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Forecasting the Resignation of Skilled Technicians in Automotive Companies Using Artificial Intelligence: A case study of large car service centers in Thailand

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Abstract

The objective of this research was to forecast the resignation of skilled technicians at a large automobile service center in the country using machine learning techniques. This study used the Random Forest algorithm along with the SMOTE (Synthetic Minority Oversampling Technique) method developed in Python. The research was conducted by preparing a questionnaire, with questions divided into 3 areas: personal factors; push factors and pull factors. Each question consisted of 31 subtopics. The total number of employees who responded to the questionnaire was 244 people, with 227 of them who were still working and 17 having resigned. Therefore, the data was unbalanced, requiring the creation of synthetic data using the Random Forest algorithm with the SMOTE technique in order to balance the two types of data. The experimental results showed that the model used to predict employee resignation using 3 types of input factors, personal factors + push factors, personal factors + pull factors, and personal factors + push factors + pull factors, was effective. When using personal factors and with only 2 push factors, it was found that the efficiency of the forecasting model had an accuracy of 100%, sensitivity of 100%, precision of 100% and F1-score of 100%. The results of the research showed that using Random Forest and SMOTE to address the data asymmetry problem resulted in high accuracy in the model's prediction performance.

Keywords: Forecasting resignation, Skilled technicians, Large car service center in Thailand, Machine learning, Synthetic minority oversampling technique.

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1. INTRODUCTION

According to the master plan under Thailand's 20-year national strategy [1], emphasis is placed on the automotive industry. In 2019, Thailand's automotive industry had a total production of more than 2 million automobiles and commercial vehicles, making it the 11th highest in the world and the highest in the ASEAN region. The value of exporting vehicles and automotive parts is approximately 6.4% of GDP. After-sales service of various service centers is crucial in the automotive industry, in addition to production and distribution having skilled technicians on staff is crucial. Especially for larger service centers where they play a key role in inspecting cars, maintaining them, calculating parts, and estimating costs. Therefore, evident that skilled technicians are very valuable human resources in the organization. This is considered one of many factors that are extremely important to the success or failure of an automobile center. Therefore, losing skilled technicians will negatively affect the management of the organization. The organization must be highly aware of this importance if it is to retain skilled technicians at the automobile center without prompting resignations and promote a positive work environment.

Resignation of a personnel from an organization is a voluntary desire to leave one's own position within the organization in which they work when there is an opportunity. This is either to work at a new organization or change careers in the near future [2, 4] or due to diminished attachment to the organization and the influence of job dissatisfaction [3, 7]. The factors that may cause employees to resign from work can be divided into 2. [4]. 1)Push factors refer to factors within the organization that create dissatisfaction among individuals, ultimately causing people to resign, such as wages, interpersonal relationships in the organization, size of organization, and communication. 2) Pull factors refer to factors outside the organization that attract people to move or resign from their current position to a new organization, such as opportunities in the labor market with higher compensation and opportunity for career advancement.

Several research studies have been conducted on the causes of employee resignation as a way to prevent and resolve the loss of employees. Fizza Saeed presented the issues that drive employee turnover and how to retain them in an organization [5]. The results of the study showed that the basic issues of work stress, career advancement, financial stability, workplace environment, ambition, salary and rewards play an important role in employee resignation. Leonilo M. Cruz et al. conducted a quantitative research study that showed that factors in work including development, participation pay, supervision and work environment had a negative impact on employees' intentions to resign [6]. Walid Abdullah Al-Suraihi et al. conducted research with the aim of understanding the reasons for employee turnover and employee retention strategies in an organization [7]. Key research findings indicated that employees had a variety of reasons for leaving the workplace, such as work stress, job satisfaction, stability in work, work environment, incentives, wages and rewards. Additionally, employee turnover has a significant impact on organizations due to the costs associated with employee resignation. This may adversely affect production efficiency, sustainability, competitiveness and ability to make a profit.

The above studies on factors influencing employee resignation show that factors affecting the resignation of skilled technicians should be studied to create understanding and prevent timely resignations. Creating a resignation trend analysis system to assess the risk of resignation is therefore an important issue that deserves to be studied and developed. Therefore, creating a data analysis system with Artificial Intelligence (AI), which plays an important role in the large data analysis process, is considered an effective tool. [8] To analyze such turnover trends, artificial intelligence is applied, including artificial neural networks, machine learning models, and data mining techniques are used in risk assessment and forecasting employee resignation. Kumar P., et al. [9] used systematic machine learning models to assess the risk of employee resignation to protect the company's most valuable resource (employees). Francesca Fallucchi, et al. [10] applied artificial intelligence to guide employee-related decision-making within human resource management because the quality and skills of employees are considered factors of growth and success. A. Chaurasia, et al. [11] used artificial neural networks to predict employee resignation. Soumyadeb Chowdhury, et al. [12] used machine learning (ML) prediction models of artificial intelligence to predict the trend of employee turnover in the organization. (AI) can help identify the tendency for employees to voluntarily quit their jobs.

From the turnover factors and artificial intelligence research mentioned above, this research aims to predict the turnover of skilled technicians in large automobile service centers in the country. This study used machine learning techniques, a branch of artificial intelligence, specifically the random forest algorithm along with the SMOTE (Synthetic Minority Oversampling Technique) method developed in Python. The prediction model in this study can be used to predict employees who are likely to leave the organization, warn corporate executives to change their strategy or behavior, and to recommend executives to increase policies to retain employees in the organization.

2. METHODOLOGY

The process of developing employee resignation forecasts using artificial intelligence consisted of 6 steps, as shown in FIGURE 1. These include: data preparation, data correlation, data balancing, data splitting, random forest algorithm, employee resign prediction. The details in each step are as follows:

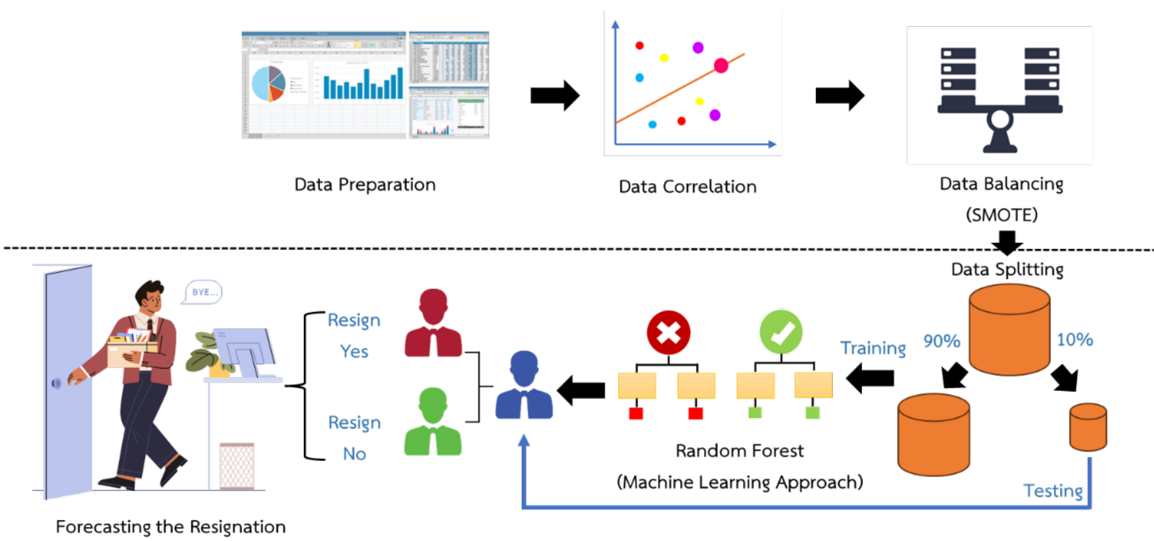


Figure 1: Process for developing employee resignation as predicted.

