Journal of Theoretical and Applied Information Technology
30th April 2026. Vol.104. No.8

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

MACHINE LEARNING CLASSIFICATION OF JUVENILE AND YOUTHFUL OFFENDERS USING SOCIO-GEOGRAPHIC CRIME INDICATORS FROM MALAYSIAN ADMINISTRATIVE DATA

NURAZEAN MAAROP[1], GANTHAN NARAYANA SAMY[1], ROSLINA MOHAMMAD[1], NORZIHA MEGA MOHD ZAINUDDIN[1], WAN ROSANISAH WAN MOHD[1]

[1]Lecturer, Faculty of Artificial Intelligence, Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia

E-mail: [1]nurazean.kl@utm.my, [1]ganthan.kl@utm.my, [1]mroslina.kl@utm.my, [1]norziha.kl@utm.my, [1]wanrosanisah@utm.my

ABSTRACT

Examining the determinants of juvenile and youthful offending is essential for understanding youth crime patterns and supporting evidence-based prevention strategies. This study applies machine learning techniques to classify individuals into juvenile offenders (children in conflict with the law) and youthful offenders using administrative crime records obtained from Malaysia's Department of Social Welfare (Jabatan Kebajikan Masyarakat). The dataset comprises 3,879 cases, including 2,743 children under the age of 18 and 1,136 youthful offenders aged between 18 and 21 years. The analysis incorporates demographic attributes and socio-geographic crime indicators, including gender, ethnic group, type of crime, state, state crime rate, state crime density, population percentage, and crime ratio. Four supervised machine learning algorithms, namely Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine, are employed to evaluate predictive performance. Model evaluation is conducted using accuracy, precision, recall, and F1-score, with stratified five-fold cross-validation applied to assess model robustness. The results indicate that tree-based models outperform linear models in this classification task. Decision Tree and Random Forest achieve the highest performance, with an accuracy of approximately 97.6%, while Random Forest attains a mean cross-validation accuracy of 97.86%. Feature importance and SHAP analyses reveal that crime ratio, type of crime, state, and ethnic group are the most influential predictors. Overall, the findings demonstrate that integrating demographic characteristics with socio-geographic indicators enhances the predictive classification of youth offenders. The proposed framework provides a data-driven approach for analyzing administrative crime data and offers valuable insights into regional and demographic patterns associated with youth offending.

Keywords: *Machine Learning, Crime Analytics, Juvenile Offenders, Random Forest, Socio-Geographic Indicators, Data Mining.*

1. INTRODUCTION

Juvenile delinquency and youth violence continue to pose significant social challenges for communities and criminal justice systems worldwide. Evidence from prior research suggests that punitive or ineffective responses to youth crime may inadvertently reinforce deviant behavior, thereby increasing the likelihood of long-term criminal involvement among young people [1]. Studies across diverse national contexts indicate that juvenile offenders often emerge from complex social environments characterized by family instability, socio-economic disadvantages, and limited educational opportunities. For instance, research conducted in Turkey highlights the importance of structured rehabilitation and educational programs in supporting reintegration and reducing recidivism among young offenders [2]. Beyond individual and social influences, environmental factors also play a critical role in shaping juvenile crime patterns.

Recent urban studies demonstrate that spatial characteristics, including street design, neighborhood structure, and population density, can influence opportunities for delinquent behavior and affect social interactions linked to youth crime [3]. Collectively, these findings emphasize the need to examine juvenile delinquency through both individual-level characteristics and broader socio-environmental contexts.

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In Malaysia, concerns surrounding juvenile delinquency have intensified in recent years, with various forms of youth-related misconduct showing an upward trend. Empirical studies within the Malaysian context identify peer influence, family background, and socio-economic conditions as key contributors to delinquent behaviors among adolescents [4], [5]. Official reports further indicate a growing number of cases involving youths in conflict with the law. For example, more than 360 juvenile offences were recorded in Integrity Schools and Henry Gurney Schools during the first half of 2025, encompassing incidents related to drugs, criminal misconduct, and sexual offences [6]. Additionally, over 5,000 cases involving children in conflict with the law were documented between 2023 and mid-2025 under the Child Act 2001, with individuals aged 16 to 18 years comprising the largest proportion of offenders [7]. Behavioral issues within educational settings also reflect this trend. Data from the Malaysian Ministry of Education show that bullying incidents increased from 6,528 cases in 2023 to 7,681 cases in 2024, representing an approximate 17% increase, with the majority occurring in secondary schools [8]. These statistics highlight the growing psychological, social, and behavioral challenges faced by Malaysian youths and underscore the urgency of proactive approaches to early identification and intervention.

