

## Machine learning prediction of petty corruption intention among law enforcement officers

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### ABSTRACT

Law enforcement agencies face a widespread problem of corruption, which jeopardizes their credibility and institutional integrity. Thus, the primary goal of this study is to develop a machine learning prediction model for petty corruption intentions as an early warning system for law enforcement officials who fail to perform their duties and obligations with integrity. Using a questionnaire survey of two hundred twenty-five participants, from senior officers to rank and file police officers, this study presents the fundamental knowledge on the design and implementation of machine learning model based on six selected algorithms; generalized linear model, fast last margin, decision tree, random forest, gradient boosted trees, and support vector machine. In addition to demographic factors, the efficacy of each machine learning algorithm on petty corruption was evaluated using general strain theory (GST) attributes: financial stress, work stress, leadership pressure, and peer pressure. The findings indicated that peer pressure has given the highest weight of contributions to most of the machine learning algorithms. The most outperformed machine learning in terms of the classification accuracy is gradient boosted trees with accuracy above 90%. This paper presents useful knowledge to enhance the realization of implementing intelligent corruption detection tools.

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## 1. INTRODUCTION

Corruption is a major issue in many law enforcement agencies around the world [1], [2]. This institutional disease halts the application of the rule of law and denies equitable access, putting the country's security, justice, and economic progress at risk. Corruption, generally defined as abuse of authority by civil servants for private gain and interests [3]. According to previous research [4], [5], there are two categories of corruption: grand corruption and petty corruption. Grand corruption is frequently connected with high-ranking public officials who may be harmful to a long-term functioning economy. For example, high-level influence over the awarding of government contracts for the construction of new schools may result in unqualified companies controlled by high-level public official cronies receiving these contracts. Petty corruption, often

known as bureaucratic corruption, involves low-level public officials who cause public benefit to be distorted. Examples of petty corruption include bribery, embezzlement, and favoritism.

Similar to other law enforcement authorities, corruption is one of the key difficulties that police institutions face [6], [7] and it undermines the legitimacy of the agency. As an enforcer of the rule of law of the country, corruption is often entwined with the police as criminal networks make extensive use of the institution to carry out criminal activity, avoid investigation and escape prosecution [8]. According to Kleinig [9], police officers commit corruption when they exercise or neglect to exercise their authority with the primary goal of advancing personal or departmental gain. Making false reports and perjury, shielding illicit gaming, theft of drugs on the street, theft of confiscated property, receiving discounts on purchases, and selling information about police operations are the most typical forms of corruption among police officials [10]. Furthermore, according to the Transparency International Global Corruption Barometer [8], police officers are the most frequently reported recipients of bribes. Transparency International's Advocacy and Legal Advice Centre received over 1,500 reports of police and military abuse during the COVID-19 outbreak [11]. Levi [11] adds that the bribes required by police and soldiers from civilians who pass through checkpoints, stay out past curfew, and want to leave the quarantine center were the source of the corruption reports.

Efforts against corruption both petty and grand, have been implemented by most governments around the world. In Malaysia, the government has launched the National Anti-Corruption Plan (NACP) 2019-2023, with the goal of making the country free of corruption by 2023. The NACP was developed with practical goals based on the initiatives done by government and private agencies to address issues around corruption, integrity, and governance for the coming five years.

Despite the government's effort to fight corruption in the country, Malaysia was ranked 61<sup>st</sup> out of 180 countries in the 2021 corruption perception index (CPI), with a score of 52 out of 100. The CPI index measures the public's opinion of official corruption in a given country. The lower the CPI score, the greater the public view of the chance of Malaysian public officials being involved in corruption. Furthermore, according to the Enforcement Agency Integrity Commission's (EAIC) annual report 2021 [12], the Royal Malaysia Police (RMP) receives the most public complaints of misconduct including corruption among Malaysia's law enforcement authorities. Since the EAIC commenced in 2004, more than 75% of the institution's total misconduct complaints every year involved RMP officers.