2.1 Data Preparation

Data was collected through questionnaires answered by 244 skilled technicians from 155 large automobile centers nationwide, with 227 employees still working and 17 employees having resigned. The information in the questionnaire was divided into 2 main topics: personal factors questions as shown in TABLE 1, which consisted of 10 questions. Part 2 consisted of the push factor questions and pull factor questions, as shown in TABLE 2. The push factor questions covered 6 main areas, each area with 14 sub-questions while the pull factor questions consisted of 4 questions and 7 sub-questions.

Table 1: Personal factor questions entered into the model.

Data	**Data format**
1. Age	Number
2. Educational Level	Number Primary School = 1, Secondary School = 2, Vocational = 3, Diploma = 4, Bachelor = 5
3. Work Year	Number
4. Income	Number 10,000-20,000 = 1, 20,001-30,000 = 2, 30,001-40,000 = 3, more than 40,000 = 4
5. Financial Status	Number Have less income than expenses = 1, Have income equal to expenses = 2, Have more income than expenses = 3
6. Family Burden - No Burden - Parent Burden - Spouse Burden - Children Burden - Relative Burden	Number You can have more than one response. The corresponding data will display the number 1 if a question is selected; otherwise, no numbers will be displayed.

Age	Education	work_year	Income	Finacial_status	Family	Parent_burden	Children_burden	Relative_burden	Spouse_burden	Workload	Pround	Policy	Coorperate	Train_manual	Justice
36	3	17	2	1	1	0	0	0	0	4	4	4	5	5	4
37	4	12	2	2	1	0	0	0	0	4	4	3	3	4	3
45	3	16	2	2	0	0	0	0	1	4	5	5	4	3	4
36	3	11	2	1	0	0	1	0	1	3	4	4	4	4	4
33	5	15	2	1	0	0	1	0	1	5	5	3	4	5	5
42	5	23	2	2	0	1	0	0	0	3	3	3	3	3	3
38	3	19	2	2	1	0	0	0	0	4	4	4	4	4	3
43	4	20	2	1	0	1	1	0	1	3	5	3	3	4	5
46	4	25	2	2	0	1	1	1	1	4	5	3	2	2	2
42	4	20	1	3	0	0	0	0	1	4	5	5	5	4	4

Figure 2: Example of sample data in the questionnaire from 244 employees.

The data obtained from the questionnaire was entered into a table to prepare for input into the analysis process, as shown in FIGURE 2, which shows a sample data. (questionnaire data from 10 employees). This includes information from questions in the questionnaire regarding personal factors and push factors, totaling to 24 questions.

Table 2: Push factor and pull factor questions entered into the model.

Push Factor	Pull Factor
1. Job characteristics - Workload is appropriate for the position - Pride in the work performed	**1. Job characteristics** - Expectations of changing jobs
2. Supervisor - Company policy is clear - Supervisory justice - The supervisor's readiness to take responsibility in the event of work errors - Performance evaluation system that is accurate and fair	**2. Personal aspects** - Lack of pride in work - Personal problems such as family problems, health, marriage, moving
3. Colleague - The willingness of co-workers to help each other (Teamwork1) - Receiving advice from colleagues regularly (Teamwork2)	**3. Advancement and stability in work** - Requirement for promotion to a higher position (higher position) - Resign to advance one's studies (higher education)
4. Advancement and stability in work - Clear training and work manual (Train Manual)	**4. Remuneration** - Desire to work somewhere else with a higher income (other company) - Appropriateness of salary in relation to skills and abilities (proper salary 2)
5. Return - Salary appropriateness in relation to duties and responsibilities (suitable salary)	
6. Organizational environment - Good internal coordination system (Cooperation) - Suitable noise levels, temperature, and lighting for work (Environment) - Sufficient cafeteria space, resting places and bathrooms (Facilities) - Sufficient equipment and tools used in performing work (Equipment)	
Data format: numbers Rating of importance level: very little = 1, little = 2, medium = 3, very much = 4, very much = 5	

2.2 Data Correlation

Finding Data correlation [13]. Before importing the model, it is important to determine the correlations within the large dataset and identify which data points have relatively positive and negative correlation. Therefore, only data with relatively high positive and negative correlations are selected into the model for training. Finding the relationship is done by calculating the prepared data using the Pearson Correlation method [14]. The results of the calculation are displayed in the form of a

Heat map, which shows different shades and percentages of the relationship between the various data factors.

Figure 3 shows the Heat Map table of the correlation between personal factor data and push factor data. The light orange shade indicates a relatively high percentage of positive correlation among the questionnaire items. The dark purple to black shades indicate the relationship of data in each questionnaire, with a relatively high percentage of negative correlation. The middle shade of purple shows a minimal correlation between questionnaire items. For example, clear company policy information and a good internal cooperation system exhibited a positive correlation of 78%, which is considered to be a relatively high positive relationship. In contrast, financial status data had a negative relationship with a suitable salary in relation to duties and responsibilities (proper salary) of 34%.

The personal factor and pull factor data are shown in FIGURE 4. The dark blue shades indicate a relatively high percentage of positive correlation, while the light yellow shade indicates a relatively high percentage of negative correlation. The middle shade of blue indicates a minimal relationship between questionnaire items. It is observed that personal factors and pull factors have a moderate to very low relationship, which may result in the model's forecast being less accurate.

FIGURE 5 shows the relationship between personal factor data, push factor data and pull factors data. Dark red shades indicate a relatively high percentage of positive correlation among the questionnaire items, while the light orange shade indicates a relatively high percentage of negative correlation. The shades of orange indicate a minimal relationship between questionnaire items. Notably, some data indicate relatively high positive relationship between push factors and pull factors, as shown in the yellow frame in the figure. This high correlation shows that if data from both factors are used as input data, the model may result in more accurate predictions.

