Universiti Sains Malaysia (USM) Talent Management Dashboard

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***Abstract*—In this competitive knowledge-based world, it is vital for management to handle the attrition issue. When employees leave an organization, they bring invaluable tacit knowledge, which is often the source of competitive advantage for the business. For an organization to continually have a higher competitive advantage over its competition, minimizing employee attrition is crucial. Promotion is another issue that the organization must address to keep its employees for the long term. This study aims to develop a talent management dashboard that focuses on the attrition and promotion structures at the USM main campus involving permanent staff only and identify the attrition trend for the upcoming 3 years. A descriptive analysis of these two issues has been performed using the PowerBI platform. The prediction of the attrition trend for the upcoming three years' model has been developed using time series algorithms. As the dataset is static, the autoregression (AR), Moving Average (MA), and ARIMA models have been developed and evaluated using the Root Mean Square Error (RMSE) score. Based on the result, the ARIMA model has the best performance with an RMSE score of 4.901 compared to other models chosen to represent the attrition trend.**

Keywords—attrition, promotion, dashboard, PowerBI, prediction, trend, ARIMA Model, AR Model, MA Model.

I. INTRODUCTION

Attrition is the reduction of controllable or uncontrollable workforce size due to retirement, death, sickness, and relocation [1]. It denotes that the employee's or expert's mobility to other locations is faster than the institution hired. Somehow, it can be one way for institution management to reduce their workforce size without taking overt action, but unpredictable employee attrition can leave gaps in an institution. It can be stated that employee attrition is one of the institution's major problems and a solid strategy is needed to cope with it [2].

There are four types of employee attrition: voluntary attrition, involuntary attrition, internal attrition, and demographic-specific attrition as shown in Fig.1 [3]. The most serious concern about voluntary attrition and demographic-specific types of attrition is that the organization may lose some of its valuable staff or expertise due to structural issues of the organization's management [3].

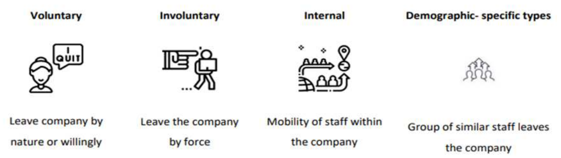

Fig. 1. Type of attrition

In addition, there are differences between employee attrition and employee turnover terms which are usually conflated and confused with each other but both terms refer to the process of employees leaving the company [4]. The most significant difference between turnover and attrition is the cause of leaving the company. According to [4], turnover refers to layoffs caused by the negative environment of organizational cultures, such as toxic management, burnout, lack of recognition, and others, while attrition occurs due to natural causes like retirement, termination, health issue, elimination of the job position, etc. In other words, turnover is caused by the company's management, whereas attrition is caused by the natural progression of life [5].

For turnover, if the company's turnover rate is high, it indicates that the working conditions are not optimal and reflects a negative image of the company environment. In contrast to attrition, employers do not fill positions left by former employees. Thus, employee attrition is often viewed as a way companies can reduce labor costs when facing financial difficulties. Some companies do not seem to emphasize the attrition issue, as it is still possible for companies to grow despite having a high turnover rate. However, if it is consistently high, downsizing of the company can occur.

The Human Resources department at Universiti Sains Malaysia faces challenges in understanding employee attrition due to limited and disconnected data. The current dashboard only shows the total number of employees leaving per year, making it impossible to study the attrition rate effectively. The data, originating from various sources, lack integration, hindering a comprehensive analysis of factors influencing attrition. Furthermore, the issue of overdue promotions among academic staff is a significant concern at USM. Human Resource management consistently receives complaints about promotion problems, both formal and informal. Academic staff express dissatisfaction when promotions are not based on factors like working experience, staff Key Performance Indicators (KPIs), and services. The absence of an effective promotion structure may impact staff productivity and create a dissatisfying work environment, potentially leading to attrition among academic staff.

This paper aims to create a dashboard that outlines the current attrition structure at the USM main campus, focusing on permanent staff. It utilizes data from the Human Resources department, covering employee demographics, job history, and positions from 2020-2022. Additionally, since job satisfaction data is lacking, the study explores the promotion rate patterns in USM main campus clusters, highlighting their potential influence on attrition and the expertise loss resulting from it.

II. LITERATURE REVIEW

A. Feature Selection For Employee Attrition

The purpose of this section is to ease in identifying the common features that were used to investigate this studies area. The feature that relevance was used for descriptive analysis part as a way to visualize the USM attrition structure.

