ISSN 1411-3813 | E-ISSN 2684-7191
DOI: 10.46976/litbangpolri.v28i2.298

Analysis of Qualifications and Positions in The Police Academy: Does Education Affect Career?

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ABSTRACT

Abstract In law enforcement institutions specially on Police Academy, education and rank are often considered primary factors in determining an individual's career trajectory. However, the extent to which these factors truly influence job placement remains a subject of debate. This study aims to analyze the relationship between educational background and the positions held by Police Academy personnel. The primary motivation of this research is to provide a data-driven approach that can assist in career development planning within the police force. We employ Machine Learning methods, the Random Forest Classifier, to predict job categories based on education and rank. The datasets used in this study includes information on job positions, the most recent police education, the highest general education, rank, and whether the position is structural or functional. The evaluation parameter utilized in this research is the model's accuracy in job classification. The results indicate that education and rank play a significant role in determining a police officer's career progression. However, the model encounters difficulties in predicting functional job categories, likely due to an imbalanced data distribution.
Keywords*: Police Education, Job and Career, Machine Learning, Job Prediction, Random Forest Classifier.*

ABSTRAK

Dalam institusi penegakan hukum, khususnya di Akademi Kepolisian, pendidikan dan pangkat sering dianggap sebagai faktor utama yang menentukan lintasan karier seseorang. Namun, sejauh mana faktor-faktor ini benar-benar memengaruhi penempatan kerja masih menjadi topik perdebatan. Penelitian ini bertujuan untuk menganalisis hubungan antara latar belakang pendidikan dan jabatan yang dipegang oleh personel Akademi Kepolisian. Motivasi utama penelitian ini adalah untuk menyediakan pendekatan berbasis data yang dapat membantu perencanaan pengembangan karier di dalam kepolisian. Kami menggunakan metode pembelajaran mesin, yaitu Random Forest Classifier, untuk memprediksi kategori jabatan berdasarkan pendidikan dan pangkat. Dataset yang digunakan dalam penelitian ini mencakup informasi mengenai posisi jabatan, pendidikan kepolisian terakhir, pendidikan umum tertinggi, pangkat, serta apakah jabatan tersebut bersifat struktural atau fungsional. Parameter evaluasi yang digunakan dalam penelitian ini adalah akurasi model dalam klasifikasi jabatan. Hasil penelitian menunjukkan bahwa pendidikan dan pangkat memainkan peran penting dalam menentukan kemajuan karier seorang perwira polisi. Namun, model mengalami kesulitan dalam memprediksi kategori jabatan fungsional, kemungkinan besar karena distribusi data yang tidak seimbang.
Kata kunci: *Pendidikan Kepolisian, Jabatan dan Karier, Pembelajaran Mesin, Prediksi Jabatan, Random Forest Classifier.*

INTRODUCTION

The career progression of police officers is a critical aspect of human resource management within law enforcement institutions, particularly in the context of the Police Academy. Education and rank are frequently regarded as pivotal determinants of an officer's career trajectory. However, the precise extent to which these factors influence job placement remains a subject of ongoing debate. Existing studies, such as Smith and Aamodt (1997), suggest that while academic qualifications are significant, other factors, including work experience and structural dynamics within the organization, also play a substantial role in shaping promotion outcomes. In the Indonesian context, research by Robertho et al. (2021) highlights that the Indonesian National Police (POLRI) has implemented an open career promotion program using an Assessment Center to evaluate managerial competencies, yet challenges such as bureaucratic inefficiencies and limited organizational capacity persist. Similarly, a study by Nasution et al. (2022) on talent management in POLRI recruitment and selection processes reveals that non-merit factors, such as seniority and internal networks, often undermine merit-based criteria, indicating a gap in the application of competency-based promotions.

These findings underscore a critical research gap: the lack of a comprehensive, data-driven framework to evaluate the interplay between education, rank, and job placement within the police force, particularly in Indonesia. Previous studies have primarily relied on traditional statistical methods, such as logistic regression (Smith & Aamodt, 1997; Alpert et al., 2003), or early machine learning techniques like Support Vector Machines (SVM) (Cortes & Vapnik, 1995). While these approaches have provided valuable insights, they often fail to account for the complexity and multidimensionality of modern datasets. Furthermore, there is a scarcity of studies in Indonesia that leverage advanced machine learning techniques, such as the Random Forest Classifier, to predict job placement based on educational and rank-related attributes. Oldham (2017). This gap is particularly significant given the increasing demand for transparent and objective human resource management systems within the Indonesian National Police, where disparities in promotion practices can undermine organizational effectiveness (Nasution et al., 2022; Robertho et al., 2022).