2.3 Synthetic Minority Oversampling Technique (SMOTE)

The data was unbalanced because 227 of the 244 employees who answered the questionnaire were still employed, while 17 had resigned. Therefore, there were far more employees working than there were employees who had resigned (Employees 93% active, 7% resigned). Using the Random Forest algorithm alone may result in ineffective forecasts. This is because the model learning process requires a balanced data [15], with an equal or nearly equal representation of each class. The algorithm used to balance the data in this research was the SMOTE (Synthetic Minority Oversampling Technique) method. This method was used to help create synthetic data (Synthetic Samples), which balanced both types of data. The SMOTE method solves the problem of unbalanced data by oversampling the minority class and generating synthetic data without excluding rows that correspond to the majority class, achieving approximately the same number of rows for both the majority and minority classes. This improves the accuracy of the model and prevents the model from being biased in predictive results that favor the majority class. FIGURE 6 shows sample data before and after creating synthetic data using the SMOTE technique.

The results of using the SMOTE technique to balance the data are shown in FIGURE 7. FIGURE 7(a) shows the imbalance between the data before using the SMOTE technique. FIGURE 7(b) shows the amount of data after using the SMOTE technique to add synthetic data. Oversampling of

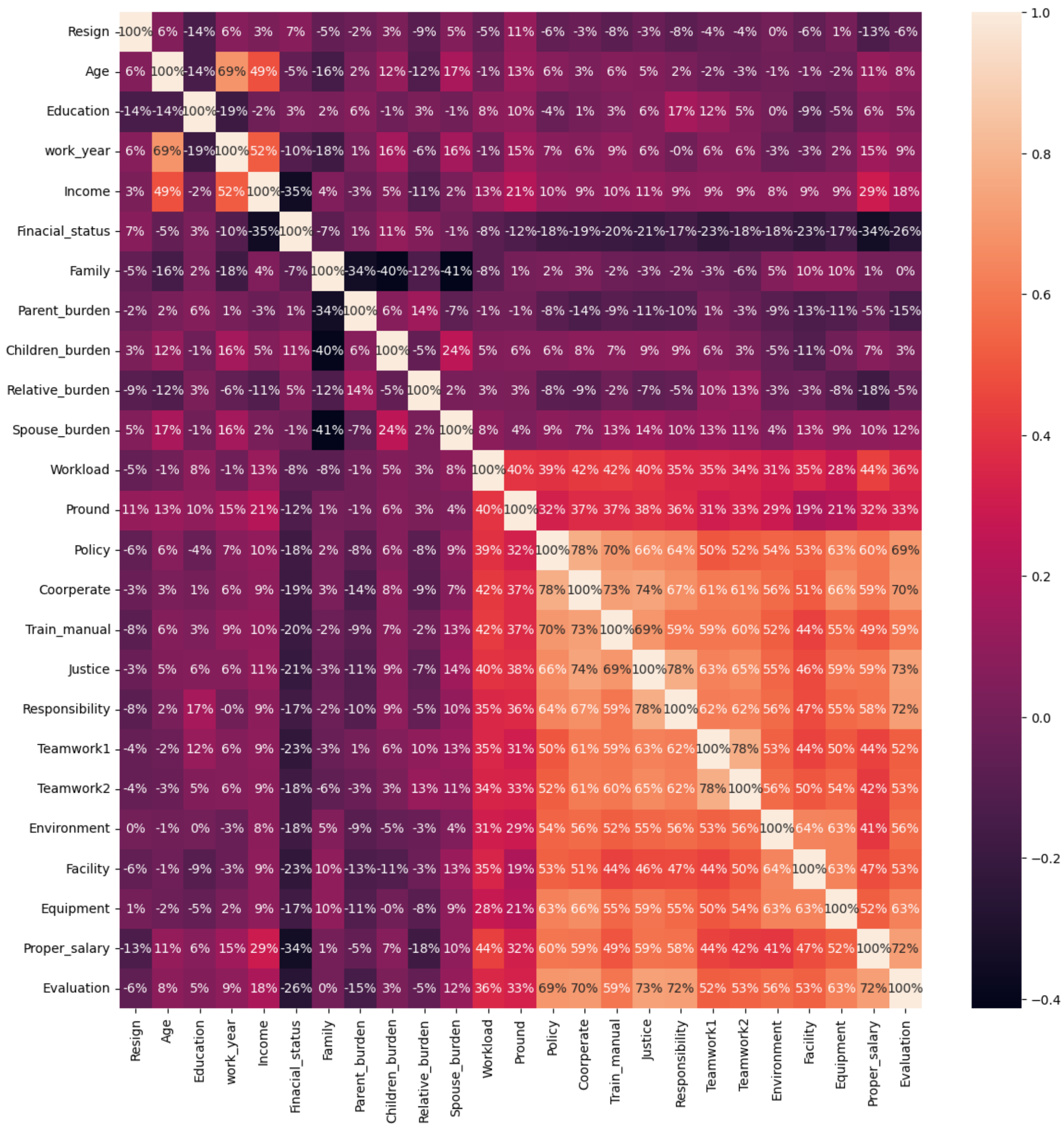


Figure 3: The Heat Map of the correlation between personal factor data and push factor data.

the employees who resigned was performed to increase the data, which increases the efficiency of the model. The added synthetic data is calculated and augmented based on the original data.

2.4 Data Splitting

The data was divided into training and testing sets in this step. The model was trained using 90% of the total data, or 219 data points [(244 * 90) / 100]. The model was tested using the remaining