According to [6] study, the data and the method used is important for predicting employee attrition . Besides, the selection of the features varies as it based on the project's aim. The best predictor for voluntary attrition was age, tenure, pay, overall job satisfaction, and employee perceptions of fairness, which lean more toward measuring employee perception than demographic [7]. However, [1] suggested that demographic characteristics, especially age, gender, sex, education, and marital status, were important attributes in predicting employee attrition. Studies that focused on other factors such as salary, sales, satisfaction level, work accidents, and others [6] and [8].

Based on [9], the exploration of attrition features is done by selecting the features from the HRM dataset by IBM Analytics, which contains 35 features relating to 1500 observations and referring to U.S. data. Fig. 2 depicts all the features in the HRM dataset that focus on employees' lives and personal characteristics. In addition, data exploration has been done by generating descriptive statistics to identify the relationship between features and attrition. The results show that monthly income, age, distance from home, entire working years, overtime, etc. are the most important factors of attrition, as illustrated in Fig. 3 below.

Age	Monthly income
Attrition	Monthly rate
Business travel	Number of previous employers
Daily rate	Over 18
Department	Overtime
Distance from home	Per cent salary hike
Education	Performance rating
Education field	Relations satisfaction
Employee count	Standard hours
Employee number	Stock option level
Environment satisfaction	Total working years
Gender Training times	last year
Hourly rate	Work-life balance
Job involvement	Years with company
Job level	Years in current role
Job role	Years since last promotion
Job satisfaction	Years with current manager
Marital status	

Fig. 2. The list of features in HRM dataset [9]

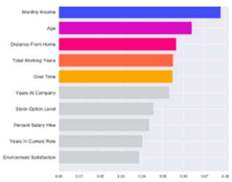

Fig. 3. Importance of each feature [9]

B. Related Work on Attrition Prediction

The purpose of this section is to describe the existing related paper which most of them focuses on determining the probability of attrition and the factor that influenced the attrition to occur using standard machine learning techniques rather than forecasting the attrition trend.

[9] research focuses on identifying the best model that can predict the greatest number of people who may leave the company, with a low false negative score as the goal. Therefore, the confusion matrix of each proposed prediction algorithm, like Naïve Bayes, Logistic Regression, K-Nearest Neighbor, Decision Tree, and others, was calculated. The Gaussian Naïve Bayes classifier is the optimal model as it has a low false negative score (recall score).

[8] present study exhibits performance estimation of various classification algorithms such as the Decision Tree classifier, Random Forest classifier, Support Vector Machine classifier, and Linear Model classifier and compares the classification accuracy. The error matrix and pseudo-R squared estimate of the error rate is used to evaluate the model's performance. The study found that the performance accuracy revealed that the Random Forest model could be effectively used for classification. This analysis concludes that employee attrition depends more on employees' satisfaction levels than other attributes.

[10] investigates employee turnover in the Indian hospitality sector, utilizing various time series models like Johansen co-integration, Vector Autoregression (VAR), and Vector Error Correction. The study relies on data from the Journal of Annual Survey of Industries, covering average workers, labor turnover, accession, and separation over 24 months. Initial attempts using ANOVA and Kruskal-Wallis for seasonal patterns proved unsuitable for trend series. Autocorrelation (ACF) and partial autocorrelation (PACF) were then employed to identify seasonal, autoregressive, and moving average patterns. Augmented Dickey-Fuller (ADF) confirmed the data's stationarity, making it suitable for time series analysis. While VAR showed the highest holdout R^2, normally distributed residuals, and white noise, the research concludes that the dynamic regression model is optimal for this time series data. The average number of workers emerges as the primary predictor of labor turnover, with accession and separation being insignificant. However, this technique isn't applicable to total attrition per month due to the data's categorical nature, unsuitable for time series analysis, and the numerical data structure not being suitable for this application.

Other studies also have tried to build the attrition prediction using the time series analysis [11]. The dataset consisted of over 8,000 observations from one of U.S.A organizations has been used. The turnover data has been represented the total number of leaving the organization within 135 months span from November 2000 to January 2012. The ARIMA method with univariate model and multivariate model has been compared to identify the accurate model fit. The highest holdout R^2, normally distributed residual and white noise has been considered to identify the best model. The study also found that multivariate models are better than univariate models. However, univariate models are preferred than multivariate models as it has less chance for outliers and errors.