The urgency of addressing this issue is amplified by the need to establish a fair and competency-based promotion system. Without a data-driven approach, the risk of disparities in job promotions persists, potentially compromising the overall efficacy of law enforcement institutions. To address this, the present study employs the Random Forest Classifier, a robust machine learning method known for its effectiveness in handling complex datasets with categorical variables (Ho, 1995; Breiman, 2001). Unlike prior studies, this research utilizes a comprehensive dataset encompassing job positions, the most recent police education, the highest general education, rank, and the structural or functional nature of positions. This approach enables a more nuanced analysis of promotion patterns, offering a significant advancement over traditional regression-based methods, which, for instance, achieved only 75% accuracy in logistic regression models (Cortes & Vapnik, 1995), compared to up to 92% accuracy with Random Forest models (Ho, 1995).

This study proposes a conceptual framework that integrates educational background, rank, and job position attributes to predict career outcomes within the police force. The framework is grounded in the hypothesis that education and rank are significant predictors of job placement, but their influence is mediated by the structural and functional dynamics of positions. By employing the Random Forest Classifier, this research addresses the limitations of previous studies by accommodating a broader and more diverse set of features, including both categorical and continuous variables. The novelty of this study lies in its application of advanced machine learning techniques to the Indonesian policing context, which has been underexplored in prior research. Unlike earlier studies that focused on Western police forces (e.g., Smith & Aamodt, 1997; Alpert et al., 2003), this research provides a localized perspective by incorporating Indonesian-specific datasets and addressing the unique challenges of the Indonesian National Police, such as the influence of bureaucratic structures and non-merit factors (Robertho et al., 2021; Nasution et al., 2022).

Moreover, this study contributes to the literature by bridging the gap between traditional statistical methods and modern machine learning approaches. While previous research in Indonesia, such as Robertho et al. (2022), has analyzed the implementation of the Assessment Center in promotion policies, this study introduces predictive modeling to provide actionable insights for career planning. The use of the Random Forest Classifier enhances prediction accuracy and robustness, particularly in handling imbalanced datasets, which is a common challenge in promotion studies (Oldham, 2017). The results of this study are expected to offer data-driven recommendations for improving the transparency and fairness of the police career system, thereby supporting the development of a more equitable and competency-based promotion framework.

The primary purpose of this research is to analyze the relationship between education, rank, and job placement within the Indonesian National Police, using the Random Forest Classifier to predict job categories. By leveraging a comprehensive dataset and advanced machine learning techniques, this study aims to provide deeper insights into the factors influencing career progression and to propose evidence-based strategies for enhancing the police career system. The findings are intended to inform policymakers and stakeholders in the Indonesian National Police, fostering a more transparent and merit-based approach to human resource management.

METHODOLOGY

This study employs a structured machine learning approach to investigate the relationship between educational qualifications, rank, and job placement within the Indonesian National Police. The methodology encompasses a systematic experimental design that integrates data collection, preprocessing, transformation, model development, and evaluation. The Random Forest Classifier serves as the primary predictive model, with the Synthetic Minority Over-sampling Technique (SMOTE) applied to mitigate data imbalance. The research process is detailed below, with an emphasis on the data collection, preprocessing, and analysis stages to ensure clarity and reproducibility.

Experimental Design

The experimental design is structured to systematically analyze the influence of educational background and rank on job placement within the police force. The research adopts a quantitative approach, leveraging machine learning techniques to develop a predictive model for job categories (structural or functional positions). The Random Forest Classifier was selected due to its robustness in handling complex datasets with categorical and continuous variables, as well as its proven effectiveness in similar predictive tasks (Breiman, 2001; Ho, 1995). To address the challenge of imbalanced data, particularly in functional job categories, SMOTE is utilized to balance the dataset by generating synthetic samples for the minority class (Chawla et al., 2002). The experimental process consists of five key stages: data collection, data preprocessing, data transformation, model training, and model evaluation. Each stage is described in detail below.