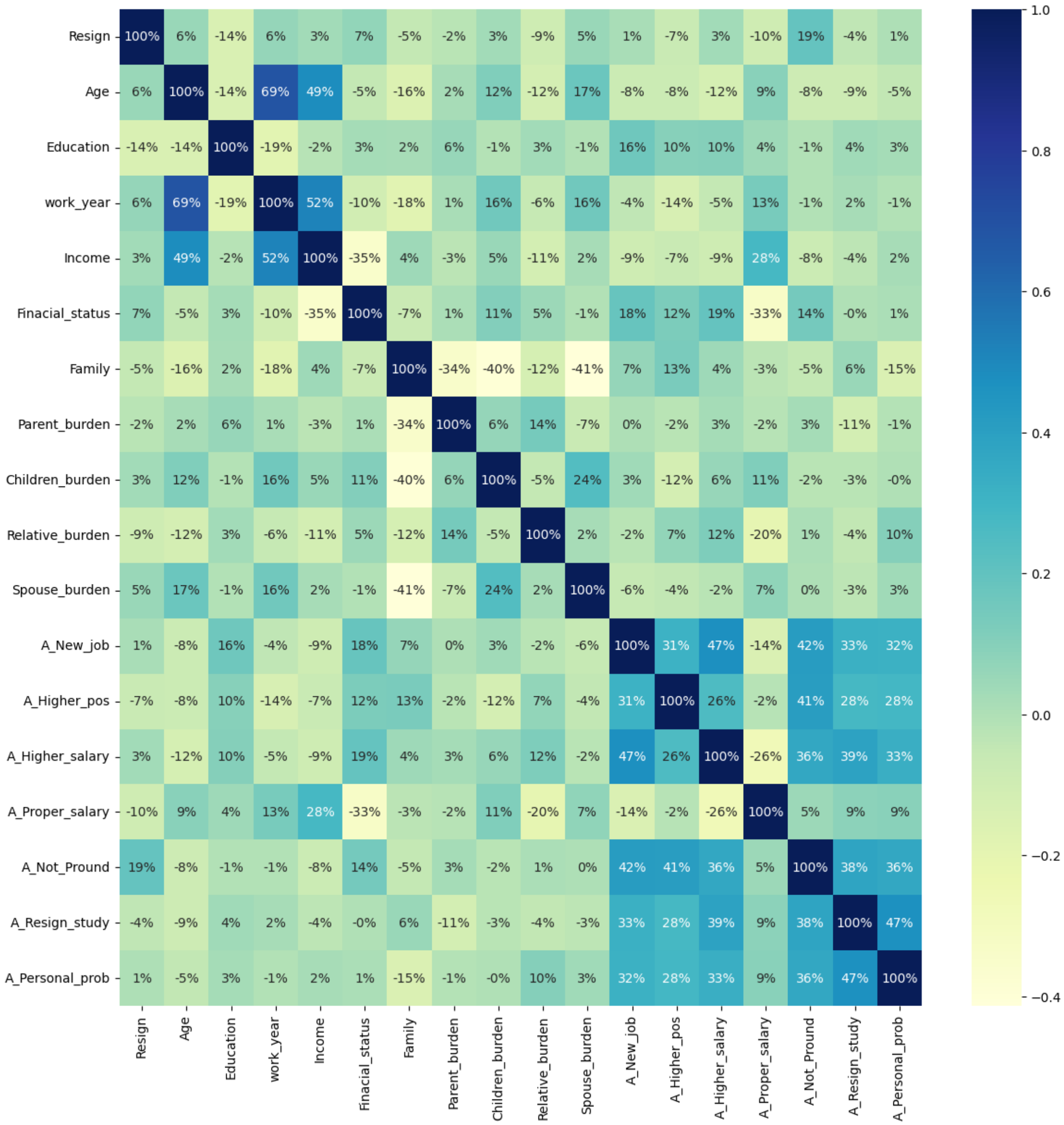


Figure 4: The Heat Map table of the correlation between personal factor data and pull factor data.

10% of the data, or 25 data points [(244 * 10) / 100. The 25 data points were divided into data that the model had not previously learned to avoid model bias or overfitting, as shown in FIGURE 8.

2.5 Random Forest Modeling

Random Forest is a type of machine learning model developed from a decision tree algorithm [17]. Besides dividing it into many trees, each tree represents important features within the dataset.

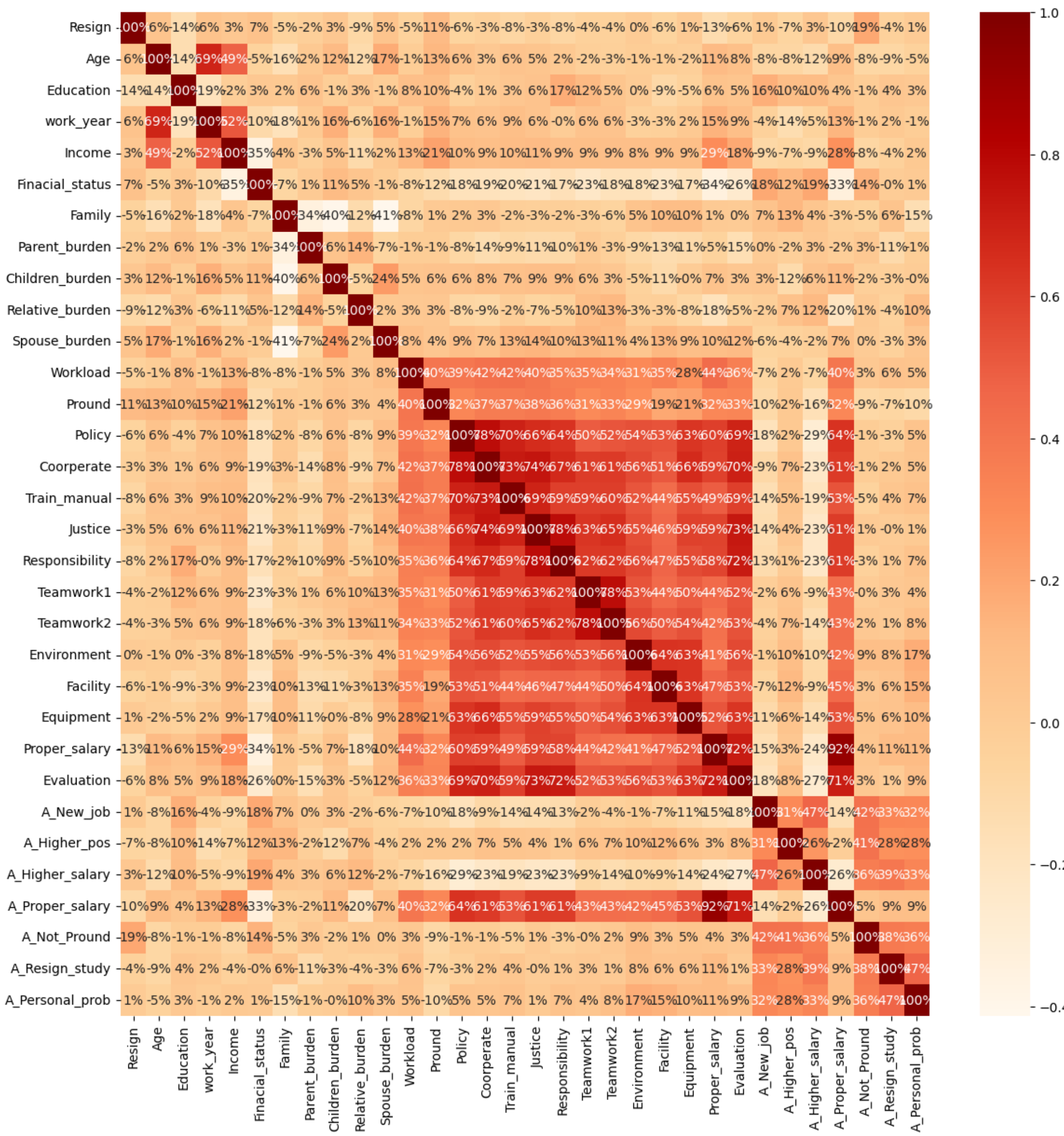
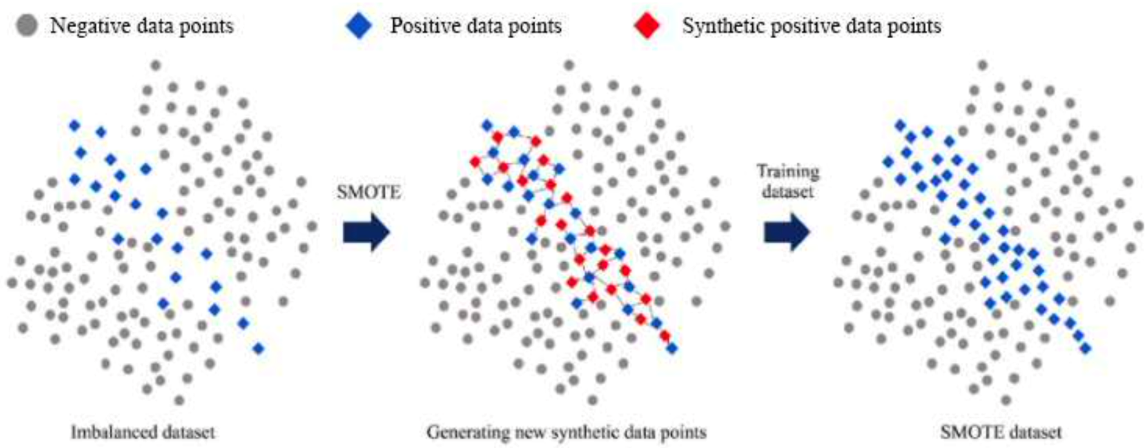