Given that, there is an urgent need to identify more effective measures to combat police corruption. There have been very few studies on police corruption in Malaysia so far. Hence, this study aims to add to the existing body of knowledge by investigating the use of machine learning classification algorithms for predicting RMP petty corruption intentions using four general strain theory's (GST) attributes: financial stress, work stress, leadership, and peer pressure. This study focuses on petty corruption as [8] argue that it is more dangerous than grand corruption because it might be institutionalized and lead to more serious misconduct.

There are two major contributions to this work. Firstly, it attempts to build on previous work [13], [14] by presenting evidence on a machine learning-based police petty corruption intention prediction model in a developing and non-western country research setting: Malaysia. This study chooses Malaysia as the research setting because [10] stress that police corruption is more widespread and obvious in developing countries than in developed countries. Therefore, it is critical to explore the options of using automated prediction of corruption based on intelligent software tools. Secondly, this paper presents a new design and execution of machine learning prediction on police petty corruption based on GST constructs.

The rest of the paper is laid out as follows. The second section discusses previous research on corruption prediction that used machine learning techniques. The data set for this investigation, as well as the machine learning technique are detailed in section 3. The experimental findings for each algorithm are shown and discussed in section 4. The summary and conclusions are presented in the concluding section.

## 2. LITERATURE REVIEW

According to a review of the literature on corruption, most previous research relied on correlations and regression-based statistical techniques [15], [16]. Nevertheless, recently, the use of artificial intelligence and machine learning approaches in identifying and comprehending governmental fraud and corruption has gained traction in the literature [13], [14], due to its ability to discover trends and patterns in a wide range of data [13]. This paved the way for real-time surveillance and identification of fraud and corruption. For example, [17] used three types of data mining approaches to predict corruption perceptions in 132 countries: random forest, support vector machine, and artificial neural networks. The data set used by the study is gathered from the World Bank, Transparency International, and the Heritage Foundation for the years of 2017 and 2018. The results show that random forest, an ensemble-type machine learning method, was the most accurate classification model, followed by support vector machines and artificial neural networks, with overall accuracy of 85.77%, 76.15%, and 73.84% respectively.

Further, study by Rabuzin and Modrušan [18] aims to predict indications of corruption in the public procurement process using machine learning methods and text-mining techniques such as Naive Bayes, logistic regression, and support vector machines. As a data set of prediction model, the study used content of the tender documentation from the croatian procurement portal and grouped them into food, beverages, tobacco and related products, medical equipment, pharmaceuticals and personal care products, construction work, repair and maintenance services, architecture, construction, engineering and inspection services, health and social work services, sewage, refuse, cleaning and environmental services and IT services. The results indicate that support vector machines and logistic regression were better in producing predictions linked to health and social work services, whereas the naive bayes algorithm performed better in almost all other groupings.

Meanwhile, using police archives [19], deploy machine learning algorithms to predict corruption crimes in Italian municipalities from 2012-2014. Over 70% of municipalities that will have corruption incidents have been correctly identified by the study. In line with [14], [17]–[19] aims to develop a robust predictive machine learning model on local-government corruption in Brazil. This study used budget accounts data of Brazilian municipalities from 2003 to 2010. Employing a gradient boosted classifier that consisted of an ensemble of decision trees, the model was able to detect the existence and predict the intensity of corruption with accuracy of 76% and an AUC of 0.834.

This study aims to extend prior works [14]–[17] by utilizing GST attributes to construct machine learning prediction models on police petty corruption intentions in Malaysia. Robert Agnew's GST, a criminology theory, has often been used to better understand the phenomena of white-collar crime, including corruption [20]. The theory holds that stress and pressure are significant predictors of workplace wrongdoing. It's because strain or stress often lead to unfavorable feelings like anger, frustration, depression, and despair which, in turn, create pressures for corrective action, with crime or delinquency being one possible response [21]. In police jobs, stress/pressure appears to be a substantial component, thus GST could provide a robust explanation for police behavior and intention to commit petty corruption. Following prior research [20], [21], this study uses four GST stress/pressure attributes namely financial stress, work stress, peer pressure and leadership pressure.