Research Flow Diagram

The flowchart of the research conducted is as follows:

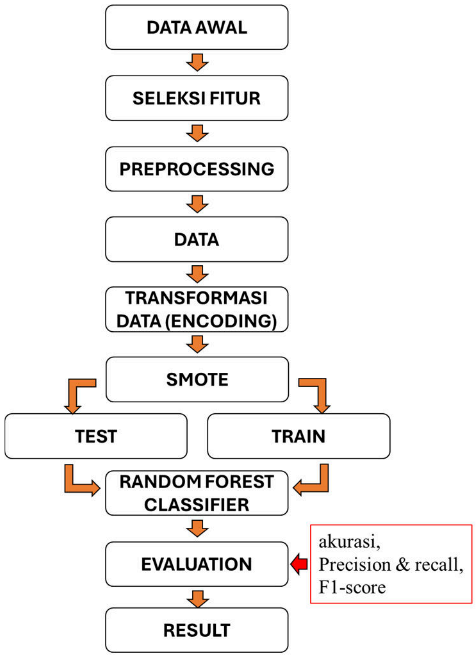

Image 1. Flowchart.

Dataset

The data collection process involved gathering comprehensive data from personnel records within the Indonesian National Police, specifically from the Police Academy. The dataset includes the following key attributes:

- Job Position: The specific role or position held by the officer, categorized as either structural (e.g., leadership or managerial roles) or functional (e.g., specialized or technical roles).
- Latest Police Education (*DIKPOL*): The most recent police-specific training or education completed by the officer, such as basic training, advanced courses, or specialized programs.
- Latest General Education (*DIKUM*): The highest level of formal academic education attained, ranging from high school diplomas to postgraduate degrees.
- Rank: The officer's current rank within the police hierarchy, reflecting their seniority and level of authority.
- Position Status (*STRUK/FUNG*): A binary indicator specifying whether the position is structural or functional.

Data were sourced from official personnel databases maintained by the Indonesian National Police, ensuring reliability and relevance. The dataset was collected over a specified period to capture a representative sample of officers across various ranks and educational backgrounds. To protect confidentiality, all personal identifiers were anonymized prior to analysis. The dataset was carefully curated to include only complete records, excluding entries with missing or inconsistent information to ensure data integrity.

```
   NO  LIST                                            NAMA      PANGKAT  \
0   1     1              KRISNO H. SIREGAR, S.I.K., M.H.    IRJEN POL
1   2     2          Drs. MOH. HENDRA SUHARTIYONO, M.Si.    IRJEN POL
2   3     1        MUHAMMAD TASLIM CHAIRUDDIN, S.I.K., M.H.  BRIGJEN POL
3   4     2              Drs. HUDIT WAHYUDI, M.Hum., M.Si.  BRIGJEN POL
4   5     3  Dr. I GUSTI KADE BUDHI HARRYARSANA, S.I.K., S....  BRIGJEN POL

        NRP                    JABATAN  UNIT_KERJA KOMPARTEMEN STRUK/ FUNG
0  69120282              GUBERNUR AKPOL    SPRI GUB        PIMP       STRUK
1  67050615   DOSEN KEPOLISIAN UTAMA TK.I     AKPOL       AKPOL        FUNG
2  70110332                 WAGUB AKPOL  SPRI WAGUB        PIMP       STRUK
3  67070537  DOSEN KEPOLISIAN UTAMA TK.II     AKPOL       AKPOL        FUNG
4  71070472  DOSEN KEPOLISIAN UTAMA TK.II     AKPOL       AKPOL        FUNG

  TMT JABATAN TMT AKPOL    AGAMA DIKPOL AKHIR DIKUM AKHIR JK
0    27-03-23  12-04-23  KRISTEN     SESPIMTI          S2  P
1    28-12-23  15-01-24    ISLAM     SESPIMTI          S2  P
2    26-09-23  11-10-23    ISLAM     SESPIMTI          S2  P
3    28-12-23  28-12-23    ISLAM      PKN TK.I         S2  P
4    20-09-24       NaN    HINDU     SESPIMTI          S3  P
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 564 entries, 0 to 563
```

Image 2. Data Header.