Despite increasing scholarly attention, many studies on juvenile delinquency in Malaysia rely on traditional statistical or qualitative methods to examine social and behavioral factors. While these approaches provide valuable insights, they often lack the capacity to analyze complex relationships among multiple demographic, environmental, and crime-related variables simultaneously. Moreover, existing research tends to focus on identifying risk factors or describing crime trends rather than developing predictive models that could assist policymakers and social welfare agencies in anticipating offender patterns. With the growing availability of administrative records and demographic statistics, advanced analytical techniques such as machine learning present new opportunities to uncover hidden patterns in youth crime data.

Despite the growing body of research on juvenile delinquency in Malaysia, a clear gap remains in the ability of existing studies to support predictive and data-driven decision-making. Most prior studies focus primarily on identifying risk factors or describing trends using traditional statistical or qualitative approaches, which may not adequately capture complex, non-linear relationships among multiple socio-demographic and environmental variables. Furthermore, limited attention has been given to integrating administrative crime data with advanced analytical techniques to distinguish between different offender categories, such as juvenile and youthful offenders. This gap restricts the development of proactive intervention strategies and limits the ability of policymakers and social welfare agencies to effectively anticipate offender patterns.

The findings of this study are expected to benefit multiple stakeholders. For researchers, this study extends existing literature by integrating machine learning approaches with socio-demographic and socio-geographic crime data. For practitioners, particularly social welfare agencies and rehabilitation institutions, the results provide insights that support early identification and targeted intervention strategies for juvenile and youthful offenders. For policymakers, the predictive models developed in this study offer a data-driven basis for designing more effective youth crime prevention and rehabilitation policies within the Malaysian context.

Unlike previous studies that primarily focus on descriptive or inferential analyses of juvenile delinquency, this study introduces a predictive modelling approach that leverages machine learning techniques to classify offender types. In addition, this study integrates socio-geographic indicators with administrative offender data, thereby providing a more comprehensive analytical framework. This approach enables the identification of complex patterns and interactions that are often overlooked in conventional analyses, offering a more robust understanding of youth offending behavior.

This study applies machine learning techniques to analyze offender data obtained from the Malaysian Department of Social Welfare (Jabatan Kebajikan Masyarakat, JKM). The dataset comprises 3,879 recorded cases, including 2,743 children in conflict with the law (juvenile) and 1,136 youthful offenders, with demographic attributes and crime-related indicators drawn from official administrative records. In Malaysia, the legal framework distinguishes between juvenile and youthful offenders based on age. Under the Child Act 2001 [9], individuals below the age of eighteen who commit offences are classified as children in conflict with the law, with an emphasis on rehabilitation rather than punishment. Meanwhile, individuals aged between eighteen and twenty-one may be designated as youthful offenders under the Criminal Procedure Code and may receive rehabilitative consideration depending on the nature of the offence.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

By integrating these variables with engineered socio-geographic indicators, predictive classification models are developed to distinguish between juvenile and youthful offenders. Four widely used machine learning algorithms, namely Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine, are implemented and compared to evaluate predictive performance. Additionally, feature importance analysis and statistical association tests are conducted to examine the influence of demographic and geographic variables on offender classification. Accordingly, the objectives of this study are: (1) analyze the influence of selected socio-demographic and socio-geographic variables on offender classification; (2) develop machine learning classification models using administrative crime data; and (3) evaluate model performance and identify the most significant predictors distinguishing offender groups.

2. BACKGROUND

This section reviews prior studies on juvenile delinquency and the use of machine learning in crime analysis. It first considers research on demographic, social, and environmental factors influencing youth offending, with particular attention to geographic variations. It then examines applications of machine learning in crime prediction and offender classification. Together, these strands highlight the role of demographic and spatial indicators in prior work and identify gaps that motivate the present study.

2.1 Determinants of Juvenile Delinquency

Juvenile delinquency, often referred to as juvenile crime, has traditionally been defined as a range of unlawful behaviours committed by young individuals. This includes both criminal offences and status offences acts considered illegal solely due to the offender's age, such as truancy or violations of curfew regulations [10]. Juvenile delinquency is widely acknowledged as a multifaceted social phenomenon shaped by the interplay of individual, social, and environmental factors. Prior research has identified a range of predictors associated with youth offending, including socio-economic disadvantage, family instability, educational disengagement, and peer influence [11–12]. Criminological perspectives such as social learning theory and social control theory provide further explanatory frameworks, suggesting that delinquent behaviour may be acquired through peer interactions or facilitated by weakened bonds to social institutions such as family and school [13]. These insights underscore that juvenile crime is not the product of isolated causes but rather emerges from a constellation of influences operating across both individual and societal levels.