C. Data Visualization: Dashboard

A well-designed dashboard is intentionally designed to give an overview of the specific area of the organization that needs to be tracked rather than displaying large amounts of data that take time to process and understand. Data dashboards are often aligned with and developed due to an organization's strategic plan. Dashboards make it easy for users to review the data and focus the conversation on areas where the program needs improvement or where goals are being achieved. In short, dashboards help the organization get and see important information quickly [12]. In addition, the implementation of data visualization in the dashboard can convey specific information or purposes using suitable graphic representation for better understanding and aid decision-making. [12] stated that a dashboard is a focused tool for analysis and tracking. It needs to be regularly updated to do timely data tracking efficiently. The dashboard should be designed in real-time, including historical and future data (if possible), and colored graphs and charts for better visualization [13].

The functionality and content of the dashboard must fit the dashboard's purpose and consider the user's characteristics. Dashboard functionality must be well-defined to support visual interpretation and decipherment of information properly. Additionally, the dashboard's content should be defined to effectively support decision-making in performance management and support activities within the continuous improvement process.

In [5] research, the application of PowerBI in developing the data visualization of employee turnover prediction applications was made. The data exploration and prediction findings have been visualized across multiple dashboard pages such as the prediction page, analysis report page, executive report page, and employee information overview page. On the prediction dashboard page, focus on visualizing the prediction result and attrition pattern by a specific characteristic, while on the analysis report dashboard page, emphasize and display the correlation between the factors. The executive report dashboard and employee information overview page display the data exploration obtained from the dataset.

III. METHODOLOGY

A. Data

Dataset given by USM HR department in excel format: "Active Staff Data" and "Leave Staff Data" that retrieved from the main database named smu_db. The "Active Staff Data" file consists of the information regarding the permanent staff that is still active until 2022 while the "Leave Staff Data" file, consists of information on leaving staff from 2020 until 2022. The active staff dataset consists of 2896 staff from 2020 until 2022 while the attrition staff dataset consists of 393 numbers for the past three years. Each dataset consists of 26 features such as campus, staff number, roles, department, retirement date, and others. The dataset focuses on staff job data rather than working satisfaction. The limitation of the dataset is that there are no data regarding the staff's perceptions toward their work environments, such as job satisfaction, job involvement, and others. Irrelevant fields, such as the name and staff number has been removed before the modeling process starts and a new field that can be utilized for the study of attrition has been created using some of these existing fields. Table I shows the list of attributes used throughout this development.

TABLE I. The List of Attributes

Attributes	Description	Data Types
Age	Current age	Numerical
Roles	Staff position	Categorical
Department	Current department	Categorical
Klas	Staff current class	Categorical
Category	Category of staff whether Non-Academic Officer”,” Academic”,” Non-Academic Administrator.”	Categorical
Gender	Staff gender	Categorical
Date First Appointed Roles	Date of first position in USM	Ordinal
Average Performance	Performance grade of staff for the past 3 years	Numerical
Total year working	Service year	Numerical
Last Promotion Year	Last got promotion	Numerical
Status	Active or non-active staff	Categorical
Type attrition	Type of staff leave	Categorical

B. Data Preparation for Dashboard

The data was exported in PowerBI for the descriptive analysis of the attrition issue in USM. The dimension table for all categorical columns in the dataset has been created, as shown in Table II below. This process is essential for PowerBI as it can filter, group, or summarize the model data. Some of the data come in Malay as the data get from the client without alteration, while data in English was generated manually when developing the model.

TABLE II. List of the Dimension Table

Dimension Table Name	Derive From
dcalendar	Generate using DAX expression which also detects the minimum date and maximum data in the dataset.
djabatan	Generate from the department column of the fact table. Consists of all unique departments.
djantina	Generate from the gender column in the fact table. Consists of male and female index number
djawatanlantik	Generate from the role’s column in the fact table. Consists of unique roles and their index number
djenistamat	Generate from the type of attrition column in the fact table. Consists of 5 types of leave such as • Bersara Wajib = Mandatory retirement • Bersara Pilihan = Optional Retirement • Kematian = Death • Letak Jawatan = Resignation • Ditamatkan = Termination
dkategori	Generate from the category column in the fact table. Consists of the category of staff based on their grades such as Non-Academic Officer, Academic, and Non-Academic Administrator.”
dklas	Generate from the Klas column in the fact table. Consists of Klas staff such as D, S, W etc.
dpencapaian	Generate from the average performance column. Consists of a performance scale such as “>80”,”70-80”,”60-69”,”50-59”,”40-49” and “<40”.