### 3. METHOD

#### 3.1. Sample of data

The data for this study was gathered from 225 RMP officials using a questionnaire survey. The collected data can be used on evaluating different prediction models that use different machine learning algorithms. There were two sections of the questionnaires developed for collecting the data. The first section consisted of gender, age, race, marital status, education level, work experience, department, and position level as proxies for demographic factors. Meanwhile, section 2 featured four GST attributes that contributed to petty corruption. To measure each attribute of the theory and petty corruption intention, several indicators have been developed and employed based on previous studies [22]–[29]. The questionnaire used a five-point Likert scale, allowing respondents to choose whether they strongly disagree, disagree, neutral, agree, or strongly agree with each of these indicators. The average values of each construct's indicator were used to calculate the estimate. Table 1 shows the indicators of GST's attributes and the petty corruption, as well as the source of measurements.

Table 1. Attributes of GST

Attributes	Description	References
Work stress	10 indicators to measure the degree of work stress among police officials.	[22], [23]
Financial stress	8 indicators to measure the degree of financial stress among police officials.	[24]
Leadership pressure	10 indicators to measure the degree of leadership pressure among police officials.	[25], [26]
Peer pressure	10 indicators to measure the degree of peer pressure among police officials.	[27], [28]
Petty corruption	5 indicators to measure the police officials' intention on petty corruption.	[29]

The total means of petty corruption indicators was used to specify the petty corruption intention among the RMP officials. If the total means is equal and above 2.5, they were considered to have the intention (class 1). Otherwise, the intention is categorized as class 0 or no intention of petty corruption. Therefore, if the prediction models gain prediction probability at 0.5 and above, the model will classify the officer as class 1, meaning the possibility to have petty corruption. Table 2 lists the distribution of the dating violence (DV) from the dataset, which shows that major data consists of class 0 or no intention of petty corruption. Figure 1 depicts the examples of prediction from one of the prediction models executed in RapidMiner software.

Table 2. Optimal hyper-parameters

Class	Label in RapidMiner	Count	Percentage
0 (no petty corruption intention)	Range1	181	80.44%
1 (petty corruption intention)	Range2	44	19.56%

Row No.	DV	prediction(DV)	confidence(range2)	confidence(range1)
1	range1	range1	0.181	0.819
2	range2	range1	0.316	0.684
3	range1	range1	0.064	0.936
4	range1	range1	0.084	0.916
5	range1	range1	0.066	0.934
6	range2	range2	0.525	0.475
7	range1	range1	0.059	0.941
8	range1	range1	0.462	0.538

Figure 1. The prediction sample's

Take for example the data at row 1, the real case is categorized as range 1 or class 0 (no petty corruption intention) and the model can truly predict the case because the probability of prediction for range1 is 0.82 confidence. Otherwise in row 2, the real case is range 2 (class 1), but the confidence for range 2 is 0.64 that caused the prediction model to set the prediction value as range 1 (class 0). In this case, the model wrongly predicts the class.

**3.2. Attributes of the prediction models**

Figure 2 presents the attributes from demography and GST that were selected as the independent variables (IVs) in predicting the petty corruption intention DV. Based on the Pearson correlation test, most attributes have low to very weak correlation to the DV. Nevertheless, all of the IVs were considered to have some degree of information to give knowledge to the machine learning algorithms in making the predictions. The diversity of the IVs in the different prediction models with different machine learning algorithms will be discussed in the results part.