Beyond family and individual determinants, demographic and environmental characteristics have also been shown to shape patterns of youth crime. Empirical studies demonstrate that factors such as age distribution, gender composition, socio-economic inequality, and urban conditions contribute to regional variations in delinquency [12]. Community-level attributes, including neighbourhood structure and socio-economic disparities, may create environments that either facilitate or constrain opportunities for offending. Consequently, analysing the demographic and geographic distribution of crime is essential for identifying spatial patterns of youth delinquency across different contexts.

Although previous studies have provided valuable insights, much of the existing literature relies on survey-based or qualitative approaches that primarily capture psychological and social dimensions of delinquency. While these perspectives contribute to understanding behavioural factors, such information is not consistently available in official administrative records. In practice, government agencies and law enforcement institutions typically maintain datasets comprising demographic attributes, geographic identifiers, and crime-related indicators. Although such datasets may not fully reflect the underlying social dynamics of delinquency, they remain essential for examining population-level patterns of youth offending.

In Malaysia, the management of juvenile offenders is governed by the Child Act 2001 [9], which emphasises rehabilitation and protection for children in conflict with the law [14]. Institutions such as Henry Gurney Schools and community-based supervision programmes play a central role in facilitating rehabilitation and reintegration. Concurrently, administrative records maintained by agencies such as the Department of Social Welfare, Malaysia, serve as critical data sources for analysing youth crime trends.

The examination of demographic and geographic crime indicators derived from these administrative datasets enables researchers to identify spatial variations and socio-demographic patterns associated with juvenile delinquency across regions. Such indicators provide an empirical foundation for understanding regional disparities in youth offending and for informing targeted prevention and intervention strategies. Moreover, the structured nature of administrative datasets

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

creates opportunities for the application of data-driven analytical approaches, including machine learning techniques, to explore and interpret complex crime patterns.

2.2 Machine Learning in Crime Analysis

The increasing availability of administrative crime records and demographic datasets has stimulated the adoption of machine learning techniques in crime analysis and delinquency assessment. Unlike conventional statistical approaches, machine learning algorithms are capable in modelling complex and non-linear relationships across multiple predictor variables, thereby uncovering hidden structures in crime data and enhancing predictive accuracy. Recent studies have shown that, by integrating demographic, environmental, and spatial indicators into predictive frameworks, machine learning models can effectively analyse crime trends and offender characteristics [15–16].

Several machine learning algorithms have been widely applied in crime prediction and offender classification studies. Logistic Regression is commonly used as a baseline classification model due to its statistical interpretability and its ability to estimate the probability of crime-related outcomes and class membership [17–18]. Decision Tree models provide transparent rule-based structures that allow researchers to interpret how different variables contribute to classification decisions, particularly when dealing with categorical attributes. Ensemble learning techniques such as Random Forest have been shown to improve predictive performance by combining multiple decision trees, reducing variance, and minimising the risk of overfitting. Random Forest models are particularly useful when analysing high-dimensional datasets that contain demographic and geographic variables associated with crime patterns [19–20]. Support Vector Machines (SVM) have also achieved strong results in classification tasks involving complex datasets. By constructing optimal decision boundaries within multidimensional feature spaces, SVM models can effectively differentiate between categories of crime-related observations. Collectively, these approaches enable researchers to analyse crime data from multiple perspectives, capturing non-linear interactions among socio-demographic and environmental indicators that influence criminal behaviour [21].

Table 1 provides a summary of representative studies that apply machine learning and empirical approaches in crime analysis, focusing on juvenile delinquency and crime prediction through diverse analytical techniques. The table summarises representative studies that employ machine learning techniques in the analysis of juvenile delinquency and crime prediction. The literature indicates that algorithms such as Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine are frequently utilised to examine crime-related datasets. Logistic Regression and Decision Tree models are commonly adopted as baseline classifiers due to their interpretability and suitability for categorical data. Ensemble approaches, particularly Random Forest, have demonstrated robust predictive performance in crime-related research by effectively modelling non-linear relationships among variables while reducing variance and mitigating overfitting.

Table 1: Machine Learning Applications in Juvenile Delinquency

Study	Focus	Data & ML Techniques
[22]	Crime prediction using machine learning models	Public crime datasets; RF, SVM, deep learning
[17]	Juvenile delinquency prediction linked to education	Educational datasets; LR, DT
[23]	Decision support system for delinquency probability	Behavioral datasets; SVM
[16]	Ensemble learning for delinquency risk assessment	Adolescent behavioral data; RF ensemble
[15]	Predict juvenile traditional and cyber offences	Behavioral datasets; DT
[20]	Classification of adolescent delinquency typologies	Youth datasets; RF, SVM
[3]	Influence of urban environment on juvenile crime	Spatial datasets; RF
[19]	Automated assessment of adolescent delinquency levels	Behavioral datasets; ensemble ML

Note: LR = Logistic Regression; DT = Decision Tree; RF = Random Forest; SVM = Support Vector Machine.

