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Machine Learning in Reverse Migration Classification

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ABSTRACT

Reverse migration has become a more pressing issue in recent times, owing to a range of factors like economic downturns, political instability, natural disasters, and the COVID-19 pandemic. The pandemic, in particular, has highlighted the vulnerability of migrant workers in urban areas, leading many to return to their rural homes. As a result, reverse migration necessitates focused attention and planning by governments, policymakers, and communities to ensure favourable outcomes for all parties involved. This paper aims to provide a fundamental research framework from research that utilized a machine learning approach to classify reverse migration based on evidence from Selangor, Malaysia. The research methodology involves selecting features for reverse migration classification models and identifying optimal hyperparameters and experimental settings through auto model preliminary analysis. Furthermore, based on the findings of the auto model, the methodology was enhanced with a manual setting of machine learning. Three machine learning algorithms, namely Decision Tree, Random Forest, and Gradient Boosted Trees were used. The results of the auto model and the manual process that used different split ratios were compared. All the machine learning algorithms performed with a high accuracy of over 90% and were efficient in completing prediction tasks in under a minute across various settings. The best machine learning model with an accuracy of 97.6% is Gradient Boosted Trees with a split ratio of 60:40. The paper presents findings that could prove useful for governments, legal planners, investors, and the community in strategizing and surviving through an artificial intelligence prediction approach.

1. Introduction

Reverse migration refers to the phenomenon where people who had previously migrated from rural or less developed areas to urban areas return to their places of origin. The impact of reverse migration is complex and depends on a range of factors such as the nature of the migration, the specific context, and the policies in place to manage migration [1,2]. Reverse migration can impact the economy in both the origin and destination areas [3,4]. The return of migrants can lead to a

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decline in the labor force in urban areas and an increase in the labor force in rural areas [5,6]. This can affect the availability of labor and wages in both areas and also impact local businesses. Furthermore, reverse migration can impact social relations and community dynamics in both the origin and destination areas [7,8]. In the origin areas, the return of migrants can lead to changes in family structures and roles, and potentially improve community ties. In destination areas, the departure of migrants can lead to social dislocation, especially if migrants were an integral part of the community. In addition, the trend of reverse migration can have long-term implications for the sustainability of rural areas. As more people return to rural areas, there may be a need for improved infrastructure and services to accommodate the influx of people. If reverse migration is not managed effectively, it can result in overcrowding, the strain on resources, and environmental degradation [9].

Predicting reverse migration is important for governments and businesses to plan and respond to the potential impacts of this phenomenon [9,10]. It can help anticipate changes in the labor market, demand for services, and strain on resources in both rural and urban areas [11]. Predicting reverse migration can also be useful for developing effective policies and programs to manage and support reverse migration, such as targeted programs to encourage the return of skilled workers to rural areas or providing training and support to returning migrants [12]. Businesses can adapt their strategies to changing market conditions by adjusting recruitment and retention strategies or investing in automation technologies.

Accurately predicting reverse migration patterns can be challenging and requires the use of advanced analytical techniques such as artificial intelligence. Machine learning is a powerful artificial intelligence tool that can be used to predict complex phenomena such as human migration, including reverse migration but the implementation is still limited [13]. In the past, traditional models were used to analyze migration patterns, which have more difficulty in handling low-quality data compared to robust machine learning methods [11,12,14]. Additionally, machine learning algorithms can often identify non-linear relationships and interactions between variables, which can be missed by conventional methods [15].

According to Kadar and Pletikosa [16], Random Forest was used to mining large-scale human mobility including migration in predicting long-term crime prediction. Researchers by Luca *et al.,* [17] present their findings of literature and challenges of human mobility and provide a discussion on how deep learning techniques can potentially overcome the constraints of conventional models in addressing these challenges. Responding to the complex problem of predicting human migration, the hybrid Particle Swarm Optimization and Support Vector Machine model was proposed by researchers to predict the staying time of international migrants [18]. By using XGBoost and Artificial Neural Network (ANN), two models of human migration with different features selection were analyzed and reported by Robinson and Dilkina [19]. XGBoost was utilized in the research to identify the ranking of feature importance that was constructed based on United States of America features and global features. The researchers revealed that machine learning models offer greater levels of modeling flexibility with the possibility to explore many input features to be customized to the problem or country at hand. According to Micevska [20], Random Forest were used to estimating the complex relationships of factors that forced migration abroad. All the studies mentioned above indicate the need for further and continuous research in machine learning for reverse migration. Considering the lack of reverse migration research conducted in Malaysia, there is a great need to explore the research gaps that exist within the Malaysian context.