All the related columns from the fact table have been linked with the dimension table using their index number. Thus, the relationship between the fact and dimension table has been generated. The cardinality of the dimension table and fact table is one to many. The overview of the relationship for all tables involved in this study is shown in Fig. 4 below.

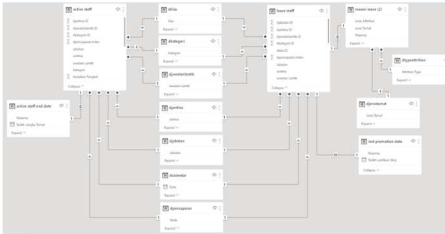

Fig. 4. Relationship diagram

For promotion analysis, an additional column named "Promotion Status" has been added in order to ease the promotion analysis as the data given is how long they are last appointed in a particular role ("Last Promotion Year"). Based on "PEKELILING PERKHIDMATAN SUMBER MANUSIA", an average year that allows the staff to be promoted is 7 years. Thus, the staff that has the last promotion year bigger than 7 years’ categories as "Exceed 7 years" represent the staff can be promoted while below 7 years as "Promoted".

C. Data Preparation for Time Series Prediction

For time series analysis, the dataset that was preferred is in continuous or discrete-time which can represent the chronological order. Besides, this forecasting focuses on the univariate time series, the dataset consists of the total staff turnover every month for the past 3 years and has been extracted from PowerBI and imported to Python. The data was plotted into a graph to see the attrition pattern by month as shown in Fig. 5.

Fig. 5. Attrition data pattern per month

D. Time Series Prediction (Attrition Pattern)

The dataset has been split into two sets for training and testing of the model with a ratio of 80/20 as performed in [5] which means the data from 1/1/2020 to 1/4/2022 is train data other is test data. Stationary of the dataset is checked to get better time series results in order to choose which model is suitable for this dataset. Stationary datasets mean that the mean and standard deviation remains constant over time and have no seasonal pattern. The Augmented Dickey-Fuller test (ADF Test) was performed, and it found that this dataset is a stationary dataset as the p-value is lower than the significance level of 0.05. Thus, AR, MA, and ARIMA models perform well for stationary datasets [14]. RMSE metrics are used to assess the prediction models' accuracy. RMSE is used to gauge the error's average magnitude. RMSE tends to avoid using absolute value and penalizes significant errors more severely on outliers.

The AR technique is formulated by predicting the current point in a series dependent on the previous point, which indicates it is a regression of variables against itself. In AR, the number of lags is important in finding the optimal model. It is because lags are used for the predictor [15]. To find the number of lags, the PACF graph needs to be plotted to determine the number of lags suitable for tuning the AR model [16]. PACF graph is able to convey the correlation between the series and its lag. In this study, the number of lags for this series is 6, as most of the lag does not pass the significant level. So, an AR model with six lags has been performed as shown in Fig. 6.

The MA technique is more focused on the sharp spikes in the time series data [17]. Besides, the difference between the actual and expected results is considered an error in MA modeling [18]. So, the MA model relies only on the lagged predicted error occurring in the series [15]. The autocorrelation function (ACF) plot is utilized to get the total correlation between the different lags (q-value). Fig. 7 shows the ACF graph plot with 1 q-value.

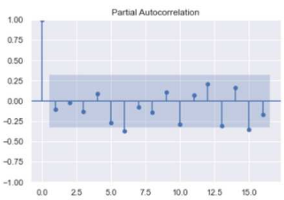

Fig. 6. PACF graph

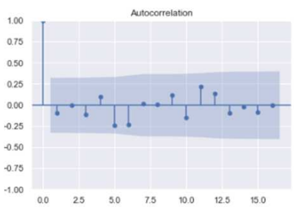

Fig. 7. ACF graph

The development of a time series prediction model using the ARIMA model is widely used for forecasting the future based on historical data and is suitable for non-stationary time series [19]. ARIMA technique is a combination of AR and MA with the integration of Integrated Moving Average (I) Thus, the parameter that needs to be tuned is the value of p, q, and d.

- p-value represents the order of the autoregressive part [20].
- d-value represents no seasonal differences [20].
- q-value is the number of lagged predictive biases [20].

itertools technique has been used to search the optimal p, q, and d values with a range from 0 – 5. The smaller value of RMSE, the better the prediction model.