These models are particularly effective when applied to high-dimensional datasets that incorporate demographic and geographic attributes associated with crime patterns. Support Vector Machines have likewise demonstrated strong classification performance in complex datasets by constructing optimal decision boundaries within multidimensional feature spaces. Taken together, these findings reinforce the utility of machine learning approaches in analyzing crime data and provide a clear rationale for the selection of these algorithms in the present study.

This study is guided by the following research questions (RQ): RQ1: How do socio-demographic and socio-geographic factors influence the classification of juvenile and youthful offenders? RQ2: Which machine learning model demonstrates the best predictive performance in classifying juvenile and youthful offenders? RQ3: Which variables are the most significant predictors in distinguishing between juvenile and youthful offenders?

Based on the research framework, the following hypotheses (H) are proposed: H1: Socio-demographic and socio-geographic variables significantly influence the classification of juvenile and youthful offenders; H2: The integration of multiple predictor variables improves the classification performance of machine learning models; H3: Predictor variables differ in their relative importance in distinguishing between juvenile and youthful offenders.

The subsequent section outlines the dataset, feature engineering procedures, and machine learning models employed in this research.

3. METHODOLOGY

This study adopts a quantitative, supervised machine learning research design to classify juvenile and youthful offenders based on socio-demographic and socio-geographic variables derived from administrative records. This design enables the identification of patterns and predictive relationships between explanatory variables and offender classification outcomes. The proposed approach is consistent with prior studies that employ machine learning techniques for crime prediction and classification, in which structured datasets are analyzed to identify complex patterns and predictive relationships [24].

The methodological framework consists of several stages, including data preprocessing, feature engineering, model development, and performance evaluation. Four supervised learning algorithms namely Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine are implemented to assess the predictive capacity of the selected variables. The overall workflow of the approach is illustrated in Fig. 1.

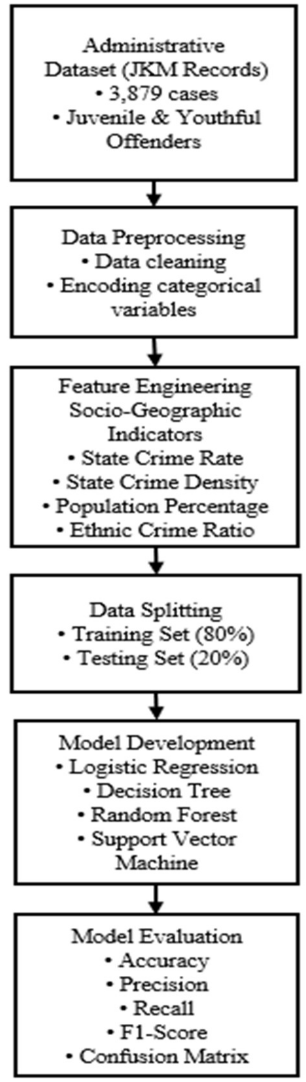

Fig 1: Machine Learning Workflow for Juvenile and Youthful Offender Classification

The dataset used in this study was obtained from administrative records maintained by the Department of Social Welfare (Jabatan Kebajikan Masyarakat), Malaysia. The dataset consists of 3,879 recorded cases from the year 2023 involving individuals categorized as either children in conflict with the law or youthful offenders. The year 2023 was selected because it represents the most recent complete dataset available from the Department of Social Welfare at the time the research was initiated. According to the Child Act 2001 (Act 611), a child in conflict with the law refers to an individual under the age of 18 who has committed an offence, while youthful offenders refer to individuals aged between 18 and 21 years.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The dataset includes several attributes describing the demographic characteristics and geographic context of the offenders, including gender, ethnic group, type of offence, and state location. A summary of the variables employed in this study is presented in Table 2.