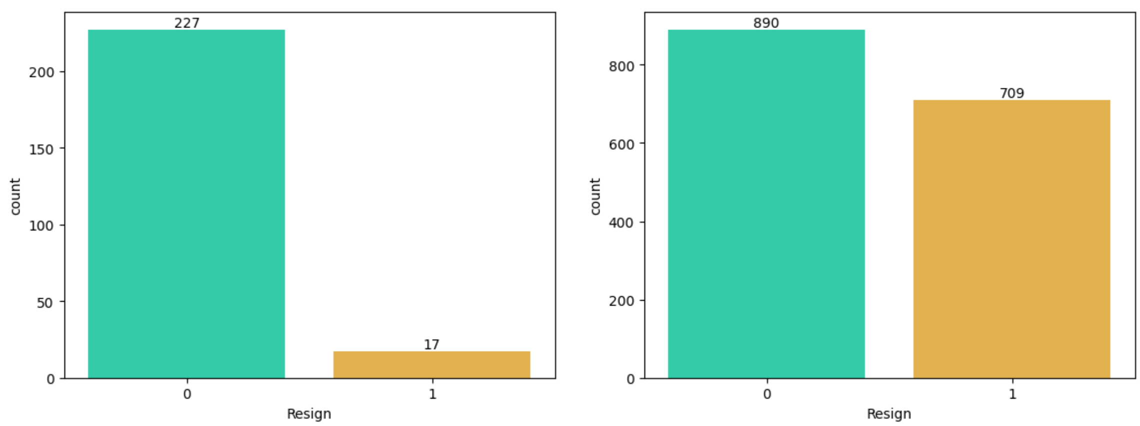
Figure 5: The Heat Map table showing the correlation between personal factor data, data on push factors and data on pull factors.

Therefore, the characteristics of each tree are not be the same, ensuring the trees more diverse and independent, which gives the model high efficiency [18]. FIGURE 9 shows the Random Forest model using personal factors and push factors. FIGURE 10 shows the Random Forest model using data on personal factors and pull factors. FIGURE 11 shows the Random Forest model using personal factor data, push, and pull factors.



(a) (b) (c)

Figure 6: (a) Original Dataset (b) Generated Samples (c) Resampled Dataset [16]



(a) (b)

Figure 7: Data balancing (a) before using SMOTE technique (b) after using SMOTE technique.

2.6 Analysis of Forecast Performance

The results of the predictions are expressed in the form of a table showing the classification performance of the Random Forest model, measured in terms of Accuracy, Sensitivity, Precision and F1-Score as follows [19]:

- Accuracy is a value that measures the proportion of a model's correct predictions across the dataset. It is calculated as the ratio between true positives (True positive; TP) and true negative (True negative; TN) to the total number of samples, as shown in equation (1)

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{1}$$

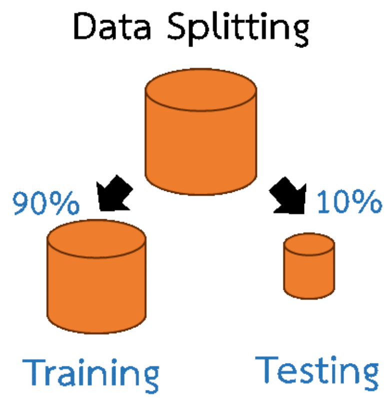


Figure 8: Data division for training and testing the model.

- Sensitivity also referred to as true positive rate, measures the proportion of true positive predictions out of all true positive cases. It is calculated as the ratio of true positive results (TP) to the sum of true positive results (TP) and false negatives (False negative; FN), as seen in equation (2)

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

- Precision is a value that measures the proportion of true positive predictions out of the total positive predictions made by the model. It is calculated as the ratio of true positives (TP) to the sum of true positives (TP) and false positives (False positive; FP), as shown in equation (3)

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

- F1-score is a measure that balances precision and sensitivity. It is calculated as the harmonic average of precision and sensitivity. The F1 score is useful when looking for a balance between high precision and high sensitivity, as shown in equation (4)

$$F1 - score = \frac{2 \times Precision \times Sensitivity}{Precision + Sensitivity} \tag{4}$$

3. RESULTS AND DISCUSSION

The results of using the Random Forest algorithm together with the SMOTE technique to create a model used for predicting the resignation of skilled technicians were expressed in the form of a confusion matrix performance table. The classification of the Random Forest model in FIGURE 12, shows a confusion matrix performance table. classification of the Random Forest model using input data are personal factors and push factors. The figure shows the predictions on the 25 test data used as input, which have not been learned by the Random Forest model before. It has data on 23 employees who are still working and 2 employees who have resigned. The results of the model using