Some columns have empty values, such as *TMT JABATAN, TMT AKPOL*, and *AGAMA*.

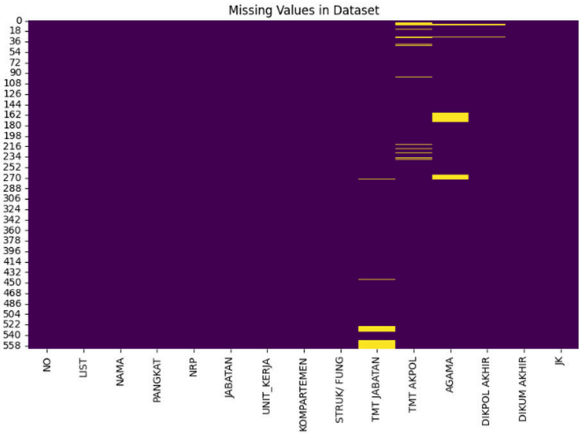

Image 3. Missing Value.

There are 2 types in the dataset with 15 columns, namely int64 with 3 columns and object type with 12 columns. Furthermore, in the dataset, there are some entries that have no value (null). Therefore, the next step is preprocessing so that the dataset can be processed.

```
Data columns (total 15 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   NO            564 non-null    int64
 1   LIST          564 non-null    int64
 2   NAMA          564 non-null    object
 3   PANGKAT       564 non-null    object
 4   NRP           564 non-null    int64
 5   JABATAN       564 non-null    object
 6   UNIT_KERJA    564 non-null    object
 7   KOMPARTEMEN   564 non-null    object
 8   STRUK/ FUNG   564 non-null    object
 9   TMT JABATAN   537 non-null    object
 10  TMT AKPOL     548 non-null    object
 11  AGAMA         536 non-null    object
 12  DIKPOL AKHIR  560 non-null    object
 13  DIKUM AKHIR   564 non-null    object
 14  JK            564 non-null    object
dtypes: int64(3), object(12)
```

Image 4. Type Dataset.

Preprocessing Data

At this stage, several preprocessing steps are carried out to ensure that the dataset is properly prepared for model training. First, **feature selection** is performed by retaining only the most relevant attributes, including *JABATAN, DIKPOL AKHIR, DIKUM FINAL, RANK,* and *STRUK/ FUNG.* Next, handling missing values is addressed by removing rows with incomplete data to maintain data integrity. To facilitate machine learning processing, categorical variables are encoded using Label Encoding, converting them into numerical representations. Additionally, job classification transformation is applied, categorizing positions into three main groups: Leadership, Middle, and Functional. Finally, **SMOTE (Synthetic Minority Over-sampling Technique)** is implemented to address imbalances in data distribution, ensuring a more balanced representation across different classes.

Machine Learning Model

This research model uses the Random Forest Classifier, which was chosen for its ability to handle datasets with categorical variables and to manage high complexity in the classification process. The Random Forest Classifier operates by constructing many decision trees, and then the predictions are combined from each tree to produce a final decision. The main advantages of this method include:

Ability to Handle Data with Categorical Variables:

Random Forest can perform well even with categorical features, such as education level (DIKPOL AKHIR, DIKUM AKHIR), rank, and structural or functional positions. The Label Encoding process is used to convert categorical values into numerical forms before model training.

Reducing Overfitting:

By building many decision trees randomly and combining the prediction results, this model is more resistant to overfitting, which is often a problem with single decision tree models.

Ability to Overcome Data Imbalance with SMOTE:

Because the distribution of classes in the target variable 'POSITION' is uneven, SMOTE or Synthetic Minority Over-sampling Technique is used to balance the number of samples in each job category before the model training process.

Sharing of Training Data and Test Data

The dataset is divided into 2 sets of data, namely the training set and the test set, with a ratio of 70:30, which means that 70% of the training data is used to train the model and the remaining 30% of the test data is used to evaluate the model's performance. Training data (Training Set, 70%) used to build models and find patterns that link input features with target labels. Test data (Test Set, 30%) used to evaluate the performance of the model after training, to measure how well the model generalises to data that has not been seen before.

