Hybrid Machine Learning for Crime Prediction in Indonesia toward Society 5.0

Manuscript received September 2, 2025; revised November 18, 2025

Nadya Sikana*
Information Technology, Informatics Faculty
Universitas Mikroskil
Medan, Indonesia
nadya.sikana@mikroskil.ac.id

Rivaldi Lubis
Information Technology, Informatics Faculty
Universitas Mikroskil
Medan, Indonesia
rivaldi.lubis@mikroskil.ac.id

Gilbert Fernando Situmorang
Computer Science, Informatics Faculty
Universitas Mikroskil
Medan, Indonesia
gilbert.situmorang@mikroskil.ac.id

Naomi Prisella
Computer Science, Informatics Faculty
Universitas Mikroskil
Medan, Indonesia
221111798@students.mikroskil.ac.id

***Abstract*—Crime remains a major social challenge in Indonesia, requiring innovative approaches to enhance prevention and law enforcement. This study proposes a hybrid machine learning framework that integrates the Temporal Fusion Transformer (TFT) for time-series forecasting and Extreme Gradient Boosting (XGBoost) for classification and feature analysis. Using socio-economic and demographic data from the Indonesian Central Bureau of Statistics (2010-2023) across 38 provinces, the framework aims to predict crime incidence and classify crime resolution effectiveness. The results show that TFT effectively captures temporal dependencies, achieving robust forecasting accuracy (R^2 = 0.9893), while XGBoost delivers high classification performance (Accuracy = 98.87%). Feature importance analysis highlights the dominant role of case resolution rate, government consumption expenditure, school participation rates and life expectancy in shaping crime patterns. Compared to baseline models such as LSTM and Random Forest, the hybrid TFT + XGBoost approach demonstrates superior balance between accuracy, robustness and interpretability. These findings provide actionable insights for policymakers to design data-driven crime prevention strategies, align with Indonesia's digital transformation agenda, and support the vision of Society 5.0.**

***Keywords*—Artificial Intelligence, Crime Prediction, Digital Transformation, Hybrid Machine Learning, Society 5.0**

I. INTRODUCTION

A. Background

Crime remains a significant social issue that continues to evolve alongside the growing complexity of modern society [1], [2]. In Indonesia, the increasing number of criminal cases underscores the urgency of developing more effective strategies for both prevention and case resolution [3]. Various socio-economic factors further complicate crime control, while limitations in resources and infrastructure often reduce the efficiency of law enforcement. These challenges highlight the need for innovative and data-driven approaches in addressing crime.

The relevance of this study lies in the application of advanced technologies to improve the accuracy and effectiveness of crime analysis. Traditional methods are often inadequate in capturing dynamic crime patterns, whereas artificial intelligence (AI) and machine learning (ML) offer more adaptive and reliable solutions. This direction aligns with Indonesia's national digital transformation agenda, particularly the *Asta Cita* vision, which emphasizes the integration of technology into legal reform to strengthen both law enforcement and crime prevention [4].

The concept of Society 5.0 has further reinforced the role of digital technologies in solving complex social problems, including criminality. By utilizing AI, Big Data, and the Internet of Things (IoT), society gains opportunities to develop innovative systems that enhance public welfare [5]. In this context, hybrid machine learning approaches provide strong potential for analyzing crime patterns with greater precision and enabling more accurate prediction models.

The proposed framework aligns with the vision of Society 5.0, which emphasizes the integration of artificial intelligence and human-centered technology to solve complex social problems. By applying hybrid AI modeling to socio-economic data, this research contributes to data-driven decision-making and public policy formulation that supports social stability and digital transformation in Indonesia.

B. Related Works and State of the Art

Previous research has shown promising results in applying AI to crime prediction. Malik et al. [6] compared several algorithms, including SVM, KNN, Naïve Bayes, Random Forest, and LSTM, demonstrating the effectiveness of both machine learning and deep learning techniques. Tamiselvi et al. [7] proposed the Hybrid Deep Learning-based Crime Prediction (HDLCP) model, combining deep learning and Decision Tree to achieve improved classification accuracy. Karthik et al. [8], through a review of more than 150 studies, emphasized the critical importance of machine learning approaches in crime analysis, demonstrating their potential to uncover hidden patterns and improve predictive accuracy. Similarly, Ibrahim et al. [9] integrated CNN and K-means clustering, which achieved prediction accuracy of up to 90%, surpassing conventional models such as Random Forest and Decision Tree.

In addition, recent works have highlighted the benefits of hybrid and optimization-based approaches. Abubakar et al. [10] enhanced the Random Forest model using Artificial Bee Colony optimization, achieving 95% accuracy and

 EISSN: 2961-872X ● PISSN: 2961-8924 ● DOI: 10.56741/IISTR.esl.001359

outperforming traditional classifiers such as Decision Tree and KNN. Likewise, Mwaniki et al. [11] demonstrated that a hybrid tree-based algorithm reached an accuracy of 94.4%, slightly exceeding that of standalone Decision Trees and conventional Random Forests. These findings reinforce the growing shift toward optimized and hybrid architectures for improved crime prediction performance.

While previous studies demonstrated promising results, they often relied on individual deep learning architectures that lacked interpretability and stability on socio-economic datasets. CNN models capture spatial dependencies effectively but perform poorly on irregular temporal data, whereas LSTM models, despite achieving high accuracy, are prone to overfitting and limited transparency. In contrast, the proposed hybrid framework integrates the Temporal Fusion Transformer (TFT) for long-term temporal modeling with XGBoost for interpretable classification, addressing the limitations of prior approaches and enhancing both predictive robustness and explainability.

To address this gap, this study builds upon both theoretical and applied perspectives. The research framework integrates Grand Theory (understanding the causality and patterns of crime), Middle Theory (highlighting the role of hybrid machine learning approaches), and the identified Research Gap (the limited integration of socio-economic indicators with hybrid models for crime prediction in Indonesia). On the applied side, this study develops a hybrid framework that integrates the Temporal Fusion Transformer (TFT) for time-series analysis and Extreme Gradient Boosting (XGBoost) for classification, with the aim of enhancing both predictive accuracy and interpretability.