IV. Results and Discussion

A. Descriptive Part (Dashboard)

The dashboard has five pages and each of the pages has its specific purposes. Each page has its own filter and the data display will change according to the selected filter. As the purpose of the graphic is to show quantitative data, the majority of the graph is in values rather than percentages. The overview page focused on visualizing the active staff information such as the total active employee in USM Penang for 2022, the total of female and male staff, and others. The attrition page is more toward displaying the descriptive analysis of the leave staff information. Next, the Promotion and Attrition vs Promotion page is used to visualize the descriptive promotion pattern for active and leave staff. The prediction page focused on showing the prediction result found from the prediction model.

Dashboard Page 1: Overview Page

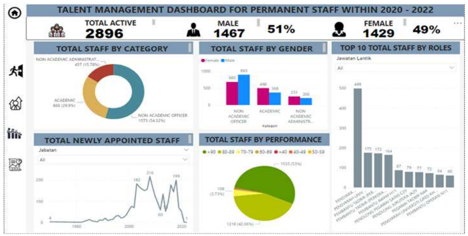

Fig. 8. Overview page

Found that the USM main campus have 2896 employees in 2022, with men accounting for 51% of the workforce. Of the 2896 active permanent staff, 457 (about 15.78%) are administrators, 866 (about 29.9%) are academic staff, and more than half are officers. Although USM has many officers, the university has more lecturers than officers in terms of roles as the top first and second role is a lecturer. Besides, most of the staff at USM Penang have a score of more than 80% for their performance results over the last three years, indicating a high level of performance. As a result, it is critical for USM management to have a competent staff retention strategy, as it will be a waste of their talent if the staff turnover. Total newly appointed staff is more concerned with demonstrating how many employees USM hired per year from 1980 to 2022. It can be concluded that, over the last three years, USM has not enrolled any permanent staff and has leaned more toward contract staff.

Dashboard Page 2: Attrition Page

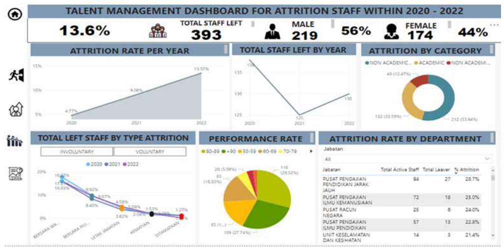

Fig. 9. Attrition page

The overall attrition rate over three years is 13.6%, with 393 employees leaving, the majority of whom are men. Therefore, the attrition rate can be calculated using the formula total of the left staff for the year divided by the total active staff that year. As the pinpoint of the study is to identify the attrition trend occurring in USM, the first chart presents the trend of attrition for the past 3 years. It can be said that the attrition trend is moving upward every year. In percentage format, the attrition trend may be easier to read than in total amount. According to the total left staff chart, staff turnover in 2021 will be significantly lower than the previous year but slightly higher than the year before.

Most of the staff attrition is due to retirement every year, but it is also crucial for the HR department to highlight the optional retirement and the resigned staff. As shown in the "Type of Attrition" chart, the percentage of staff willing to leave the USM is increasing, so the HR department needs to find the reason behind it. After filtering the attrition among non-academic staff, most of the staff leave due to retirement, and the percentage of the staff that resigns is relatively low. However, compared to the academic staff, the attrition rate is higher, with a higher percentage of resignations which is almost 9%. Most of the leaving staff have a higher performance rate, as the more extensive pie chart represents the staff who left with more than 80 average scores for the last 3 years before they left. The main reason for this performance chart is that USM lost many quality staff that are very useful for the organization's sustainability.

Dashboard Page 3: Promotion Page

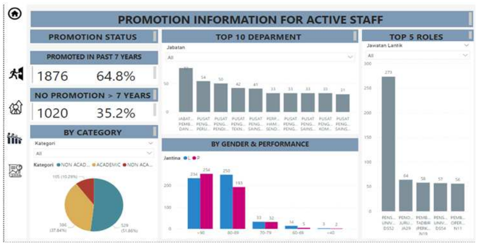

Fig. 10. Promotion page

The chart only shows staff due for a promotion, which means they have been in the position for more than 7 years. The staff already promoted within the past 7 years is classified as "Promoted" while the staff due for promotion is called "Exceed 7 years". the total number of active staff due for promotion is nearly 50% and mostly comes from the officer category, followed by academic and administrative staff. Based on the overview of the performance scale, the promotion of staff does not relate to their performance, as most of the staff with higher performance are still due for promotion. For the top 10 departments and top 5 roles, the column was sorted in descending order based on the total staff due for promotion. The percentage of due promotion is calculated using the total number of staff due promotion divided by the number of staff in the department or roles. It reveals that the housing school has the highest percentage of due for 44 promotion staff, with 42 total employees representing 62.7% of the total due for promotion staff.