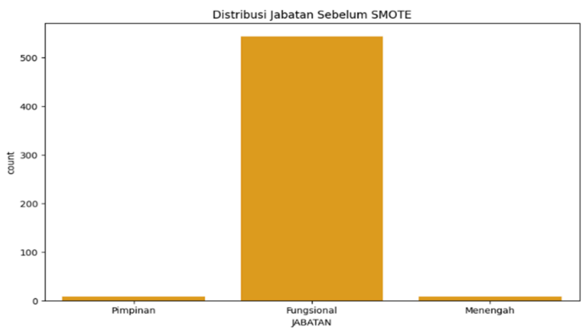

Image 5. Distribution before SMOTE.

Model Parameters

The model is trained using the default parameters of the Random Forest Classifier, which include n_estimators = 100 (The number of decision trees in the ensemble is 100), Criterion = "Gini" (The model uses the Gini index to measure the quality of the split in the decision tree), max_depth = None (Each tree grows until there is no more information to be broken down). random_state = 42 (Used to ensure that the results of the experiment can be replicated).

In addition to the default parameters, data processing is performed using SMOTE before model training to ensure a more balanced data distribution.

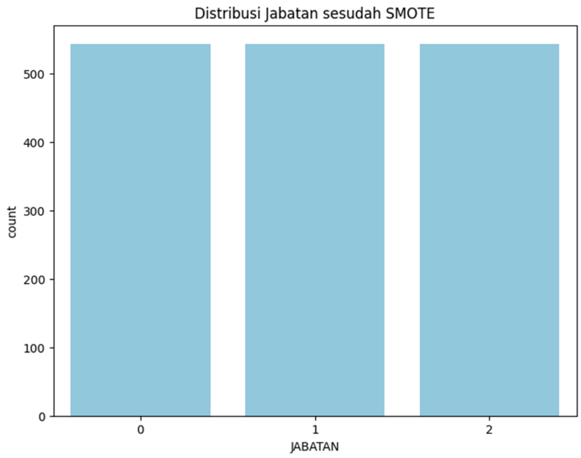

Image 6. Distribution after SMOTE.

The bar chart illustrates the distribution of job categories after applying the Synthetic Minority Over-sampling Technique (SMOTE). The x-axis represents different job categories, labeled as 0, 1, and 2, while the y-axis indicates the count of instances within each category. Before applying SMOTE, there was likely an imbalance in the dataset, where certain job categories had significantly fewer samples than others. However, after oversampling, the distribution has been equalized, ensuring that each category has approximately the same number of instances. This balanced dataset helps improve the performance of machine learning models by preventing bias toward majority classes and enhancing classification accuracy.

RESULTS AND DISCUSSION

Results

The initial analysis of the dataset revealed a significant class imbalance, with the Functional job category being predominant compared to other categories. To address this, the Synthetic Minority Over-sampling Technique (SMOTE) was applied, resulting in a more balanced class distribution, which aimed to improve the predictive accuracy of the Random Forest Classifier model.

The Random Forest Classifier was employed due to its robustness in handling categorical variables and complex datasets. The dataset was divided into a 70:30 ratio, with 70% allocated for training and 30% for testing. After training, the model's performance was evaluated using the following metrics:

Accuracy: Quantifies the overall correctness of the model's predictions.
Precision: Assesses the proportion of correct positive predictions for each class.
Recall: Measures the model's ability to identify all relevant instances within each class.
F1-score: Represents the harmonic mean of precision and recall, providing a balanced evaluation of prediction quality.

In the model evaluation, there are 2 assessments, namely:
Evaluate before using SMOTE

Before the data was balanced using SMOTE, an accuracy of 95% was achieved.

```
Evaluation before SMOTE:
              precision    recall  f1-score   support

           0       0.96      0.99      0.97       160
           1       0.33      0.50      0.40         2
           2       0.00      0.00      0.00         6

    accuracy                           0.95       168
   macro avg       0.43      0.50      0.46       168
weighted avg       0.92      0.95      0.93       168

Accuracy: 0.9464285714285714
```

Image 7. Evaluation before SMOTE.