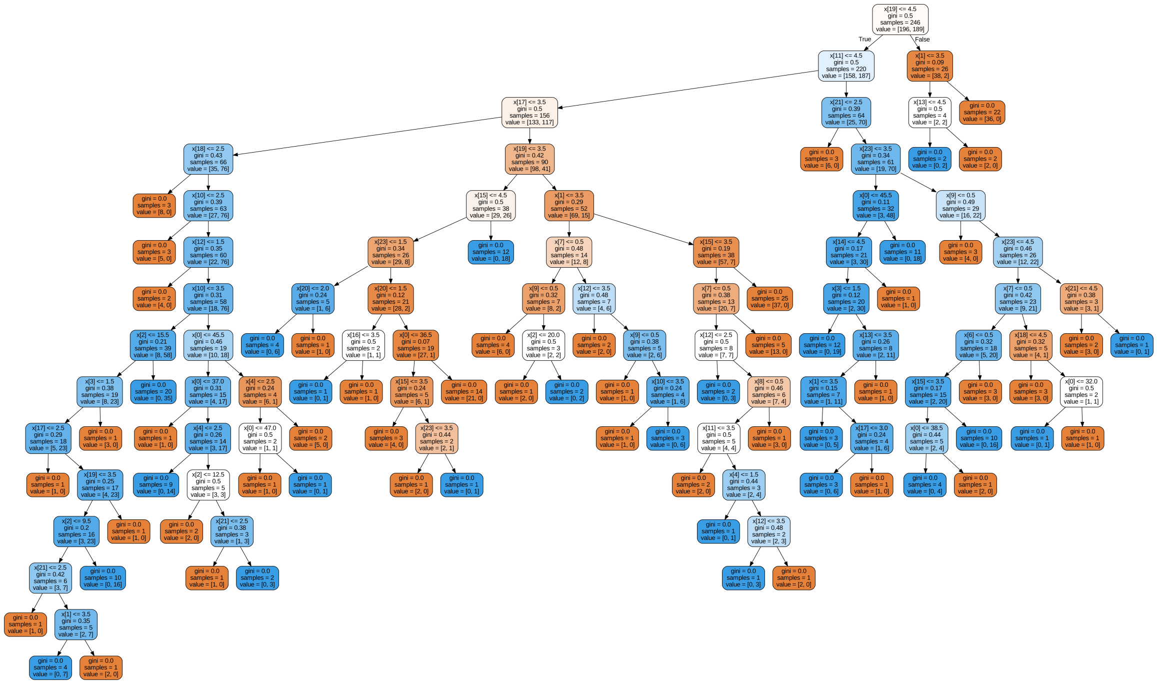


Figure 9: Partial Random Forest model obtained from training with employee questionnaire response data using personal and push factors.

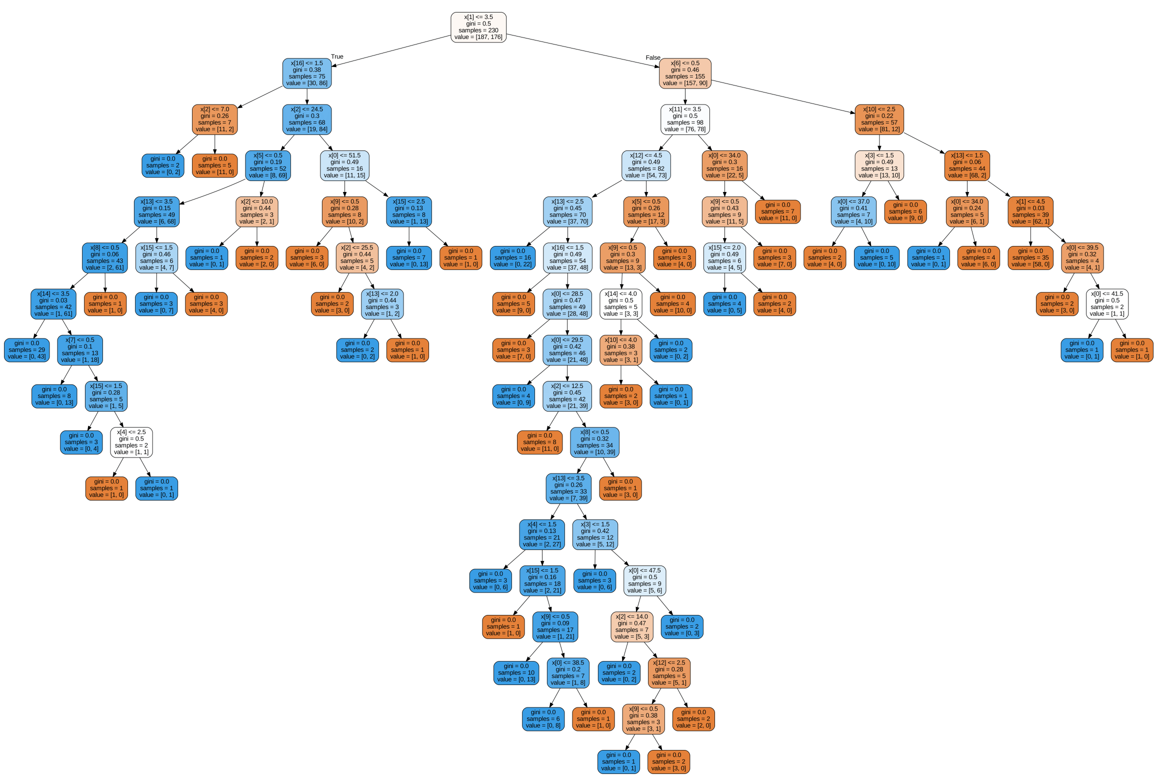


Figure 10: Partial Random Forest model obtained from training with employee questionnaire data using personal and pull factors.

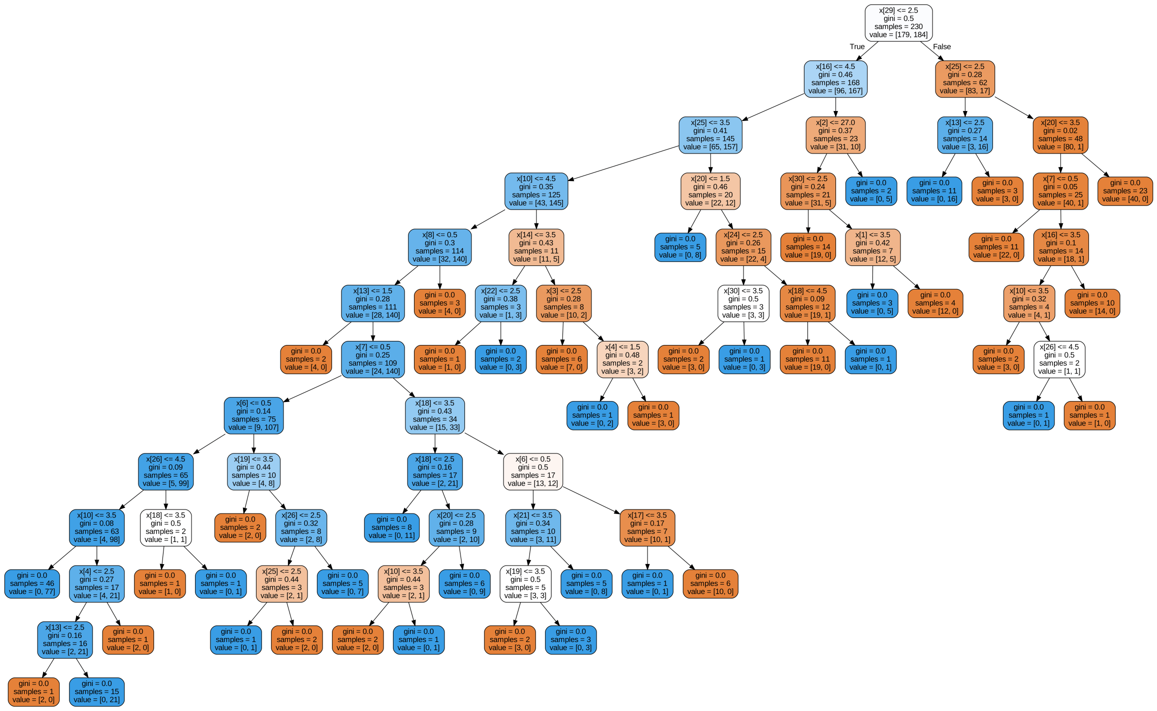


Figure 11: Partial Random Forest models obtained from training with employee questionnaire response data using personal factors, push factors, and pull factors.