Table 2: Description of Variables Used in the Study

Variable	Type	Description
Gender	Categorical	Male / Female
Ethnic Group	Categorical	Ethnic classification of offender
Type of Crime	Categorical	Offence category
State	Categorical	Malaysian state where offence occurred
State Crime Rate	Continuous	Crime rate per state
State Crime Density	Continuous	Crime density per geographic area
Population Percent	Continuous	Ethnic population percentage in the state
Crime Ratio	Continuous	Ratio of crime relative to ethnic population
Offender Group	Target Variable	Juvenile or Youthful offender

Prior to model development, data preprocessing procedures were conducted, including data cleaning and the encoding of categorical variables to ensure compatibility with machine learning algorithms. In addition to these attributes, several socio-geographic indicators were incorporated through a feature engineering process, including state crime rate, state crime density, population percentage, and crime ratio, derived from external statistical sources. These indicators provide contextual information that reflects variations in crime patterns across different regions and population groups.

The target variable in this study is the offender group, which classifies each case as either juvenile (children in conflict with the law) or a youthful offender. This variable serves as the dependent variable in the classification models developed in this study. An 80:20 split was applied to partition the dataset into training and testing subsets. The selected machine learning algorithms were trained on the training dataset, and their performance was evaluated on the testing dataset using standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. Stratified five-fold cross-validation was also conducted to assess model robustness and generalizability.

Model performance is further interpreted using standard classification metrics. Accuracy represents the overall proportion of correctly classified instances, while precision and recall assess the model's ability to correctly identify specific classes. The F1-score provides a balanced measure of precision and recall, particularly in cases of class imbalance.

In this study, the models with higher values across these metrics are considered to demonstrate better predictive performance. Confusion matrix analysis is used to examine classification errors and the distribution of correctly and incorrectly classified instances. Cross-validation results are used to assess model stability and generalizability across different data subsets. All analyses were implemented in Python using widely adopted libraries, including Scikit-learn, Pandas, NumPy, Seaborn, and SHAP. The experiments were conducted in a Google Colaboratory environment.

4. RESULTS

This section presents the experimental results obtained from the machine learning models applied in this study. The performance of the selected algorithms, namely Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine, is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. In addition, feature importance and model interpretation analyses are conducted to identify the key socio-geographic factors influencing the classification of juvenile and youthful offenders.

4.1 Machine Learning Model Performance

The predictive capabilities of four machine learning algorithms namely Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine (were assessed using standard evaluation metrics: accuracy, precision, recall, and F1-score, with comparative outcomes summarized in Table 3.

Table 3: Performance Comparison of ML Models

Model	Acc	Prec	Rec	F1
LR	0.814	0.732	0.512	0.602
DT	0.976	0.925	0.991	0.957
RF	0.976	0.925	0.991	0.957
SVM	0.959	1.000	0.850	0.919

LR: Logistic Regression; DT: Decision Tree; RF: Random Forest; SVM: Support Vector Machine

Among these models, the Decision Tree and Random Forest classifiers demonstrated superior performance, each attaining an accuracy of 0.976, precision of 0.925, recall of 0.991, and F1-score of 0.957. The identical performance observed for Decision Tree and Random Forest may be attributed to the structure and distribution of the dataset, where both models capture similar decision boundaries due to dominant predictor patterns. These findings highlight the effectiveness of tree-based approaches in modeling complex socio-geographic crime indicators, with Random Forest benefiting from its ensemble design that enhances predictive robustness and reduces variance. The SVM classifier also yielded strong results, achieving an accuracy of 0.959 and perfect precision (1.000), underscoring the reliability of its positive classifications. Nonetheless, its recall score of 0.850 indicates that certain youthful offender cases were not fully captured. In contrast, Logistic Regression produced the weakest outcomes, with an accuracy of 0.814 and an F1-score of 0.602, likely to reflect the limitations of its linear assumptions in addressing non-linear socio-geographic crime patterns.

Collectively, these results affirm that non-linear, tree-based models outperform linear methods in this context, suggesting that socio-geographic indicators interact in intricate ways, best captured by ensemble and non-parametric learning techniques.

4.2 Cross-Validation Analysis

A stratified five-fold cross-validation was conducted to assess model robustness and generalizability, with class proportions preserved across folds to minimize imbalance bias. The Random Forest classifier achieved accuracy scores of 0.9755, 0.9768, 0.9858, 0.9742, and 0.9806, yielding a mean accuracy of 0.9786. The narrow variation across folds demonstrates stable predictive performance and confirms that the high accuracy observed in the initial train–test split was not due to random sampling. These findings underscore the effectiveness of tree-based methods, particularly Random Forest, in modeling socio-geographic crime indicators for youth offender classification.

4.3 Feature Importance

A feature importance analysis using the Random Forest model was conducted to evaluate the relative contribution of each predictor variable, as shown in Fig. 2. The results reveal that crime ratio is the most influential factor in the classification process, followed by state location, ethnic group, and state crime rate. These findings emphasize the central role of socio-geographic characteristics in distinguishing juvenile offenders from youthful offenders, with the prominence of crime ratio suggesting that population-adjusted crime statistics substantially shape offender categorization.