Fig. 1 illustrates the positioning of this research within the broader state of the art. It outlines the theoretical foundation, the current research trends, the identified research gap, and the applied novelty of this study.

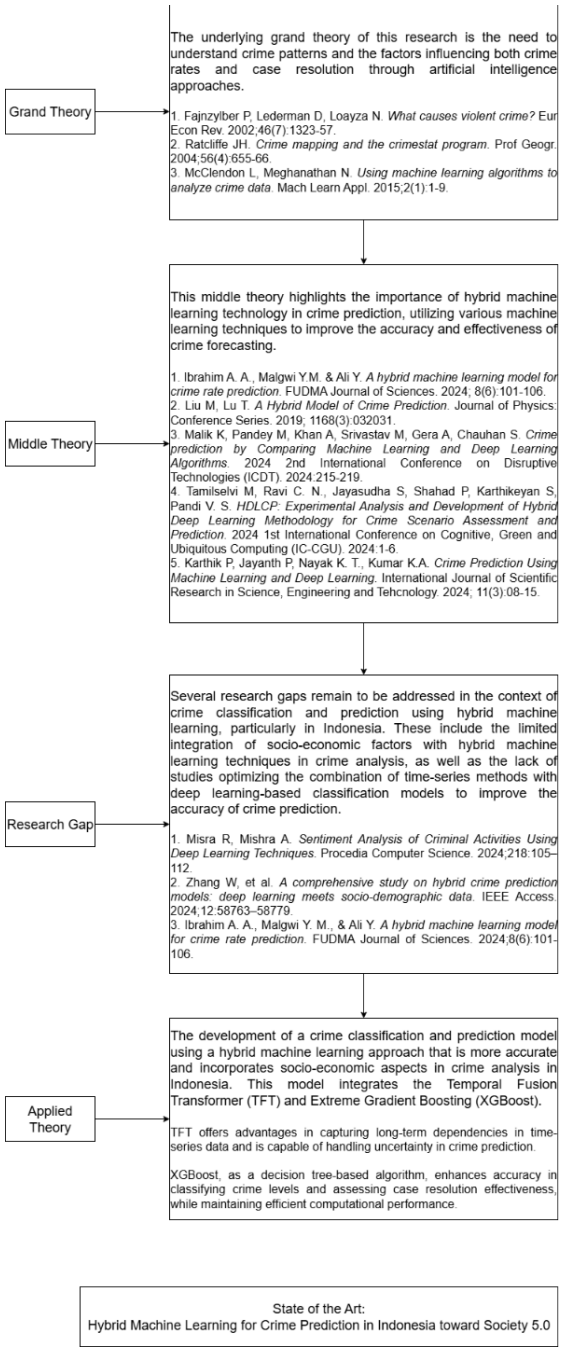


Fig. 1. Research positioning and state of the art in crime prediction studies

 EISSN: 2961-872X ● PISSN: 2961-8924 ● DOI: 10.56741/IISTR.esl.001359

C. Research Gap and Contribution

Although various studies have applied machine learning and deep learning models to crime prediction, several gaps remain unaddressed:

1. Limited integration of socio-economic indicators.
   Most existing works focus only on crime data, without incorporating broader socio-economic and demographic factors that influence criminal activity.
2. Reliance on single models.
   Previous approaches frequently utilize a single algorithm, such as Random Forest, CNN or LSTM, which restricts their capacity to capture both temporal dynamics and classification interpretability.
3. Lack of contextual focus on Indonesia.
   Research in the Indonesian context is still scarce, especially regarding the combination of time-series crime prediction and crime level classification across provinces.
4. Limited interpretability for policymaking.
   Few models provide explainable insights into feature importance, making it difficult for policymakers to translate predictions into actionable strategies.

To address these gaps, the main contribution of this study are outlined as follows:

1. Hybrid framework integrating the Temporal Fusion Transformer (TFT) for long-term temporal dependency modeling and Extreme Gradient Boosting (XGBoost) for efficient classification and feature importance analysis.
2. Comprehensive dataset that incorporates 30 socio-economic and demographic indicators from *Badan Pusat Statistik (BPS)* across 38 Indonesian provinces (2010 – 2023).
3. Dual focus on both crime prediction (time-series forecasting) and classification of crime resolution effectiveness, offering a more holistic perspective.
4. Policy relevance by aligning the research outcomes with Indonesia's digital transformation agenda and the vision of Society 5.0, thereby contributing not only to technical advancements but also to practical governance and law enforcement strategies.

Furthermore, this study introduces contextual novelty specific to Indonesia by integrating 30 socio-economic and demographic indicators from the *Badan Pusat Statistik (BPS)*, across 38 provinces during 2010-2023. This integration enables the hybrid TFT-XGBoost framework to learn region-specific socio-economic relationships that shape crime behavior.

D. Research Framework

This research is conceptually framed around the integration of socio-economic and demographic indicators into a hybrid machine learning approach. The framework emphasizes the combination of time-series forecasting and classification analysis to provide a comprehensive understanding of crime patterns and case resolution effectiveness in Indonesia. Fig. 2 shows the conceptual research framework of this study.

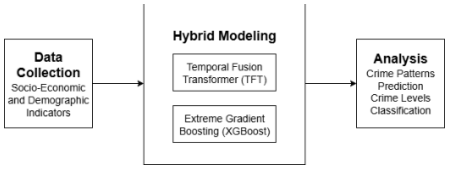


Fig. 2. Conceptual research framework of the Study

E. Research Objectives

The objectives of this research are as follows:

1. To enhance the accuracy of crime prediction in Indonesia through a hybrid machine learning approach that integrates TFT and XGBoost.
2. To classify the effectiveness of crime resolution across Indonesian provinces by leveraging socio-economic and demographic indicators.
3. To provide interpretable insights into key socio-economic factors influencing crime, thereby supporting evidence-based policymaking and Indonesia's digital transformation agenda in line with the vision of Society 5.0.