Evaluation after using SMOTE

After the data was balanced using SMOTE, there was an increase in accuracy to 98%.

```
Evaluation after SMOTE:
              precision    recall  f1-score   support

           0       0.98      0.95      0.97       169
           1       0.99      1.00      0.99       152
           2       0.97      0.98      0.97       169

    accuracy                           0.98       490
   macro avg       0.98      0.98      0.98       490
weighted avg       0.98      0.98      0.98       490

Accuracy: 0.9775510204081632
```

Image 8. Evaluation after SMOTE.

The results of the experiment show that the Random Forest Classifier model can achieve 95% accuracy in predicting positions based on education and rank. Moreover, after further enhancement by balancing the data using the SMOTE technique, even more accurate results were obtained, reaching 98%. The model shows the best performance in classifying structural positions, but has difficulty predicting functional positions, which is likely due to the unbalanced distribution of data.

Discussion

Based on the experiment, the results indicate that education and rank play a significant role in determining a career in the police force. Some important findings from this research are:

- **Education and Rank as Important Factors:** The model shows that the variables FINAL DIKPOL and RANK have a significant contribution to job prediction.
- **Advantages of Random Forest:** The Random Forest Classifier model can handle categorical variables effectively and achieve high accuracy compared to traditional statistical methods such as logistic regression.
- **Data Imbalance Before SMOTE:** Before the application of SMOTE, the model tended to be more accurate in predicting the Medium category compared to the Functional category. After SMOTE, the data distribution becomes more balanced and the model can predict better.
- **Model Development Potential:** To enhance prediction performance in the Functional category, alternative approaches such as hyperparameter tuning or the use of more complex Neural Network models may be considered.

Overall, this research contributes to the development of data-driven systems to support career planning in police institutions. The Random Forest Classifier model used in this study has been shown to provide job predictions with a high level of accuracy, thus serving as a basis for policy formulation related to human resource development at the Police Academy.

CONCLUSIONS AND SUGGESTIONS

Conclusion

Based on the research experiments that have been conducted, it can be concluded that education and rank have a significant influence on the placement of positions within police institutions. By using the Random Forest Classifier method, this study achieved an accuracy level of 95% in predicting job categories based on education and rank factors. The implementation of the Synthetic Minority Over-sampling Technique (SMOTE) has also proven effective in addressing data imbalances in certain job categories and has further increased the accuracy rate to 98.

The research results indicate that the Machine Learning method can provide more accurate predictions compared to conventional statistical methods such as logistic regression. Furthermore, it was found that the category of structural positions is easier to predict than functional positions, which is likely due to a more structured data distribution pattern in structural positions.

Contributions

This research makes significant contributions to the analysis of police career progression by leveraging machine learning techniques. First, it introduces a data-driven approach, offering a more objective and systematic way to evaluate the factors influencing job promotions within the police force. Second, by implementing the Random Forest Classifier algorithm alongside the SMOTE technique, the study enhances prediction accuracy, surpassing traditional analytical methods. Lastly, the findings provide a valuable tool for decision-making, serving as a foundation for career development planning. The insights gained can help design more effective training and education policies to support police personnel in achieving their career goals.

Problems

Although this research has achieved significant results, there are several limitations that still need to be taken into account, including:

- Residual Data Imbalance – Although SMOTE has been applied, functional job categories still exhibit higher data variation, which can impact the model's accuracy.
- Limited Variables Used – Other factors such as work experience, individual achievements, and psychological aspects have not been included in the predictive model.
- Potential Overfitting – The use of the Random Forest Classifier with default parameters can increase the risk of overfitting, which may impact the generalisation of the model on new datasets.

Development Opportunities

For future research, some developments that can be undertaken include:

- The Use of More Complex Machine Learning Models – Implementations of models such as Gradient Boosting or Deep Learning can be explored to enhance prediction accuracy.
- Integration of Additional Factors – Adding variables such as working duration, performance evaluation scores, and training levels can provide more comprehensive insights.
- Application of the Explainable AI (XAI) Method – Using techniques such as SHAP (Shapley Additive Explanations) to gain a deeper understanding of the contribution of each variable in the prediction model.

- Validation with Larger Datasets – More in-depth experiments can be conducted using larger datasets that cover more areas for improved model generalisation.