the Random Forest algorithm combined with SMOTE were able to predict correctly, demonstrating 100% accuracy.

FIGURE 13 shows a confusion matrix performance of the classification of the Random Forest model using the input data are personal factors and push and pull factors. The figure shows forecasts for 25 test data (this input data has not been previously learned by the Random Forest model). It includes data on 23 employees who are still working and 2 employees who have resigned. The results of the model using the Random Forest algorithm combined with SMOTE incorrectly predicted 1 person. The accuracy of the model was 96%.

Figure 14 shows the efficiency of the confusion matrix classification of the Random Forest model using the input data are personal factors, push factors and pull factors. The figure shows forecasts for 25 test data (this input data has not been previously learned by the Random Forest model). It has data on 23 employees who are still working and 2 employees who have resigned. The results of the model using the Random Forest algorithm combined with SMOTE showed 100% accuracy in prediction.

The performance of the Random Forest model can be measured in terms of accuracy, sensitivity, precision, and F1-Score using Equations (1) – (4). These measurements evaluate the classification efficiency of the model generated by the Random Forest algorithm combined with the SMOTE technique. This model was tested using 3 types of input data: personal factor data + push factor data, personal factor data + pull factor data and personal factor data + push factor data + pull factor

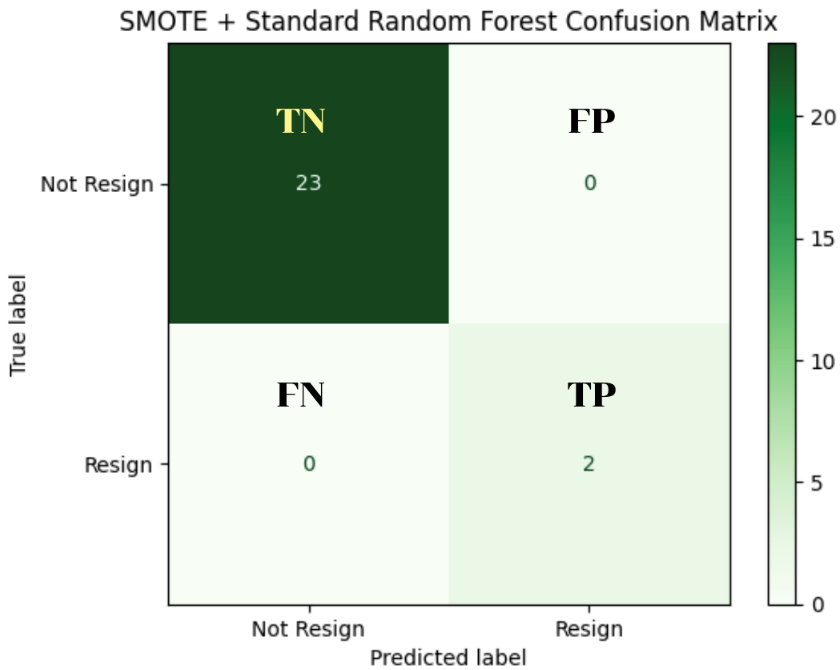


Figure 12: The classification performance of the Random Forest model with the input data as personal factor data and push factor data.

data. The results were obtained from testing with the questionnaire answers of 25 employees, as shown in TABLE 3.

Table 3: Measurement of classification performance of Random Forest model with SMOTE technique.

Random Forest with SMOTE	**Accuracy**	**Sensitivity**	**Precision**	**F1-score**
Personal factors + Push factors	100%	100%	100%	100%
Personal factors + Pull factors	96%	100%	67%	80%
Personal factors + Push factors + pull factors	100%	100%	100%	100%

FIGURE 15 shows the forecasted results of the model created by the Random Forest algorithm together with the SMOTE method using three types of input data. Three forecasting models were created: FIGURE 15 (a) personal factors and push factors, FIGURE 15 (b) personal factors and pull factors, FIGURE 15 (c) personal factors, push factors and pull factors. By comparing the actual column with the employee resigning as predicted column, the accuracy of the predictions can be assessed. From FIGURE 15 (a), it can be seen that the questionnaire response data of 2 employees, No. 14 and No. 19, have a status of resignation (Resignation status = 1). When the questionnaire response data was input into the Random Forest model, the model could make accurate predictions. As for the remaining 23 employees who were still working (Status still working = 0), the model could predict accurately.

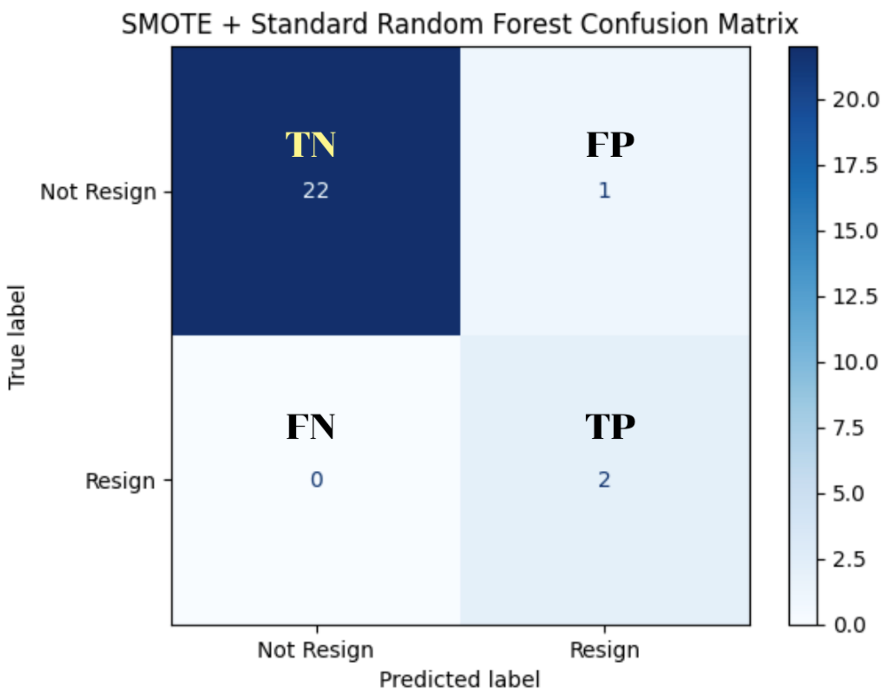


Figure 13: The classification performance of the Random Forest model with the input as personal factors and pull factors.