Dashboard Page 4: Promotion vs Attrition Page

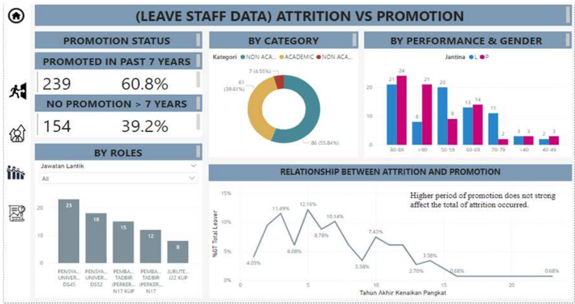

Fig. 11. Promotion vs Attrition page

This page was created to investigate the relationship between attrition and promotion. Based on the analysis, the promotion rate among the attrition staff is not higher, as it only represents 39.2% of the total staff who left USM Penang. Furthermore, as seen, the majority of female employees do not get promoted within 7 years, despite the fact that the female attrition is lower than the male attrition.

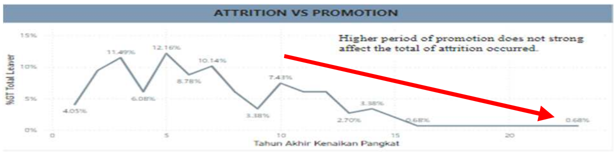

Fig. 12. Relationship between attrition and promotion

Based on the graph in Fig. 12, although the promotion years are increasing, the percentage of staff attrition is low. The promotion may have an impact on attrition, but it cannot clearly conclude that the staff left USM because of the promotion issue. This is because only 2% of staff turnover occurs, although the staff has already served in that particular role for more than 15 years. Furthermore, employees who have been promoted within the last seven years have a higher turnover rate, which is nearly 20%.

B. Prediction Result (Attrition Trend)

The evaluation of the model uses the RMSE, which measures the error between the actual value of the time series and the forecasted value. The training model has been tested with different parameters, and the evaluation of the test data and prediction scores have been recorded and compared. The best model will be used to forecast the next three years (in month format, 36 months).

TABLE III. Time Series Model Result

Techniques	Parameter	RMSE score
AR model	p = 6	5.456
MA model	q = 1	5.209
ARIMA model	4,0,4	4.9011

The ARIMA model has a smaller RMSE score than others. So, the combination parameter (4,0,4) is the best combination parameter and will be used for the future forecast. The model's findings were used to predict the total number of staff attritions that will occur over the next three years, beginning in January 2023 and ending in January 2026. Because this data is static, there is no clear increase or decrease trend. However, the resulting finding has been embedded in PowerBI to make it easier to read and track the attrition trend in Fig. 13.

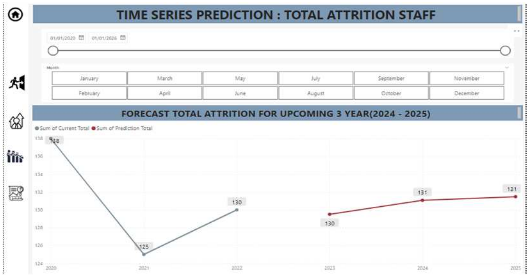

Fig. 13. Attrition trend for next 3 years

According to the chart in Fig.13, there will be a slight increase in the attrition trend in the future. Every month, at least six employees are expected to leave USM. This is worrying because, since 2020, the USM main campus has stopped taking any permanent staff, which can lead to a shortage of experienced staff. In addition, this page enables the user to drill down the attrition trend by month.

V. Conclusion

The dashboard which consists of 5 pages that display the descriptive analysis regarding the current pattern of employee attrition and promotion among permanent staff at USM Penang, which helps HR management understand the insight and make proper management strategies to cope with it. In addition, the attrition rate has increased linearly for the past 3 years. The outcome of the comparative time series prediction model, which aids in forecasting the upcoming trend. Among the three classifiers, the ARIMA model achieved the optimal model with the lowest RMSE score, allowing it to accurately forecast the number of staff attrition in the future. There are no different trends for the future, but a few staff members leaving every month may lead to a workforce shortage. Besides, the finding concluded that the promotion structure does not give staff a strong influence over turnover.

Acknowledgment

We thank AUN/SEED.Net for the partial funding of the paper to be published in the proceeding.

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