State-level indicators, particularly state location and state crime rate, also exhibit strong predictive influence, pointing to the importance of regional crime environments in shaping youth offending patterns across different states. This reinforces the view that geographic and socio-economic contexts contribute meaningfully to variations in youth crime, complementing demographic attributes in the classification framework.

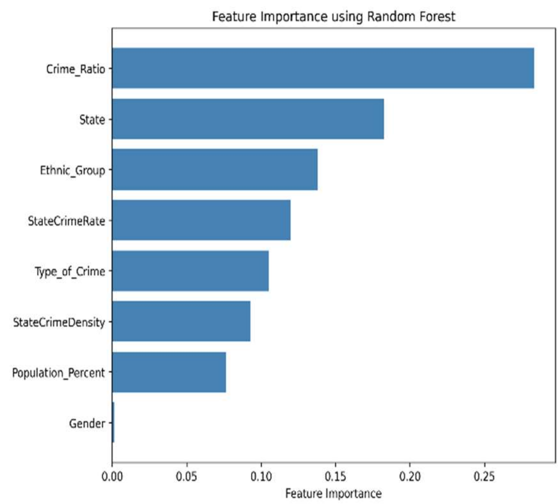

Fig. 2: Feature Importance (Random Forest)

4.4 Correlation Analysis Predictors

A correlation analysis was conducted to examine the relationships among the predictor variables and to assess potential multicollinearity. The correlation heatmap of the socio-geographic indicators is presented in Fig. 3. This analysis provides insight into whether the engineered variables capture distinct information or whether strong interdependencies exist among predictors that may influence model robustness and stability. The results reveal that most predictor variables exhibit weak to moderate correlations, indicating that the dataset is not affected by severe multicollinearity. The strongest positive association is observed between ethnic groups and crime ratio ($r = 0.74$), which is expected given that the crime ratio variable reflects population-adjusted crime statistics aligned with demographic composition. A moderate positive correlation is also identified between state and state crime density ($r = 0.48$), suggesting that certain states record higher concentrations of reported crime incidents.

Other relationships remain moderate or weak. For instance, type of crime shows moderate correlations with state (r = 0.41) and crime ratio (r = 0.40), implying that offence categories vary across geographic contexts and population distributions. Meanwhile, the correlation between the target variable (offender group) and most predictors is relatively low, suggesting that no single attribute independently determines classification outcomes.

Overall, the correlation analysis confirms that the engineered socio-geographic indicators provide complementary rather than redundant information, thereby supporting their suitability as predictors in the machine learning models. The absence of severe multicollinearity further enhances the reliability of subsequent feature importance and SHAP-based interpretability analyses.

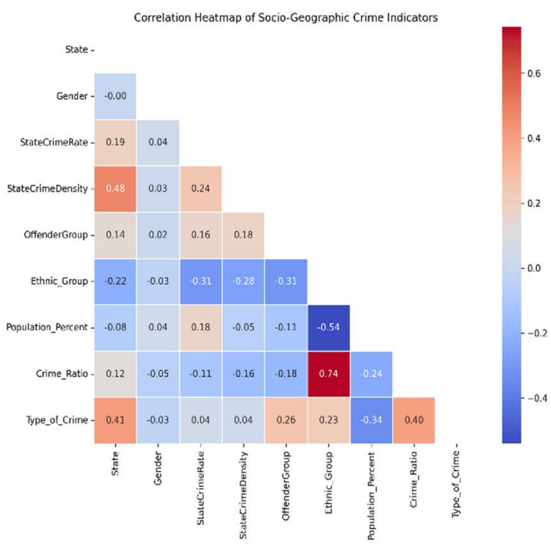

Fig. 3: Correlation Heatmap

4.5 SHAP Analysis

SHAP (SHapley Additive exPlanations), a model-agnostic interpretability method derived from cooperative game theory, was employed to quantify the contribution of individual features to the Random Forest classifier's predictions. By assigning Shapley values to input variables, SHAP provides insight into complex machine learning models by illustrating both the magnitude and direction of feature influence. The summary plot in Fig. 4 presents these effects across all predictors.