This research aims to use a machine learning approach to classify reverse migration based on evidence from Selangor, Malaysia. The objective is to identify optimal hyperparameters and experimental settings through auto model preliminary analysis and enhance the methodology with a manual setting of machine learning based on the findings of the auto model. The approach employs in this research is simple yet powerful machine learning and allows for rapid modeling making it well-suited for the complexities of reverse migration [21,22]. By filling a gap in the social science research domain, where there is a shortage of studies on this topic and a lack of expert data scientists, our methodology provides an accessible and efficient means of generating insights into this important issue. This paper presents a fundamental research framework that could be useful for governments, legal planners, investors, and the community in strategizing and surviving through an artificial intelligence prediction approach.

2. Methodology

2.1 The Framework of the Machine Learning Implementation

With a focus on providing a quick and straightforward modeling approach that is suitable for inexperienced data scientists, this research utilized RapidMiner as the platform for conducting the machine learning evaluations [22]. Figure 1 illustrates the overall framework for implementing machine learning, which includes both the auto model and manual process, along with a comparison of the results.

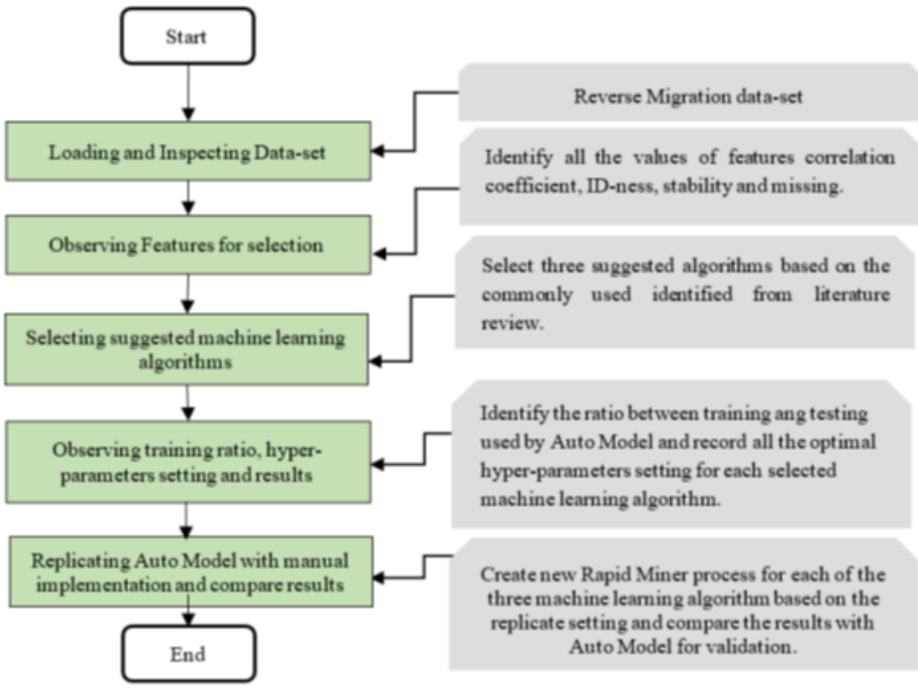

Fig. 1. The flowchart of the machine learning implementation

All the experiments were implemented with the RapidMiner software tool in a computer with 8 GB RAM. The dataset was processed from a set of secondary data provided by the Department of Statistics Malaysia (DOSM) on the migration of the year 2018. The most important step was to load the dataset of reverse migration to the RapidMiner platform, which was used for training and testing the machine learning classification models.

Observing the dataset features allow researchers to select the suitable Independent Variables (IVs) for the machine learning classification model. RapidMiner auto model is the rapid modelling tool used in the preliminary stage. It provides information on each IV correlation with the Dependent Variables (DV) as well as the ID-ness, stability, and missing. ID-ness presents the variance of the dataset, while stability indicates the identical or closeness of values. Green indicators were suggested by the auto model as the most suitable IVs for the machine learning classification models followed by yellow and red. Table 1 presents some of the dataset characteristics measured by auto model in RapidMiner.

Table 1
The correlations, ID-ness, stability and missing from some of the migration dataset

Selected	Status	Quality	Name	Correlation	ID-ness	Stability	Missing
√	Deselect: ● Red		*Kewarganegaraan*	2.69%	1.92%	93.27%	0.00%
√	Deselect: ● Yellow		*Negeri_Destinasi*	54.55%	10.58%	41.35%	0.00%
√	● Select All		*Jantina*	1.09%	1.92%	51.92%	0.00%
√	● Select All		*Umur*	0.12%	38.46%	7.69%	0.00%

Table 1 illustrates that only *Kewarganegaaan* was identified by the auto model as having the least significance, as indicated by the red status. Despite having lower correlation values, all the IVs were included in this research, with the anticipation that they could still provide some valuable information for the machine learning algorithms to predict the probability of the classification models. The DV in the machine learning prediction is a binary classification that indicates either true for migration or false for no migration, as outlined in Table 2.