II. METHODS

This study adopts a hybrid machine learning approach that integrates the Temporal Fusion Transformer (TFT) for time-series forecasting with Extreme Gradient Boosting (XGBoost) for classification and feature analysis. The methodological framework consists of several stages, as illustrated in the research workflow (Fig. 3)

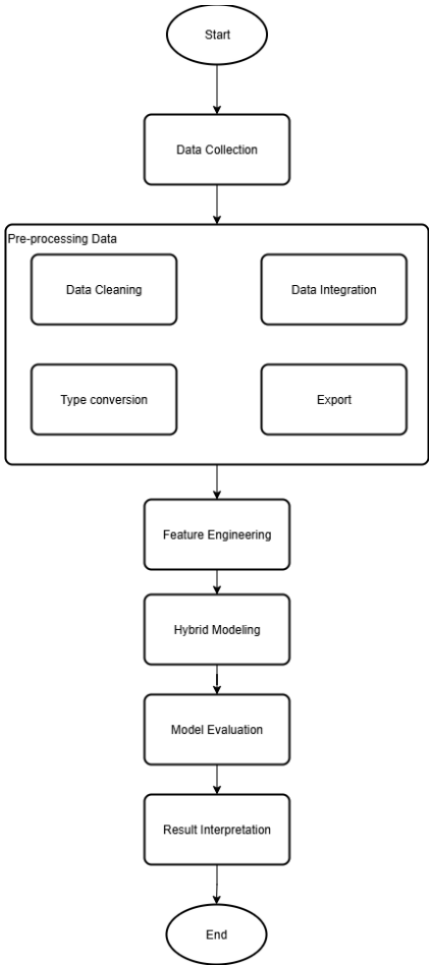


Fig. 3. Research flowchart

A. Data Collection

The dataset was obtained from the Indonesian Central Bureau of Statistics (*Badan Pusat Statistik – BPS*), covering 38 provinces from 2010 to 2023. A total of 30 variables were collected and integrated into the main panel dataset. The variables are as follows:

1. Socio-Economic Indicators
   a. Number of criminal cases

 EISSN: 2961-872X ● PISSN: 2961-8924 ● DOI: 10.56741/IISTR.esl.001359

b. Case resolution rate (%)
c. Crime interval (seconds)
d. Gross Regional Domestic Product (GRDP)
e. Household Consumption Expenditure
f. Government Consumption Expenditure
g. Non-Profit Institutions Serving Households (LNPRT) Consumption Expenditure
h. Consumer Price Index (CPI)
i. Foreign Direct Investment (Projects)
j. Foreign Direct Investment (Value)
k. Gini ratio
l. Poverty percentage
m. Poverty depth index
n. Poverty severity index
o. Gross Fixed Capital Formation
p. Inventory Change
q. Net Export
r. Number of poor population
s. Open unemployment rate
t. Human development index

2. Demographic Indicators
   a. Population density
   b. Male life expectancy
   c. Female life expectancy
   d. School participation rates: ages 7-12, 13-15, 16-18 and 19-24 years
   e. Illiteracy rate: for age groups 15+, 15–44 and 45+ years

B. Data Preprocessing

To ensure the quality and consistency of the dataset, the following preprocessing steps were performed:

1. Data cleaning: Standardized province names (e.g. METRO JAYA → DKI JAKARTA), removed whitespace inconsistencies, dropped empty rows, and replaced missing values with zero. Missing values were replaced with zero only when the absence of data represented an actual zero event (for example, no crime recorded or no investment realized). All replacements were cross-checked with official BPS data to ensure consistency and reliability.
2. Data integration: Merged all 30 datasets into a single main data frame indexed by year and province, resulting in 532 rows (38 provinces x 14 years).
3. Type conversion: Converted all numerical indicators into appropriate formats (float or integer) to maintain consistency.
4. Export: The final data frame was checked for null values and exported in CSV format for further modeling.

C. Feature Engineering

In addition to preprocessing, feature engineering was conducted to improve the quality of predictions. Several transformations and new features were created based on domain knowledge, including:

1. Annual crime trends, captured through time-based features such as year sine and year cosine to model long-term fluctuations.
2. Provincial groupings, based on geographical zones or levels of urbanization.
3. Crime categories, derived by grouping crime incidence ranges into four levels (0-3).

These features were subsequently evaluated using the feature importance analysis in XGBoost and attention weights in TFT to assess their contribution to model performance.

D. Hybrid Modeling

This study adopts a Hybrid Machine Learning Approach by integrating Temporal Fusion Transformer (TFT) for time-series forecasting and Extreme Gradient Boosting (XGBoost) for classification and feature analysis.

1) Temporal Fusion Transformer (TFT)

TFT is a deep learning model designed for time-series forecasting, capable of modeling long-term dependencies and dynamic temporal patterns [12], [13]. It integrates both static and time-varying features within a unified architecture [14] and employs attention mechanisms to prioritize relevant features [15].

Fig. 4 illustrates the architecture of TFT, which includes:

- Variable Selection Network: identifies important input features using SoftMax weighting
- LSTM Encoder: captures temporal dependencies from historical data
- LSTM Decoder: generates forecasts from processed inputs
- Temporal Fusion Decoder with Multi-Head Attention: allows the model to understand long-range dependencies
- Add & Norm Layers and Gating Mechanism: maintain stability and information relevance
- Quantile Forecast Output: produces predictions with uncertainty intervals

To improve predictive performance, hyperparameter tuning of the Temporal Fusion Transformer (TFT) was conducted using Bayesian optimization implemented through the Optuna framework. The search space encompassed parameters governing model complexity and regularization, including hidden layer size (8–64), number of LSTM layers (1–3), dropout rate (0.1–0.5), learning rate (10^{-4}–10^{-1}, log-uniform), attention head size (1–8), and hidden continuous representation size (8–32). An early stopping criterion, based on validation loss with a patience threshold of five epochs, was employed to mitigate overfitting.