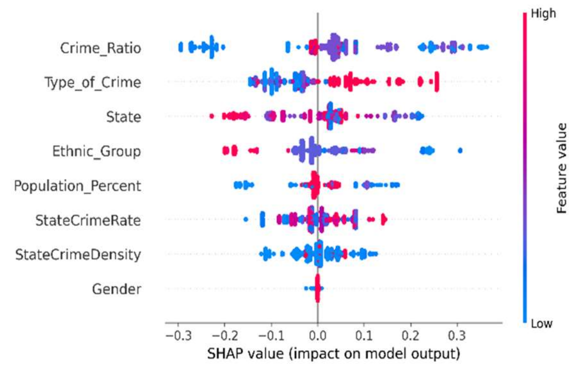

Fig. 4: SHAP Summary Plot

The analysis shows that crime ratio exerts the strongest impact on classification outcomes, followed by type of crime, state location, and ethnic group. These variables display wider distributions of SHAP values, reflecting their substantial influence on model predictions. Geographic indicators such as state crime rate and crime density also contribute meaningfully, suggesting that regional crime environments shape youth offending patterns. In contrast, gender demonstrates minimal SHAP influence, reinforcing earlier findings that demographic differences alone play a limited role compared to socio-geographic crime indicators.

By contrast, gender demonstrated only minimal SHAP influence, suggesting that demographic differences contribute little to the model's predictive behavior when compared with socio-geographic crime indicators. This reinforces the conclusion that contextual and regional factors play a more decisive role than demographic attributes in distinguishing between juvenile and youthful offenders within the dataset

4.6 Socio-Geographic Interpretation of Findings

The combined outcomes of the feature importance, correlation, and SHAP analyses underscore the critical role of socio-geographic indicators in differentiating between juvenile and youthful offenders. Variables generated through feature engineering particularly crime ratio, state location, and state crime rate consistently emerged as influential predictors across the machine learning models. These results suggest that contextual crime environments and population-based indicators provide meaningful signals for distinguishing offender categories within administrative datasets.

The prominence of crime ratio, which reflects population-adjusted crime incidence, demonstrates that crime statistics normalized by demographic composition capture structural differences in youth offending patterns. Likewise, the influence of state location and crime rate highlights regional variations in crime environments, indicating that youth offending may be shaped by broader socio-economic and geographic contexts across states.

Findings from the correlation analysis further reinforce this interpretation, showing that most predictor variables exhibit weak to moderate correlations. This suggests that the engineered socio-geographic indicators contribute complementary rather than redundant information, thereby supporting their suitability for predictive modelling. The absence of severe multicollinearity also enhances the robustness of subsequent feature importance and SHAP-based interpretability analyses.

Overall, the results demonstrate that integrating administrative offender attributes with contextual socio-geographic indicators provides a more comprehensive understanding of youth offending patterns. This approach emphasizes the value of combining individual-level data with environmental and demographic context when applying machine learning techniques to crime analytics.

5. DISCUSSION

This study investigated the effectiveness of machine learning techniques for classifying juvenile and youthful offenders using socio-geographic crime indicators derived from administrative records maintained by the Department of Social Welfare (Jabatan Kebajikan Masyarakat), Malaysia. By integrating demographic attributes with contextual crime statistics through feature engineering, the analysis demonstrates that machine learning models can capture structural variations in youth offending patterns that extend beyond individual-level characteristics. The findings contribute to the growing body of research in crime analytics by illustrating how administrative datasets can be enriched with external socio-geographic indicators to support predictive modeling and interpretable crime analysis.

5.1 Alignment with Prior Empirical Evidence

The prominence of contextual crime indicators observed in this study aligns with prior criminological research emphasizing the role of environmental and spatial factors in shaping youth offending behavior. Studies examining urban crime dynamics have shown that geographic context, crime concentration, and neighborhood characteristics significantly influence the distribution of juvenile delinquency [3], [15]. The present findings reinforce this perspective by demonstrating that population-adjusted crime indicators, particularly crime ratio, serve as strong predictors for differentiating juvenile and youthful offenders.

The importance of state location and regional crime indicators further supports theoretical perspectives that highlight the influence of environmental opportunity structures on criminal behavior. Variations in crime environments across regions may affect exposure to delinquent peer networks, economic pressures, and local crime opportunities. Similar observations have been reported in previous machine learning–based crime prediction studies, where spatial indicators and regional crime statistics were found to contribute substantially to predictive performance [16], [19].

The correlation heatmap analysis provides additional insight into these relationships by indicating that most predictors exhibit moderate or weak correlations, suggesting that the engineered variables capture distinct aspects of the socio-geographic crime environment rather than redundant information. The relatively strong association observed between ethnic group and crime ratio reflects demographic patterns in population distribution rather than direct causal relationships. Such findings are consistent with criminological literature suggesting that demographic indicators frequently act as proxies for broader social and environmental contexts influencing crime patterns [15], [20].