Table 2
DV of the machine learning prediction

DV	Probability value	Predicted class
Migration	0.5 and above	true
No migration	Below 0.5	false

In machine learning, the identification of the class of migration is based on the probability of confidence predicted by each algorithm for the given dataset classes. Table 3 shows a sample prediction in RapidMiner. For instance, for the data in row 15, the confidence probability for false is 0.857, indicating that the testing data in row 15 is falsely predicted as representing no migration class, contrary to the real DV value. On the other hand, the DV data in row 11 is correctly predicted as false (no migration) because the confidence for false is 0.857, which is higher than the confidence for true.

Table 3
Sample of prediction in the reverse migration classification

Row. No.	Real DV	Prediction DV	Confidence (false)	Confidence (true)
0	true	true	0	1
11	false	false	0.857	0.143
12	true	true	0	1
13	false	false	0.857	0.143
14	true	true	0	1
15	true	false	0.857	0.143
16	false	false	0.857	0.143
12	true	true	0	1
13	false	false	0.857	0.143
14	true	true	0	1
15	true	false	0.857	0.143
16	false	false	0.857	0.143

The use of auto model in machine learning offers the advantage of automating crucial processes such as algorithm selection. From the nine (9) suggested algorithms by auto model, Decision Tree, Random Forest, and Gradient Boosted Trees were identified as the three most accurate algorithms. In machine learning, the dataset is typically divided into training and testing sets. The training dataset enables the algorithms to explore and derive insights from the data, while the testing dataset evaluates the performance of the machine learning predictions. Table 4 outlines the optimal settings for the machine learning classification model generated by the auto model, which can be adopted in the manual process for further improvement.

Table 4
Auto model specifications

	Training	Testing
Ratio of Training: Testing	71	29
Optimal hyper-parameters		
Decision Tree	Maximal Depth = 4	
Random Forest	Number of Trees = 100, Maximal depth =4	
Gradient Boosted Tree	Number of Trees = 30, Maximal depth =2, Learning Rate= 0.001	

During the training phase, 71% of the dataset was utilized, which equated to 75 out of the total 104 records. The remaining 29% or 29 records were set aside for testing the machine learning classification results. By leveraging its optimization capability, the auto model identified that the Decision Tree algorithm yielded the lowest error rate of 6.3% when the Maximal Depth was set to 2. For Random Forest, two hyper-parameters were found to generate the lowest error rate of 3.2%, with 100 Number of Trees and Maximal Depth set at 4. Lastly, Gradient Boosted Tree produced a minimum error rate of 9.5% using the three optimal hyper-parameters presented in Table 2.

Therefore, Table 2 presents specifications that suggest one possible method for enhancing the classification models, which involves examining the ratio of training to testing. This research anticipates that exposing the machine learning algorithms to more data during training would result in more robust models. However, it is crucial to investigate the effectiveness of the splitting ratio for each of the machine learning algorithms. Furthermore, it is important to compare the accuracy results between auto model and the manual process using the same splitting ratio. As such, the manual process employed three different splitting ratios, which are presented in Table 5 for comparison with auto model.

Table 5
Different split ratios

Experiment	Training: Testing Ratio
Auto model	71:29
Manual proses	60:40
Manual proses	70:30
Manual process	80:30

Figure 2 presents an example of the manual process in RapidMiner to retrieve the migration data and split the data into training: testing using split operator. To meet the classification model requirement in RapidMiner, the original DV values of 1 and 0 were converted into true and false using the Numerical to Binominal operator. The purpose of the first Multiply operator is to assign the training data to the various machine learning algorithms, whereas the second one is used to assign the testing data to each of the algorithms.