2) Extreme Gradient Boosting (XGBoost)

XGBoost is a decision tree-based ensemble algorithm that efficiently handles structured/tabular data [17], [18]. It builds models in a stage-wise manner using boosting, where each new tree corrects the residuals of the previous one [19]. The final prediction is the sum of outputs from all trees.

Fig. 5. depicts the basic working mechanism of XGBoost:

- Data is split into multiple subsets
- Residual errors guide the training of subsequent trees
- Feature importance is derived based on gain, cover, and frequency metrics

For XGBoost, hyperparameter tuning was performed using Bayesian optimization with the Optuna framework to refine tree-based parameters and sampling strategies. The search space covered the number of estimators (50–500), maximum tree depth (3–10), learning rate (0.01–0.3), subsample ratio (0.5–1.0), column subsampling ratio (0.5–1.0), minimum child weight (1–10), and gamma regularization (0–5). Model performance was evaluated through three-fold cross-validation, using mean squared error as the primary metric.

The detailed implementation steps of the hybrid workflow, integrating the Temporal Fusion Transformer (TFT) for prediction and XGBoost for classification, are provided in Supplementary Material A.

 EISSN: 2961-872X ● PISSN: 2961-8924 ● DOI: 10.56741/IISTR.esl.001359

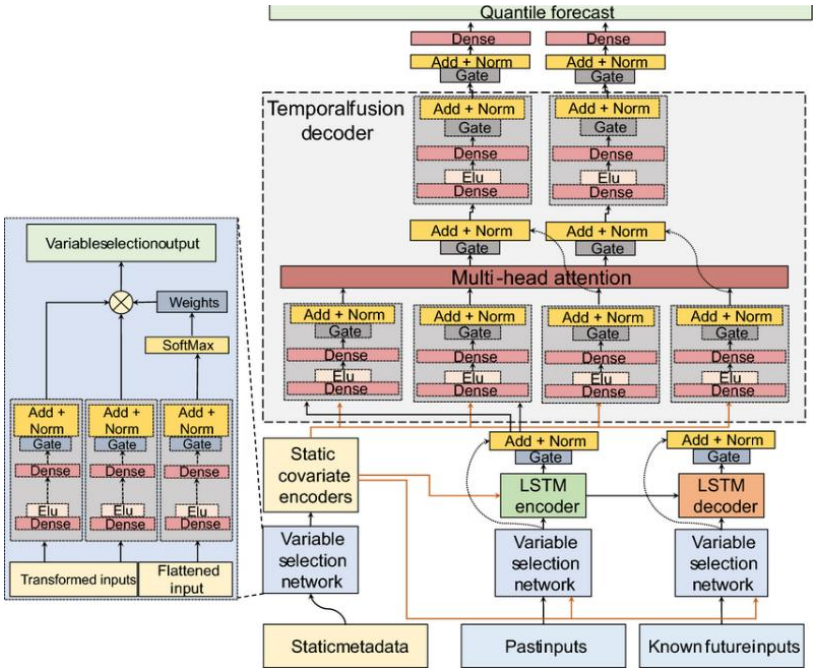


Fig. 4. Architecture of temporal fusion transformer (TFT) [16]

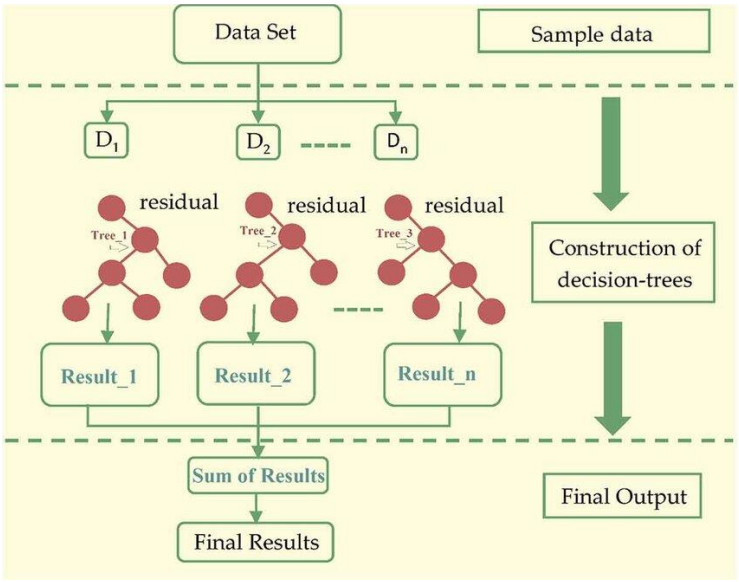


Fig. 5. Architecture of XGBoost [16]

E. Model Evaluation

Model performances was assessed using different metrics:

1. For TFT (forecasting): Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and R-Squared (R^2)
2. For XGBoost (classification): Accuracy, Precision, Recall and F1-Score

These evaluation metrics ensure a comprehensive assessment of both predictive accuracy and classification reliability.

F. Result Interpretation

The final stage involved analyzing the predicted crime patterns and identifying provinces with the highest risk of criminal activity. Results were visualized using graphs and heatmaps to highlight regional variations, trends, and influential socio-economic factors.

III. RESULTS

This section reports the outcomes of the hybrid machine learning framework, combining Temporal Fusion Transformer (TFT) for time-series forecasting and Extreme Gradient Boosting (XGBoost) for feature analysis in time-series forecasting and crime classification. The experiments were conducted using socio-economic and demographic datasets from the Indonesian *Badan Pusat Statistik* (BPS).

A. Crime Forecasting with Temporal Fusion Transformer (TFT)

The TFT models was employed to predict the number of criminal cases based on historical trends and socio-economic indicators. The results demonstrated that TFT successfully captured both short-term and long-term temporal dependencies, producing forecasts closely aligned with actual crime occurrences. Table I shows the forecasting performance of TFT compared to baseline models.