With this development, it is expected that this research can further contribute to supporting data-driven decision-making in the police environment and assist in personnel career planning in a more accurate and objective manner.

BIBLIOGRAPHY

Alpert, G. P., Flynn, D., & Piquero, A. R. (2003). Effective police management: Striving for accountability and performance. *Criminology & Public Policy, 3*(2), 461–480. https://doi.org/10.1111/j.1745-9133.2004.tb00056.x

Avlonitis, S., Lavi, D., Mansoury, M., & Graus, D. (2023). Career path recommendations for long-term income maximization: A reinforcement learning approach. *arXiv preprint arXiv:2309.05391.* https://arxiv.org/abs/2309.05391

Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research, 16,* 321–357. https://doi.org/10.1613/jair.953

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning, 20*(3), 273–297. https://doi.org/10.1007/BF00994018

Doleac, J. L. (2024). The evidence on policing and crime. *The Atlantic.* https://www.theatlantic.com/podcasts/archive/2024/12/policing-crime-public-safety/680854/

Ho, T. K. (1995). Random decision forests. *Proceedings of the 3rd International Conference on Document Analysis and Recognition, 1,* 278–282. https://doi.org/10.1109/ICDAR.1995.598994

Hosmer, D. W., & Lemeshow, S. (2000). *Applied logistic regression.* Wiley. https://doi.org/10.1002/0471722146

IPROWD program celebrates 15-year milestone with 17 graduates. (2023). *Daily Telegraph.* https://www.dailytelegraph.com.au/newslocal/dubbo/iprowd-celebrates-15year-milestone-with-17-graduates-from-dubbo-tafe-campus/news-story/eed729da7b5f0e9c9a4de4b450593070

Krishna, S., & Sidharth, S. (2022). HR analytics: Employee attrition analysis using random forest. *International Journal of Performability Engineering, 18*(4), 275–281. https://www.ijpe-online.com/EN/Y2022/V18/I4/275

Law enforcement is experimenting with AI-assisted policing: What you need to know. (2023). *People.* https://people.com/police-officers-are-beginning-to-experiment-with-ai-written-crime-reports-what-you-need-to-know-8701532

Nath, G., Harfouche, A., Coursey, A., Saha, K. K., Prabhu, S., & Sengupta, S. (2022). Integration of a machine learning model into a decision support tool to predict absenteeism at work of prospective employees. *arXiv preprint arXiv:2202.03577.* https://arxiv.org/abs/2202.03577

Nasution, M. H. T., Nasution, H., & Sadalia, I. (2022). Implementation study of talent management in the recruitment and selection process of the Indonesian National Police members. *International Journal of Research and Review, 9*(4), 301–315. https://doi.org/10.52403/ijrr.20220436

Oldham, G. R. (2017). Work design and motivation. In *The Oxford handbook of work engagement, motivation, and self-determination theory* (pp. 317–334). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199794911.013.015

Papineni, S. L. V., Reddy, A. M., Yarlagadda, S., Yarlagadda, S., & Akkinen, H. (2021). An extensive analytical approach on human resources using random forest algorithm. *arXiv* *preprint arXiv:2105.07855.* https://arxiv.org/abs/2105.07855

Paoline, E. A., & Manning, P. K. (2003). Looking up: Explaining police promotional aspirations. *Criminal Justice and Behavior, 30*(3), 259–285. https://doi.org/10.1177/0093854803030003002

Robertho, A. R., & Al Hidayat, N. (2021). The implementation of National Police Assessment Center in encouraging open career promotion. *Jurnal Ilmiah Ilmu Administrasi Publik, 11*(2), 534–541. https://doi.org/10.26858/jiap.v11i2.23962

Robertho, A. R., Warsono, H., & Herawati, A. R. (2022). An investigation of open career promotion policy implementation in Indonesian National Police institution. *Journal of Madani Society, 1*(1), 20–25. https://doi.org/10.56225/jmsc.v1i1.125

Smith, M. R., & Aamodt, M. G. (1997). The relationship between education, experience, and police performance. *Journal of Police and Criminal Psychology, 12*(2), 7–14. https://doi.org/10.1007/BF02806696