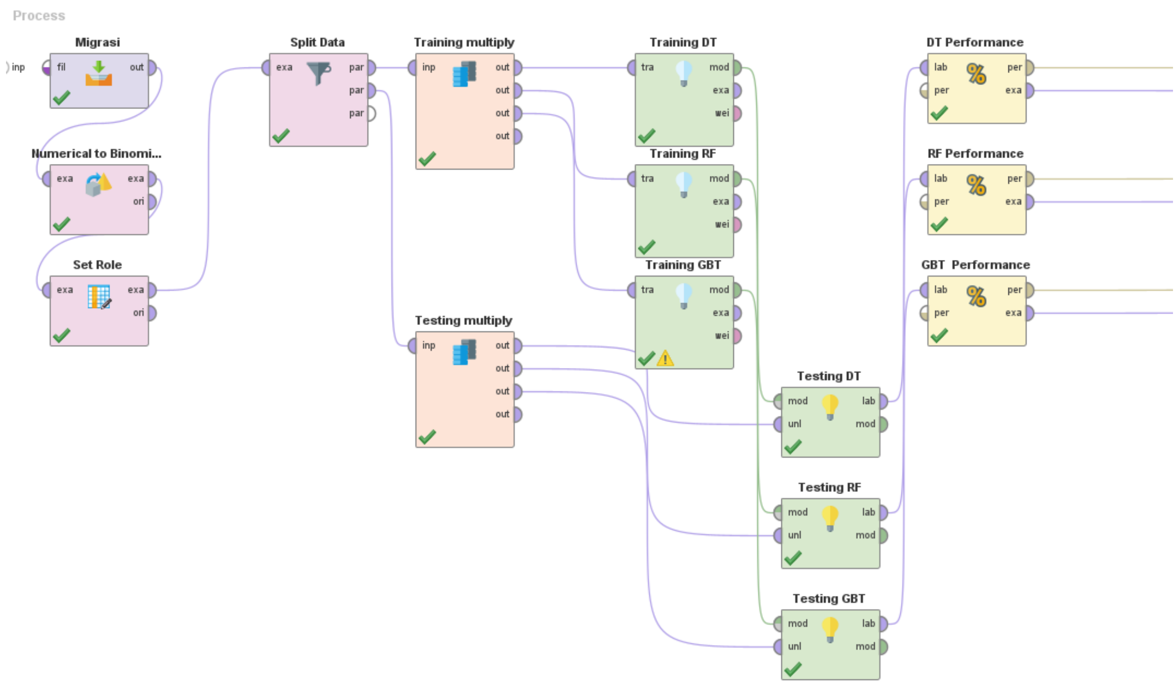

Fig. 2. RapidMiner manual processes

Performance metrics to measure the machine learning algorithms were calculated based on the accuracy and classification error, which can be derived from the confusion matrix [23-26]. Table 6 provides better description of the confusion matrix for the reverse migration classification.

Table 6
Reverse migration confusion matrix

	Real cases of false (no migration)	Real cases of true (migration)
Predicted as false (no migration)	True Negative	False Positive
Predicted as true (migration)	False Negative	True Positive

The descriptions for the reverse migration confusion matrix for each True Positive, False Positive, True Negative and False Negative can be explained as the following:

i. True Positive (TP): When the model correctly predicts reverse migration when it truly occurs. For example, the model predicts that an individual will reverse migrate, and that individual truly does reverse migrate.
ii. False Positive (TP) – When the model predicts reverse migration, but it does not actually occur. For example, the model predicts that an individual will reverse migrate, but that individual does not actually reverse migrate.
iii. True Negative (TN) - When the model correctly predicts that there will be no reverse migration, and there is no reverse migration. For example, the model predicts that an individual will not reverse migrate, and that individual does not actually reverse migrate.
iv. False Negative (FN) – When the model predicts that there will be no reverse migration, but it truly occurs. For example, the model predicts that an individual will not reverse migrate, but that individual does reverse migrate.

Therefore, from the reverse migration confusion matrix, the accuracy and classification error can be measured based on the following formulas in Eq. (1) and Eq. (2).

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (1)$$

$$\text{Classification error} = (FP + FN) / (TP + TN + FP + FN) \quad (2)$$

Accuracy is the proportion of correct predictions out of the total number of predictions while classification error is the proportion of incorrect predictions out of the total number of predictions.

3. Results and Discussion

This section presents the result of comparison between auto model that used 71:29 split ratio with manual process that used three different split ratios (60:40, 70:30, 80:20). Table 7 Specifically presents the auto model results.

Table 7 exhibits that Decision Tree and Gradient Boosted Trees demonstrate a 100% accuracy rate and zero classification errors. These outcomes indicate that either these models are capable of fitting the data exceptionally well or they might be overfitting on the training data. Overfitting happens when a model learns the random fluctuations in the training data rather than the underlying pattern, causing the model to perform poorly on new, unseen data. As a result, it is considered in this study to consider different split ratios developed with manual process Rapid Miner to enhance the machine learning's comprehension of the training data.