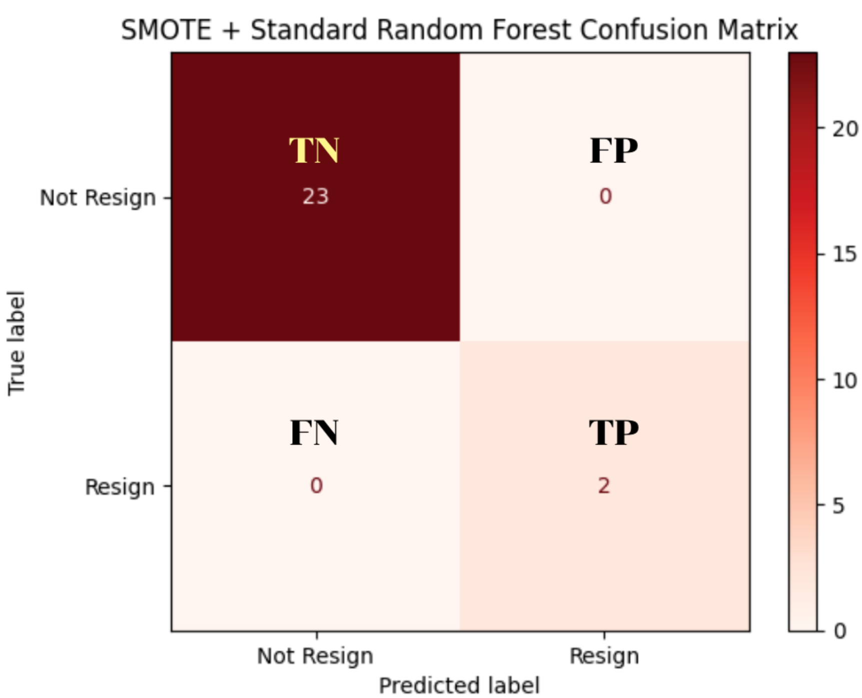


Figure 14: The classification performance of the Random Forest model with input data as personal factors, push factor data and pull factor data.

	Actual Employee Resign	Predicted
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	0	0
7	0	0
8	0	0
9	0	0
10	0	0
11	0	0
12	0	0
13	0	0
14	1	1
15	0	0
16	0	0
17	0	0
18	0	0
19	1	1
20	0	0
21	0	0
22	0	0
23	0	0
24	0	0

Personal factors and Push factors

(a)

	Actual Employee Resign	Predicted
0	0	1
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	1	1
7	0	0
8	0	0
9	0	0
10	0	0
11	0	0
12	0	0
13	0	0
14	0	0
15	0	0
16	0	0
17	0	0
18	0	0
19	0	0
20	0	0
21	0	0
22	1	1
23	0	0
24	0	0

Personal factors and Pull factors

(b)

	Actual Resign	Predicted
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
5	1	1
6	0	0
7	0	0
8	0	0
9	0	0
10	0	0
11	0	0
12	0	0
13	1	1
14	0	0
15	0	0
16	0	0
17	0	0
18	0	0
19	0	0
20	0	0
21	0	0
22	0	0
23	0	0
24	0	0

Personal factors Push factors and Pull factors

(c)

Figure 15: Forecasting results with test data from questionnaire data from 25 employees. (a) Personal factors and Push factors (b) Personal factors and Pull factors (c) Personal factors, Push factors, and Pull factors

FIGURE 15 (b) shows the questionnaire responses of 2 employees, No. 6 and No. 22, who have resigned status (Resigned status = 1). When the questionnaire response data was input into the Random Forest model, the model could make accurate predictions. However, for employees who were still working, 0, as shown in the red square (Status still working = 0), the model incorrectly predicted one resignation (resignation status = 1). Despite this, the model was able to make accurate predictions for the remaining 22 employees.

In FIGURE 15 (c), sequence no. 5 and sequence no. 13 show resigned status (resigned status = 1). The Random Forest forecast model could predict correctly. As for the remaining 23 employees who were still working (Status still working = 0).

Based on the forecast data above, it can be seen that the predictions are highly accurate, indicating that this model can be potentially applied to create a web application for forecasting employee turnover. This may allow the company to conduct tests and prepare questionnaires to compare the forecast results with what actually happens in the company, enabling the evaluation of the consistency and accuracy of the model's predictions. This may be applied to other departments as the questions in the questionnaire can be adjusted to suit the objectives of the company or agency. By importing data from the questionnaire responses into the model for further learning, the newly learned information can be used to improve the performance of the model's predictions and this can actually be applied in practice.

In future work, we plan to:

Expand the Dataset: We will actively seek opportunities to collect a larger, more comprehensive dataset from additional automotive service centers. This will allow us to validate our model with a broader representation of the technician population.

Explore Alternative Techniques: We will investigate alternative data balancing techniques, such as other oversampling or undersampling methods, or cost sensitive learning, to compare their performance with SMOTE and potentially mitigate the introduction of noise.

Compare Algorithms: We will compare the performance of our Random Forest model with other machine learning algorithms, such as Support Vector Machines (SVM), Gradient Boosting Machines (GBM), and neural networks, to identify the most effective predictive model for this application.

External Validation: We will prioritize external validation of our model using the expanded dataset, ensuring its generalizability and applicability to diverse automotive service center environments.

4. CONCLUSION

This research used machine learning techniques, a branch of artificial intelligence, to predict the resignation of skilled technicians at large automobile service centers in the country. The Random Forest algorithm was used together with SMOTE (Synthetic Minority Oversampling Technique) developed in Python language. The data on the questionnaire responses of employees who resigned from the company were significantly smaller compared to the number of questionnaires from employees who were still working. The SMOTE technique was used to generate synthetic data to the original data based on the baseline and average of the original data, resulting in a balanced data in both classes. After that, the Random Forest algorithm was used to create a model using real data together with the synthetic data obtained from the SMOTE technique.

The experimental results showed that the model used to predict employee resignation using 3 types of input factors: personal factors + push factors, personal factors + pull factors and personal factors + push factors + pull factors exhibited high efficiency and accuracy. When using personal factors and with only 2 push factors, it was found that the efficiency of the forecasting model had an accuracy of 100%, sensitivity of 100%, precision of 100% and F1-score of 100. The results of the research showed that using Random Forest together with SMOTE to address the data asymmetry problem resulted in high accuracy in the model's prediction performance.

5. ACKNOWLEDGEMENTS

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