EISSN: 2961-872X ● PISSN: 2961-8924 ● DOI: 10.56741/IISTR.esl.001359

TABLE I. FORECASTING PERFORMANCE OF TFT VS. BASELINE MODELS

Model	Metrics		
	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	R^2
TFT	981.811951	1398.304443	0.984773
TFT + XGBoost	696.943176	1168.641846	0.989364
LSTM	304.676453	519.277100	0.997900
LSTM + XGBoost	240.869080	384.871155	0.998846
Random Forest	1187.8369	1506228.4607	0.9525
Random Forest + XGBoost	1439.2445	2097395.9902	0.9338

To ensure a fair and consistent comparison across models, Bayesian optimization was also applied to the baseline models using the Optuna framework. For the LSTM model, the hyperparameter search space included the learning rate (10^{-4}–10^{-2}), hidden layer size (8–256), number of recurrent layers (1–4), and dropout rate (0.1–0.5). For the Random Forest model, the optimized parameters comprised the number of estimators (100–500), maximum tree depth (3–20), minimum samples split (2–10), minimum samples per leaf (1–5), and maximum feature selection strategy (sqrt or log2). Additionally, an early stopping criterion based on validation loss with a patience threshold of five epochs was implemented to mitigate overfitting and enhance model generalization.

B. *Crime Classification with XGBoost*

XGBoost was also utilized to classify provinces into different crime levels and to evaluate case resolution effectiveness. The model achieved strong performance in classification tasks. The performance is summarized in Table II and confusion matrix in Fig. 7.

TABLE II. CLASSIFICATION PERFORMANCE OF XGBOOST

Metric	Score
Accuracy	98.87%
Precision	98.93%
Recall	98.79%
F1-Score	98.83%

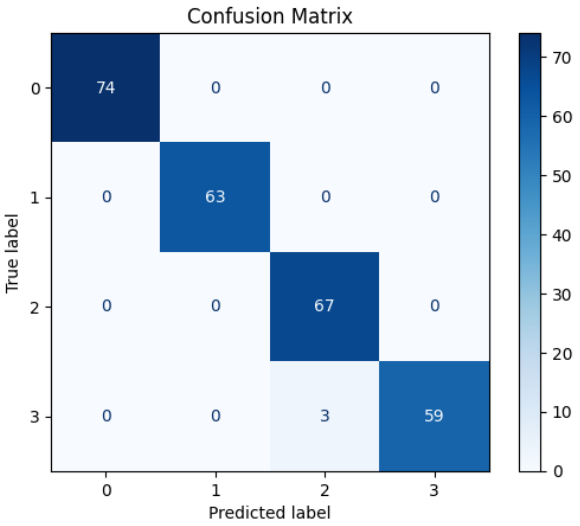


Fig. 6. Actual vs. predicted crime trends using TFT and LSTM

The feature importance analysis using XGBoost revealed that several variables exerted a dominant influence on crime classification. The importance values, derived from the gain metric of XGBoost, originally ranged between 10^7 and 10^9 and were subsequently rescaled to a 0–1 range for interpretability. Features were considered significant if their normalized importance score was equal to or greater than 0.05. This criterion captures variables representing at least 5% of the total model gain, ensuring that only statistically influential features are retained, regardless of temporal attributes such as year or date. The most influential predictors identified through this analysis are presented in Table III.

TABLE III. FEATURE IMPORTANCE RANKINGS FROM XGBOOST FOR CRIME CLASSIFICATION

Feature	Importance Score
Government Consumption Expenditure	1.000
LNPRT Consumption Expenditure	0.756
Gross Fixed Capital Formation	0.434
Illiteracy rate (15+)	0.332
Household Consumption Expenditure	0.317
Poverty percentage	0.310
Crime interval (seconds)	0.230
School participation rates (ages 13-15)	0.191
Poverty Population	0.187
Gross Regional Domestic Product (GRDP)	0.157
Human Development Index	0.139
Inventory Shift	0.121
School participation rates (ages 19-24)	0.118
Region	0.117
School participation rates (ages 16-18)	0.101
Illiteracy rate (45+)	0.099
Net Exports	0.059
Life expectancy (Female)	0.050

C. *Comparative Analysis*

The comparative evaluation of six forecasting models indicates that the hybrid TFT + XGBoost approach delivers the most balanced and reliable performance for crime incidence forecasting. Although the LSTM-based hybrid achieved a slightly higher R^2 value (0.9988), its sharper fluctuations around peak points suggest greater sensitivity to temporal noise and a higher risk of overfitting, as depicted in Fig. 7.

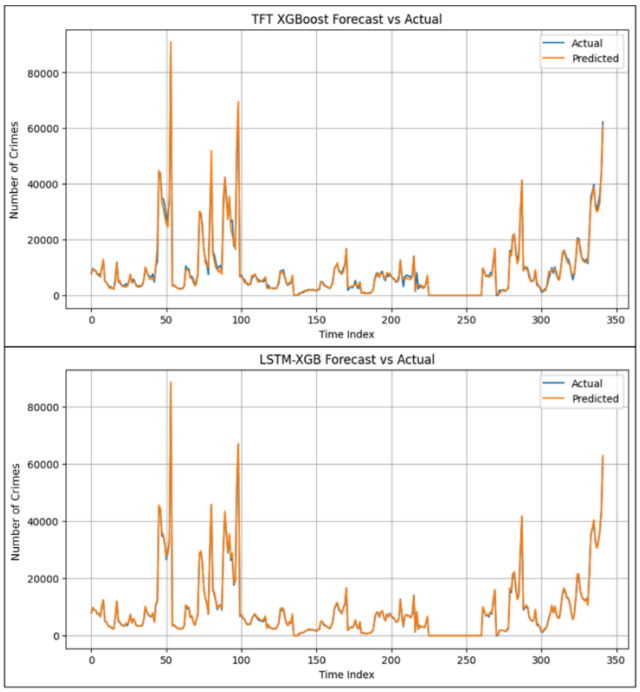


Fig. 7. Actual vs. predicted crime trends using TFT and LSTM

EISSN: 2961-872X ● PISSN: 2961-8924 ● DOI: 10.56741/IISTR.esl.001359

In contrast, the TFT + XGBoost model attained a strong R^2 of 0.9894 with notably smoother forecast alignment and reduced residual error, demonstrating superior generalization and temporal stability. The integration of XGBoost not only improved the predictive accuracy of the TFT model but also enhanced its ability to capture nonlinear dependencies and subtle socio-temporal interactions that conventional correlation-based methods could not detect.