5.2 Methodological Contribution

From a methodological perspective, this study demonstrates the value of integrating feature engineering, machine learning classification, and model interpretability techniques in crime analytics using administrative datasets. The original administrative records primarily contained demographic attributes and offence characteristics. Through feature engineering, the dataset was enriched with contextual socio-geographic indicators including state crime rate, crime density, population percentage, and crime ratio derived from external statistical sources.

These engineered variables allow the predictive models to incorporate macro-level contextual information that is not directly captured in the original administrative records. The correlation analysis confirms that these variables contribute complementary information rather than introducing significant multicollinearity, thereby enhancing the robustness of the predictive models.

Among the evaluated algorithms, Random Forest achieved the highest predictive performance, demonstrating strong classification accuracy and consistent results across cross-validation folds. These findings are consistent with prior research indicating that ensemble learning algorithms are particularly effective for modeling complex socio-demographic datasets characterized by non-linear relationships and heterogeneous predictor variables [16], [19].

An additional methodological contribution lies in the use of interpretability techniques, including feature importance analysis and SHAP (SHapley Additive exPlanations). While machine learning models are often criticized for their lack of transparency, the combined use of global importance ranking and SHAP analysis enables researchers to understand how individual predictors influence classification outcomes. This interpretability framework improves the reliability of machine learning applications in crime analytics and facilitates the translation of predictive results into meaningful criminological insights.

5.3 Implication for Crime Analysis and Practice

The findings of this study highlight the potential of machine learning–based approaches to advance data-driven crime analysis using administrative datasets. By integrating demographic attributes with engineered socio-geographic indicators, the proposed framework enables the identification of structural variations in youth offending patterns across different geographic regions.

From a policy perspective, the results suggest that regional crime environments and population-based indicators provide valuable insights into variations in youth offending dynamics. Machine learning models can assist crime analysis units and social welfare agencies in identifying regions where youth offending patterns are associated with specific socio-geographic conditions. Such insights support the design of targeted intervention strategies and preventive programs tailored to local contexts.

The study further demonstrates that administrative datasets maintained by government agencies can serve as robust resources for crime analytics when enriched through feature engineering techniques. The integration of contextual crime indicators enables these datasets to capture broader environmental influences on crime patterns, allowing machine learning models to uncover structural relationships that may not be readily observable through conventional statistical approaches.

These data-driven methodologies complement traditional criminological analyses by providing additional analytical tools for exploring complex patterns in youth offending behavior. By combining individual-level attributes with socio-geographic context, machine learning approaches offer a more comprehensive framework for understanding youth crime dynamics and for informing evidence-based policy and practice.

6. CONCLUSION

This study demonstrates a machine learning-based framework for classifying juvenile and youthful offenders using socio-geographic crime indicators derived from administrative records maintained by the Department of Social Welfare (Jabatan Kebajikan Masyarakat), Malaysia. By integrating demographic attributes with contextual crime statistics through feature engineering, the study demonstrates how administrative datasets can be enriched to support more comprehensive analyses of youth offending patterns.

The experimental results highlight the effectiveness of ensemble learning methods, particularly Random Forest, in achieving strong predictive performance. Contextual indicators such as crime ratio, state, and regional crime statistics consistently emerged as influential predictors, underscoring the importance of socio-geographic environments in shaping youth offending dynamics. Beyond predictive accuracy, the methodological contribution lies in the integration of feature engineering, correlation analysis, and interpretability techniques, which collectively enhance transparency and analytical depth in crime analytics.

Several limitations should be acknowledged. The dataset represents administrative records from a single reporting year (2023), corresponding to the most recent complete dataset available at the time the research was initiated. While the data provide a comprehensive snapshot of youth offending patterns for that year, they do not capture potential temporal variations or long-term trends. In addition, the available attributes are limited to demographic and geographic indicators and do not include psychosocial or behavioral variables that may further explain individual-level delinquency dynamics. Future research should therefore incorporate multi-year datasets, socio-economic indicators, and multi-source administrative records to enhance the robustness and generalizability of machine learning applications in criminology.

Overall, the findings demonstrate that combining feature-engineered socio-geographic indicators with interpretable machine learning models offers a promising pathway for advancing data-driven crime analysis. This approach not only enhances the empirical understanding of youth offending patterns but also provides actionable insights for policymakers and social welfare agencies seeking to design targeted interventions and preventive strategies.

ACKNOWLEDGMENT

The authors gratefully acknowledge the financial support provided by Universiti Teknologi Malaysia under the Potential Academic Staff Grant (Q.K130000.2757.03K69). The authors also extend their appreciation to the Department of Social Welfare, Malaysia for the cooperation and support in facilitating this research.

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