Table 7
Performances of auto model machine learning with 71:29 split ratio

	Real cases of false (no migration)	Real cases of true (migration)	Accuracy (%)	Classification error (%)
Decision Tree				
Predicted as false (no migration)	16	0	100	0.0
Predicted as true (migration)	0	13		
Random Forest				
Predicted as false (no migration)	15	1	96.6	3.4
Predicted as true (migration)	0	13		
Gradient Boosted Trees				
Predicted as false (no migration)	16	0	100	0.0
Predicted as true (migration)	0	13		

The performance results for the manual process, based on various split ratios, are presented in Table 8, Table 9, and Table 10. In general, the outcomes exhibit slight variations for each machine learning algorithm.

Table 8
Performances of manual process machine learning with 60:40 split ratio

	Real cases of false (no migration)	Real cases of true (migration)	Accuracy (%)	Classification error (%)
Decision Tree				
Predicted as false (no migration)	17	1	100	0.0
Predicted as true (migration)	0	24		
Random Forest				
Predicted as false (no migration)	17	0	100	0.0
Predicted as true (migration)	0	24		
Gradient Boosted Trees				
Predicted as false (no migration)	17	1	97.6	2.4
Predicted as true (migration)	0	23		

Table 9
Performances of manual process machine learning with 70:30 split ratio

	Real cases of false (no migration)	Real cases of true (migration)	Accuracy (%)	Classification error (%)
Decision Tree				
Predicted as false (no migration)	13	1	96.8	3.2
Predicted as true (migration)	0	17		
Random Forest				
Predicted as false (no migration)	13	0	100	0.0
Predicted as true (migration)	0	18		
Gradient Boosted Trees				
Predicted as false (no migration)	13	18	41.9	58.1
Predicted as true (migration)	0	0		

Table 10
Performances of manual process machine learning with 80:20 split ratio

	Real cases of false (no migration)	Real cases of true (migration)	Accuracy (%)	Classification error (%)
Decision Tree				
Predicted as false (no migration)	9	1	95.2	4.8
Predicted as true (migration)	0	11		
Random Forest				
Predicted as false (No migration)	9	0	100	0.0
Predicted as true (migration)	0	12		
Gradient Boosted Trees				
Predicted as false (no migration)	9	1	95.2	4.8
Predicted as true (migration)	0	11		

Decision Tree performed the best with split ratios of 70:30 and 80:20 with accuracy percentages above 95% but showed signs of overfitting with the 60:40 split ratio. Nevertheless, Random Forest showed signs of overfitting for all split ratios but performed well with auto model setting at 71:29 split ratio. Gradient Boosted Trees performed well (above 95% of accuracy) with split ratios of 60:40 and 80:20 but it faced low performance with the 70:30 ratio at 41.9% accuracy.

Gradient Boosted Trees with a 60:40 split ratio outperformed the other 11 models with an accuracy of 97.6%. *Negeri Destinasi* is the most important predictor for the outcome based on the tree structure of Gradient Boosted Trees as depicted in Figure 3, appearing as the root node. *Umur* is the second most important predictor, appearing as the second-level node in the right child of the root node. Even though *Negeri Destinasi* was initially considered a moderately significant variable outside the machine learning models (Refer Table 1), it has become the most feature importance in the best machine learning model (SVM 60:40).

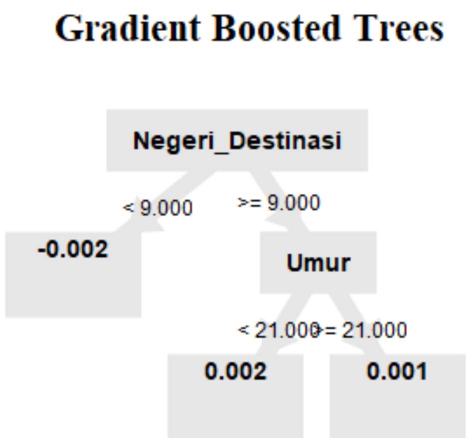

Fig. 3. The tree model of Gradient Boosted Trees

4. Conclusions

This paper presents a comparison between auto model and manual process machine learning approaches for developing classification models of reverse migration. The study found that there was no significant difference between the two approaches, regardless of the different settings of the split ratio. As such, inexperienced machine learning researchers can rely on the auto model approach. These findings provide practical implications for policymakers, governments, and communities, who can benefit from the insights and predictions provided by these models. However, further research is needed to validate these findings on different datasets and with other machine learning frameworks. Future research should aim to validate these findings on different datasets and using other machine learning frameworks. Furthermore, future studies can explore the impact of other variables, such as socio-economic factors, on reverse migration.

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