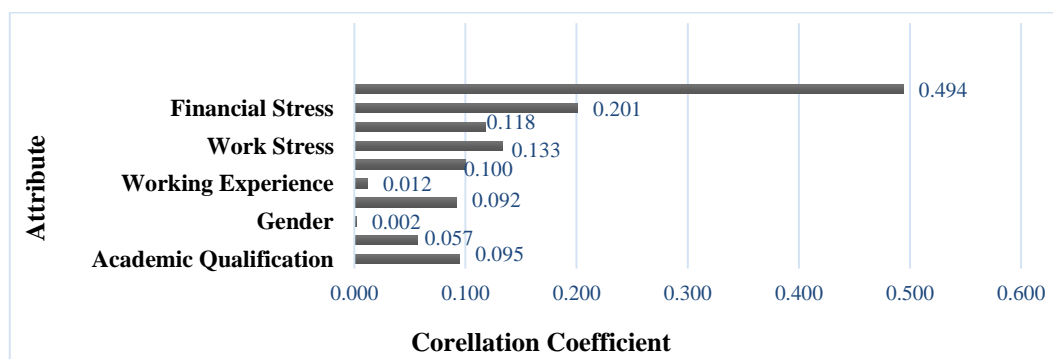


Figure 2. Correlation of each IV to DV outside the prediction model

**3.3. The machine learning algorithms**

Six machine learning algorithms namely generalized linear model, fast large margin, decision tree, random forest, gradient boosted trees, and support vector machine were used to be executed in a 16 GB computer RAM with RapidMiner software. Based on automodel RapidMiner, the six algorithms were

suggested, and the optimal hyper-parameters setting are given in Table 3. Not available (NA) denotes that the algorithm is not using the given parameters.

Table 3. Optimal hyper-parameters

Algorithm	C	Number of trees	Maximal depth	Learning rate	Gamma	Error rate (%)
Fast large margin	1	NA	NA	NA	NA	20
Decision tree	NA	NA	2	NA	NA	17.8
Random forest	NA	20	7	NA	NA	17.8
Gradient boosted trees	NA	90	7	0.1	NA	14.8
Support vector machine	1000	NA	NA	NA	0.005	18.5

Fast large margin has C as the only hyper-parameter, with the worst error rate it achieved was 22.2% if the value of C was 0.01. The optimal when it was 1 at error rate 20%. The decision tree has maximal depth as the only hyper-parameter to be observed. The most optimal maximal depth for decision tree was 2 to get 17.8% error rate value. Similarly, the lowest error rate from random forest was 17.8% at the maximal depth 7. Additionally, random forest has one more hyper-parameter besides maximal depth, namely number of trees. The optimal value for random forest number of trees was 20. Besides number of trees and maximal depth, gradient boosted trees has a learning rate, which the optimal values were 20, 7, and 0.1 respectively to achieve an error rate at 14.8%. Support vector machine has C and gamma with the optimal set for C was 1,000 and for gamma was 0.005 to get the best error rate at 18.5%. The setting for the machine learning algorithms can be referred to the Table 2 and no parameters involved for generalized linear model.

### 3.4. Validation

Another setting for the machine learning algorithms is the training and testing split technique. This research divided the 225 dataset into 161 data for training dataset and the remaining 64 data as hold-out samples for testing. As the prediction models are to classify two classes of petty corruption intention, a confusion matrix was used to measure the algorithms' accuracy, recall and precision. Figure 3 presents the confusion matrix for the petty corruption classification in the prediction models, which can be described as the following:

- True Positive (TP) is the number of class 1 (petty corruption intention) can be correctly classified.
- True Negative (TN) is the number of class 0 (no petty corruption intention) can be correctly classified.
- False Positive (FP) is the number of class 1 (petty corruption intention) incorrectly classified as 0.
- False Negative (FN) is the number of classes 0 (no petty corruption intention) incorrectly classified 1.

	Real class 1	Real class 0	Class precision
Predicted as petty corruption intention	True Positive (TP)	False Positive (FP)	$TP/(FP+TP)$
Predicted as no petty corruption intention	False Negative (FN)	True Negative (TN)	$TN/(TN+FN)$
Class Recall	$TP/(TP + FN)$	$TN/(TN + FP)$	

Figure 3. Confusion matrix of the petty corruption classification in the prediction model

TP is the total correct predictions of class 1 (petty corruption intention) while TN is the false total predictions for the class. On the other hand, FP is the total correct correction predictions of class 0 (no petty corruption intention) while FN is the false predictions for the case. Based on the confusion matrix, the accuracy can be measured with the example (1). Accuracy is the total correct prediction from the total cases of testing data. Accuracy not presenting the powerful of the prediction model to correctly classify each class, hence precision and recall can be used. Precision for predicting the intention of petty corruption is complemented with the recall for class 1.

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

**4. RESULTS AND DISCUSSION**

The results were divided into two. Firstly, the results of performances of the machine learning in the petty corruption intention prediction models were presented and discussed based on the generated confusion matrix. Secondly, the variation of correlation weights from each attribute of the prediction models are presented. Table 4 lists the performances of each machine learning algorithm in the prediction models. Real is the value taken from the collected data while predicted is the value generated from the prediction models.