D. *Visualization of Crime Patterns*

To provide more interpretable insights, visualization techniques were employed. Heatmaps were used to depict spatial variations in crime intensity across Indonesian provinces.

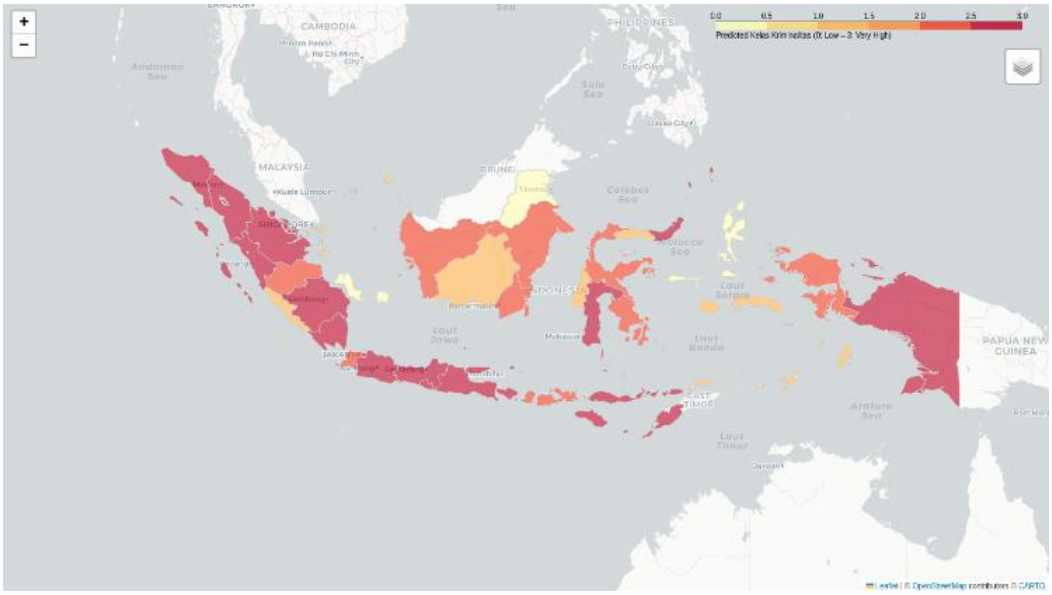


Fig. 8. Heatmap of crime levels across rovinces

The visualizations identified provinces with consistently higher crime rates, offering evidence-based insights for policymakers in targeting preventive measures and optimizing resource allocation.

IV. Discussion

The results of this study demonstrate that the proposed hybrid machine learning framework, integrating the Temporal Fusion Transformer (TFT) and Extreme Gradient Boosting (XGBoost), provides substantial improvements in both crime forecasting and classification tasks compared to baseline models.

A. *Interpretation of Forecasting Results*

The TFT model demonstrated a strong balance between error metrics (MAE and RMSE) and explanatory power (R^2), outperforming Random Forest and showing more stable performance compared to LSTM (see Table I). These results indicate that TFT is effective in capturing the complex temporal dynamics present in crime data. While traditional regression models are limited by their assumption of linear relationships and standard LSTM architectures often face difficulties in modeling long-term dependencies, TFT incorporates attention mechanisms and variable selection networks that prioritize the most relevant features over time. This ability enabled the model to represent fluctuations in crime trends with greater accuracy, as illustrated in Fig. 6.

From a practical perspective, the improved forecasting performance indicates that TFT can server as a reliable tool for anticipating crime dynamics in Indonesia. Accurate short and long-term forecasts are essential for supporting data-driven policy formulation, enabling law enforcement agencies to allocate resources proactively and design targeted interventions.

B. *Interpretation of Classification Results*

The classification results indicate that the XGBoost model achieved excellent performance, with accuracy, macro-precision, macro-recall, and macro-F1 all around 0.98, reflecting strong predictive capability across all classes. The confusion matrix confirms that misclassifications were minimal and evenly distributed, suggesting that the model generalizes well beyond the majority class. This balanced performance underscores the effectiveness of the quartile-based (qcut) transformation in creating statistically meaningful and evenly distributed target classes. Furthermore, the decision to adopt a 50:50 train–test split, despite the moderate sample size (532 observations), ensured a more rigorous and representative assessment of the model's generalization capability. As shown in Table IV and Fig. 9, this configuration produced stable and consistent results across all evaluation metrics, confirming the robustness of the XGBoost classifier in handling the classification task. Collectively, these findings substantiate the validity of the methodological choices in data partitioning and target encoding.

