 3, and Equation 4 to calculate the accuracy, precision, and recall based on the Confusion Matrix table created previously.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

2.9. Mean Squared Error

Mean Squared Error is a method for evaluating forecasting methods [22]. This method is the average of the squares between the predicted and observed values. Any small error has the potential to make a big difference. The Equation 5 is used to calculate MSE as follows.

$$MSE = \sum_{t}^{n} \quad = 1 \frac{(X_t - F_t)^2}{n} \tag{5}$$

3. RESULTS AND DISCUSSION

3.1. Data Analysis

The data were obtained from Informatics students year 2013 to 2015 under permission from the Informatics department office. From 800 collected data, the data were reduced to meet the need and resulted 319 data to be analyzed.

3.2. Data Distribution

The distribution of data was 80% training data and 20% testing data. The total number of data before resampling was 319. After resampling the data became 588. Therefore, the total training data was 470, and the testing data was 118.

3.3. The Implementation of RBM and SMOTE

In the implementation of RBM, python programming language and anaconda navigator were employed. Figure 5 and Figure 6 show the steps for building an RBM model:

a. Enter the dataset to be used.
b. Perform data processing by removing the missing values and replacing these values.
c. Convert the data from course grades, field of interest, and length of study into binary numbers
d. Initialize the values of x and y.
e. Conduct resampling using SMOTE.
f. Initialize the training and testing value.
g. Build RBM model.

```
panj = Counter(y)
# define oversampling strategy SMOTE
strategy = {0:196, 1:196, 2:196}
oversample = SMOTE(sampling_strategy=strategy)
# fit and apply the transform SMOTE
X_over, y_over = oversample.fit_resample(X, y)
panj_over = Counter(y_over)
scaler = StandardScaler()
X_over = scaler.fit_transform(X_over)
```

Figure 5. Source Code to Build RBM Model

```
#RBM
logistic                  = linear_model.LogisticRegression(solver='newto
n-cg', tol=1)
logistic.C = 6000
rbm                       = BernoulliRBM(random_state = 28, verbose=False
, learning_rate=0.000001, n_iter=1000, n_components=500
rbm_features_classifier = Pipeline(steps=[('rbm', rbm), ('logistic', lo
gistic)])
rbm_features_classifier.fit(X_train, y_train)
```

Figure 6. Source Code to Build RBM Model

The dataset used in this study had imbalanced data. Therefore, a data balancing test was carried out to prevent the majority class dominating the minority class by balancing the data using oversampling technique and combined it with SMOTE algorithm. The amount of Game data was initially far less than the Network and Software Engineering. The amount of data in Software Engineering dominated, i.e. 196 data, while 102 data for Network and 20 data for Games. It showed big difference between Games and Software Engineering. By using oversampling technique, the number of minority data were duplicated according to the number of the majority class.

The result of the classification can be seen from 11 samples of the students in Table 2. From these data, it can be seen that the chosen specialization was suitable with the specialization they desired, and it was based on their scores during study by using RBM method. The classification showed that 5 out of 11 students had inappropriate specialization based on their scores. The 6th, 9th, 10th, and 11th data showed that the students had interest in Game and Network, but the recommendation from RBM suggested to take Software Engineering. Meanwhile, the 7th data showed that the student had interest in game, but the scores from the previous semester and the RBM method suggested to take Network.

Table 2. Samples of Classification Result of Informatics Students

Student	Specialization	Classification
1	Network	Network
2	Game	Game
3	Software Engineering	Software Engineering
4	Game	Game
5	Software Engineering	Software Engineering
6	Network	Software Engineering
7	Game	Network
8	Software Engineering	Software Engineering
9	Network	Software Engineering
10	Network	Software Engineering
11	Network	Software Engineering

The visualization from Table 2 can be the recommendation for students to choose the specialization in order to reduce the prediction of graduation delay.

3.4. Evaluating the Classification Model

In this study, the classification model was evaluated by using Confusion Matrix to measure the accuracy of the model. To measure the error value, mean squared error was carried out. The results of the accuracy of the RBM model can be seen in Table 2.

Table 2. The Accuracy of RBM Model

No	Testing	Precision	Recall	Accuracy	MSE
1	RBM	0.43	0.66	0.66	0.34
2	RBM+SMOTE	0.68	0.70	0.70	0.4
3	Naïve Bayes	0.60	0.58	0.57	0.5
4	Naïve Bayes + SMOTE	0.65	0.66	0.65	0.5

From Table 2, it can be seen that the accuracy of using RBM and SMOTE was 70%. The combination of RBM and SMOTE in this study had the highest precision, recall, and accuracy score compared to the other methods. It was because the classification method had been improved by using SMOTE method to resolve the imbalance data.

4. CONCLUSION

From this study regarding the classification of specialization by using the Restricted Boltzmann Machine, the findings were as (1) the dataset used had imbalanced data class or imbalanced class, (2) using the oversampling technique, i.e. SMOTE to deal with the balancing class problem, (3) the accuracy of RBM was better than Naïve Bayes, (4) the accuracy of RBM + SMOTE was better than Naïve Bayes + SMOTE. Proving that the implementation of RBM in the classification of specialization for Informatics students of UMM had good results when combined with SMOTE for imbalanced classes on the datasets.

Notation List
The examples of notation can be described with the following information:
i: represents the number of visible neurons
j: represents the number of hidden neurons
V_i: binary state of visible unit i
H_i: binary state of hidden unit j
b_i: bias of hidden unit
W_{i_j}: weight between visible and hidden units

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