**Table 4. Confusion matrix results**

	Real class 1	Real class 0	Class precision	Accuracy
Generalized linear model				
Predicted as petty corruption intention.	7	2	77.78%	87.7%
Predicted as no petty corruption intention.	6	50	89.29%	
Class recall	53.85%	96.15%		
Fast large margin				
Predicted as petty corruption intention.	6	1	85.71%	89.0%
Predicted as no petty corruption intention.	6	51	89.47%	
Class recall	50.0%	98.08%		
Decision tree				
Predicted as petty corruption intention.	0	0	00.0%	79.7%
Predicted as no petty corruption intention.	13	51	79.69%	
Class recall	00.0%	100.0%		
Random forest				
Predicted as petty corruption intention.	5	2	71.43%	85.9%
Predicted as no petty corruption intention.	7	50	87.72%	
Class recall	41.67%	96.15%		
Gradient boosted trees				
Predicted as petty corruption intention.	5	0	100.0%	90.5%
Predicted as no petty corruption intention.	6	53	89.83%	
Class recall	45.45%	100.0%		
Support vector machine				
Predicted as petty corruption intention.	9	3	75.0%	89.2%
Predicted as no petty corruption intention.	4	49	92.45%	
Class recall	69.23%	94.23%		

Generally, the highest accuracy has been presented by the gradient boosted trees algorithm in the prediction model. Gradient boosted trees performed the best in predicting the cases of intention for petty corruption (100%) although the given training and testing data have very less numbers of this case see in Table 2. All machine learning algorithms except decision tree have better ability in classifying class 1. In others work, the models with these algorithms are powerful to detect petty corruption intentions at precision values above 70% compared to the recall values (less than 70%). Due to more exposure on class 0 from the dataset, all the six machine learning algorithms present outstanding ability in detecting the cases of no intention for petty corruption at recall for class 0 above 90%. Furthermore, it will be more interesting to get insight on how the variances of each attribute’s correlation to the DV that influenced the machine learning performances. Table 5 presents the comparison of the correlation weights.

**Table 5. The weights of correlations of each GST and demography attribute**

Attributes	Generalized linear model	Fast large margin	Decision tree	Random forest	Gradient boosted trees	Support vector machine
FTT						
Work stress	0.017	0.010	0.019	0.034	0.127	0.092
Financial stress	0.030	0.031	0.008	0.049	0.028	0.079
Leadership pressure	0.006	0.005	0.148	0.021	0.054	0.021
Peer pressure	0.183	0.177	0.008	0.148	0.135	0.167
Demography						
Gender	0.092	0.085	0.105	0.048	0.060	0.026
Race	0.002	0.058	0.004	0.017	0.013	0.071
Marital status	0.059	0.163	0.011	0.047	0.039	0.065
Working experiences	0.013	0.006	0.011	0.034	0.032	0.036
Academic qualification	0.066	0.183	0.008	0.041	0.025	0.054
Officer rank	0.083	0.185	0.014	0.034	0.066	0.105

Table 5 shows that GST has given more impact on the performances of the machine learning algorithms in the prediction models compared to demography. Majority of machine learning algorithms have gained the highest weight from peer pressure. This is consistent with the results of correlation outside machine learning prediction models depicted in Figure 1. Besides, the findings also in line with prior research, which found a significant relationship between peer exposure and employee's misconducts [30], as peers can be served as a model that influences the behaviors and attitudes of others in the group [31]. In the decision tree, leadership pressure has become the most important. Nevertheless, in fast large margin, academic qualification is the biggest influencer attribute.

## 5. CONCLUSION

This paper presents significant findings of research concerned with work ethics and integrity of professional employees. Focused on petty corruption intentions among the officers of law enforcement, this paper presents the design and empirical findings of machine learning predictive algorithms. Pressure given by the peers found to be the most influential factor of petty corruption among the officers from the tested dataset hence became the main contributor in all the machine learning algorithms. The analysis presented in this paper will convey valuable information for future research that can be explored on advanced machine learning predictive algorithms to detect corruption of law enforcement officials.

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