TABLE IV. Performance comparison across different train–test split ratios

Metric	Test Size			
	80:20	**70:30**	**60:40**	**50:50**
Accuracy	100%	99.38%	97.65%	98.87%
Precision	100%	99.34%	97.62%	98.93%
Recall	100%	99.32%	97.50%	98.79%
F1-Score	100%	99.32%	97.50%	98.83%
K-Fold Cross Validation Accuracy (5 Folds)	99.06%	99.06%	99.06%	99.06%

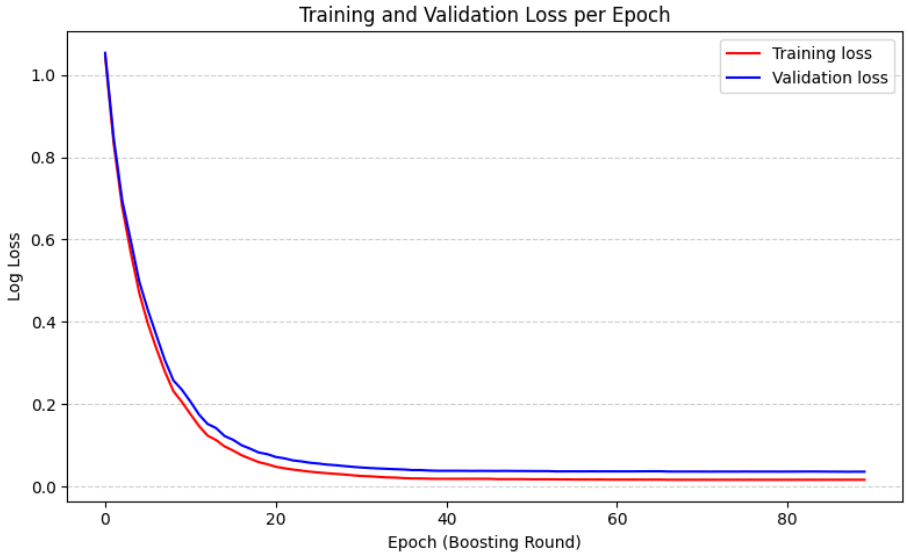


Fig. 9. Training and Validation Loss Convergence Curves of the XGBoost Model

Feature importance analysis (Table III) revealed that crime levels across Indonesian provinces are primarily driven by a combination of institutional, economic, social and demographic factors. The most influential variable was Government Consumption Expenditure (1.000), reflecting the pivotal role of public sector investment and institutional performance in maintaining law enforcement capacity and social stability. This was followed by LNPRT Consumption Expenditure (0.756) and Gross Fixed Capital Formation (0.434), both representing the strength of regional economic structures and productive investment that contribute to job creation and reduced economic inequality.

Among social indicators, Illiteracy Rate (15+) (0.332) and School Participation Rates (ages 13-15) (0.191) emerged as strong predictors, underscoring the importance of education in mitigating social vulnerability and reducing the likelihood of youth delinquency. Similarly, Poverty Percentage (0.310) and Poverty Population (0.187) highlight the persistent influence of economic disparity on crime occurrence. Demographic and welfare-related variables such as Life Expectancy (Female) (0.050) and Human Development Index (0.139) indicate that improved quality of life and social welfare are associated with lower crime intensity.

From a criminological perspective, these relationships align with social disorganization and strain theories, which posit that strong institutions, economic inclusion, and access to education reduce structural tension and the propensity for deviant behavior [20]. Furthermore, the positive influence of life expectancy and the Human Development Index supports the view that enhanced welfare and social cohesion contribute to long-term crime reduction and community resilience.

C. Comparison with Previous Studies

The findings of this study are consistent with prior works while offering notable advancements. Malik et al. [6] demonstrated that both machine learning and deep learning models are effective for crime prediction, though their study was limited to individual algorithms. Tamilselvi et al. [7] proposed a hybrid deep learning model (HDLCP) that improved classification accuracy but did not explicitly incorporate temporal dependencies. Ibrahim et al. [9] showed that hybrid models could achieve accuracy rates exceeding 90%, yet their approach relied primarily on CNN and clustering techniques.

Further supporting the effectiveness of hybrid and optimized models, Abubakar et al. [10] developed a Random Forest model enhanced with Artificial Bee Colony optimization, achieving an accuracy of 95% and outperforming conventional classifiers such as Decision Trees and KNN. Similarly, Mwaniki et al. [11] reported that a hybrid tree-based algorithm reached 94.4% accuracy, slightly surpassing the performance of individual Decision Trees and standard Random Forests. These studies collectively highlight the growing trend toward hybridization and optimization in crime prediction, aligning with the direction taken in the present research.

TABLE V. BENCHMARK COMPARISON OF PRIOR STUDIES ON CRIME PREDICTION

Study	Accuracy
Ibrahim et al. [9]	97.52%
Abubakar et al. [10]	95%
Mwaniki et al. [11]	94.4%
This Study	98.87%

As shown in Table IV, the proposed hybrid model achieves higher accuracy compared to prior studies, indicating its superior capacity to capture complex temporal and socio-economic relationships.

In contrast, the present study introduces novelty by combining TFT and XGBoost into a unified framework that addresses both temporal forecasting and interpretable classification. This dual capability bridges the gap between predictive accuracy and explainability, while the incorporation of socio-economic indicators such as case resolution rates, government expenditure, and school participation provides context-specific insights into crime patterns in Indonesian provinces. Compared to prior studies that focused on individual algorithms or hybrid models without explicit temporal considerations, this approach demonstrates stronger generalizability and offers a more comprehensive understanding of the structural and institutional drivers of crime.

D. Implications for Policy and Practice

The results hold significant implications for crime prevention and law enforcement policy in Indonesia. First, accurate forecasting of crime trends enables authorities to anticipate surges in criminal activity and take preventive measures. Second, the identification of key socio-economic

 EISSN: 2961-872X ● PISSN: 2961-8924 ● DOI: 10.56741/IISTR.esl.001359

drivers highlights areas where government intervention could reduce crime rates, such as policies aimed at reducing unemployment or improving economic development. Third, the analysis of case resolution effectiveness underscores the importance of judicial efficiency and accountability in maintaining public trust and deterring future crimes.

The findings suggest that provinces with higher school participation rates and greater government consumption expenditure tend to exhibit lower crime intensity and higher resolution effectiveness. These relationships highlight the importance of policies that strengthen educational accessibility, reduce inequality and support public sector investment. Also, the positive influence of life expectancy and HDI emphasizes that improvements in public health and welfare indirectly contribute to social stability. These insights can guide policymakers in designing targeted interventions to reduce crime and improve justice system performance in line with Indonesia's digital transformation and social development agenda.

Furthermore, the integration of AI and machine learning in crime analysis aligns with Indonesia's digital transformation agenda and the broader concept of Society 5.0, where technological innovation is leveraged to address complex societal challenges. The proposed framework provides a foundation for developing intelligent decision-support systems that can enhance the effectiveness of national security strategies.

To substantiate these strategic implications with empirical evidence, the evaluation employed the DKI Jakarta time series for 2019–2023 to assess the model's short-term generalization capacity, using a data range that reflects both a stable period (2019–2022) and a sharp structural shift in 2023. The test data were formatted identically to the training structure to ensure feature-space consistency and avoid distributional drift during inference. Because the Temporal Fusion Transformer requires a complete historical window to construct temporal embeddings, the 2019–2023 sequence was provided as contextual input before generating the 2024 prediction. The model estimated approximately 12,370 cases for 2024, compared to the observed 58,055 cases (Fig. 10). This discrepancy should not be interpreted as model failure but as a statistical consequence of the strong structural break in 2023. The preceding years exhibited a narrow and stable pattern with no historical signal indicating a forthcoming spike, making the 2023 surge anomalous relative to the learned temporal dynamics. As supported by forecasting literature, models generally cannot replicate unprecedented shocks and instead gravitate toward long-term trends (regression toward the mean) [21]. Thus, the difference between prediction and observation reflects the abrupt instability of the time series rather than limitations in model architecture or training.

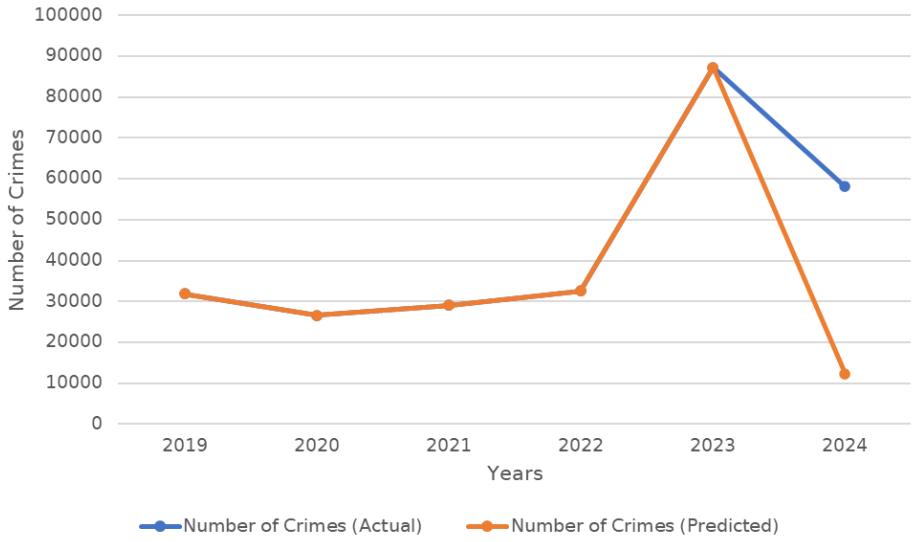


Fig. 10. Forecast vs actual *plot* of DKI Jakarta for 2024

E. Limitations and Future Work

While the proposed framework demonstrates strong performance, certain limitations should be acknowledged. The study relies on official statistical data, which may not capture real-time fluctuations in crime dynamics. Additionally, differences in data completeness and temporal resolution across provinces could influence the model's ability to generalize across heterogeneous regional contexts. Also, the annual aggregation of socio-economic indicators may not fully capture short-term or lagged effect of variables such as unemployment, poverty, and educational participation on crime rates. These delayed impacts can influence temporal relationships and should be explored using higher-frequency or lag-sensitive datasets in future work.

From a data perspective, the reliance on annual official statistics constrains the model's responsiveness to real-time or rapidly changing conditions. Future studies should consider integrating real-time or high-frequency data sources, such as social media analytics, IoT sensors, or police incident reports, to complement official datasets and improve temporal granularity.

From a modeling perspective, the current hybrid framework does not explicitly capture spatial dependencies among provinces. Incorporating spatial learning mechanisms, such as graph-based neural networks (GNNs) or reinforcement learning extensions, could enhance the model's capability to represent spatial-temporal interactions and improve interpretability of regional crime patterns.

V. Conclusion

This study presents a hybrid machine learning framework that integrates the Temporal Fusion Transformer (TFT) for time-series forecasting and XGBoost for interpretable crime classification, demonstrating superior performance compared to conventional models in predicting and analyzing crime patterns across Indonesia. By leveraging a comprehensive dataset of 30 socio-economic and demographic indicators from 38 provinces over 14 years, the proposed approach

effectively captures complex temporal dynamics and identifies key institutional, economic, educational, and welfare-related factors influencing crime levels. The model achieves high forecasting accuracy (R^2 = 0.9894) and exceptional classification performance (Accuracy = 98.87%), outperforming prior studies and highlighting the benefits of hybrid and optimization-based methods. Beyond methodological advancements, the findings offer actionable insights for policymakers, emphasizing the importance of strengthening public expenditure, educational participation, and social welfare to reduce crime and enhance case resolution effectiveness. Overall, this research supports Indonesia's digital transformation agenda and the vision of Society 5.0 by providing an interpretable, data-driven foundation for developing intelligent, human-centered crime prevention and law enforcement strategies.

ACKNOWLEDGMENT

This research was funded by the Directorate of Research, Technology and Community Service, Ministry of Education, Culture, Research and Technology of the Republic of Indonesia, under the Penelitian Dosen Pemula (PDP) program, fiscal year 2025, Contract No: 122/C3/DT.05.00/PL/2025; 37/SPK/LL1/AL.04.03/PL/2025; 515/UM.348/09/PN/2025. The authors gratefully acknowledge this support.

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