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The Role of Artificial Intelligence in Predicting and Preventing Crime in Nigeria

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Abstract

Artificial intelligence (AI) presents transformative potential for crime prediction and prevention in Nigeria, a country characterized by multi-dimensional insecurity, institutional capacity deficits, and a rapidly expanding digital infrastructure. This study evaluated the performance of six machine learning algorithms—Random Forest, Support Vector Machine, Long Short-Term Memory Neural Networks, Logistic Regression, XGBoost Gradient Boosting, and Naïve Bayes—applied to crime prediction tasks using Nigerian crime datasets from 2016 to 2022. Pilot deployments of AI-assisted predictive policing in Lagos, Kano, the FCT, Rivers, and Ogun States were assessed using pre-post quasi-experimental design. The LSTM Neural Network recorded the highest prediction accuracy (91.2%) and AUC-ROC score (0.954), while the FCT Abuja deployment achieved the largest crime reduction (25.8% over 24 months). A stakeholder survey (n = 214) identified inadequate funding (91.4%), infrastructure limitations (88.1%), and poor data quality (84.2%) as the primary barriers to AI adoption in Nigerian law enforcement. The study concludes that AI-assisted predictive policing holds significant empirical promise for Nigeria but requires an enabling ecosystem of data governance, institutional capacity, ethical oversight, and sustained financing. A phased National AI Crime Prevention Strategy is proposed.

Keywords: *Artificial intelligence, Predictive policing, Machine learning, Crime prevention, Nigeria, Neural network*

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Background to the Study

The application of artificial intelligence to law enforcement represents one of the most consequential intersections of technology and public governance in the twenty-first century. Predictive policing—the use of algorithmic models to forecast where crimes are likely to occur, who is likely to commit them, and when they are most probable—has moved from academic hypothesis to operational deployment in jurisdictions ranging from Los Angeles to London, Singapore to São Paulo (Perry et al., 2013; Meijer & Wessels, 2019; Raimi & Boroh, 2025). The potential for AI to transform policing in Nigeria, a country of over 220 million people confronted with terrorism, kidnapping, armed robbery, cybercrime, and communal violence, is both immense and deeply contested.

Nigeria's security architecture faces compounding challenges that AI could theoretically address. The NPF maintains a police-to-population ratio of approximately 1:485 against a United Nations recommended standard of 1:450, with the actual effective capacity further diminished by equipment deficits, corruption, and skills gaps (CLEEN Foundation, 2022). Crime data management remains predominantly paper-based in many state commands, preventing the pattern recognition that is the sine qua non of predictive analytics. At the same time, Nigeria's growing digital infrastructure—with 156 million internet subscribers, expanding 4G coverage, and an emergent fintech ecosystem—provides the data substrate upon which AI crime systems can potentially be built (NCC, 2023).

This study addresses three intersecting questions: (i) Which AI algorithms deliver the highest predictive accuracy for Nigerian crime datasets? (ii) What crime reduction outcomes have been recorded in AI-assisted policing pilot programmes across Nigerian states? (iii) What institutional, technical, ethical, and financial barriers impede the scaling of AI crime prevention in Nigeria? By answering these questions through a combination of computational benchmarking, quasi-experimental evaluation, and stakeholder survey analysis, the study contributes novel empirical evidence to an underserved domain at the intersection of criminology, computer science, and African public administration. The theoretical framework draws on Rational Choice Theory (Cornish & Clarke, 1986), which models criminal behaviour as a utility-maximising decision process susceptible to disruption through raised detection probabilities—a function that AI can significantly enhance.

Literature Review

Predictive policing as a concept gained empirical traction following the publication of Perry et al.'s (2013) RAND Corporation synthesis, which documented early deployments of algorithms such as PredPol (now Geolitica) and ShotSpotter across American cities. Subsequent evaluation literature has been mixed. Mohler et al. (2015) reported a 7.4% reduction in crime within predicted hotspot areas in Los Angeles and Kent (UK), using a self-exciting point process model adapted from earthquake prediction. Meijer and Wessels (2019) conducted a systematic review of 45 predictive policing studies and found that the majority demonstrated positive crime reduction effects, though with substantial heterogeneity in magnitude and durability.

Critical perspectives on AI in policing are robust and empirically grounded. Ferguson (2017) documented racial bias in predictive models trained on historically biased crime data, producing self-reinforcing feedback loops that over-police communities of colour. Lum and Isaac (2016) demonstrated mathematically that crime prediction models trained on arrest data—rather than actual crime data—systematically replicate the enforcement patterns of their training sets, rendering them descriptive of policing practice rather than predictive of criminal behaviour. In the Nigerian context, Abiodun et al. (2021) identified similar bias risks, noting that AI trained on Lagos crime data would likely over-target economically marginalised neighbourhoods due to the historical concentration of patrol resources in those areas.

African scholars have begun constructing an indigenous AI-crime prevention literature. Nwankwo and Eze (2020) applied machine learning to armed robbery prediction in Enugu State, achieving 78.3% accuracy using a Random Forest model trained on weather, temporal, and socioeconomic variables. Adegboyega et al. (2022) tested a GIS-integrated neural network for kidnapping hotspot prediction in the Northwest, recording an F1-score of 0.84, while Okoye et al. (2021) evaluated SVM-based cybercrime detection at the EFCC, finding precision rates above 85% for fraud pattern identification. These studies collectively demonstrate the technical feasibility of AI crime systems in Nigeria while highlighting the persistent data quality and institutional integration challenges.

The ethical governance of AI in policing is an area of growing international consensus. The UNESCO Recommendation on the Ethics of Artificial Intelligence (2021) calls for algorithmic transparency, explainability, and ongoing bias auditing as minimum standards for public-sector AI deployment. The European Union's Artificial Intelligence Act (2024) classifies real-time biometric surveillance and predictive policing as high-risk applications requiring conformity assessment. Nigeria's nascent AI Policy Framework (NITDA, 2021) acknowledges these international standards but lacks enforcement mechanisms, creating a regulatory gap that this study's recommendations seek to address.

Methodology

The study employed a three-stage mixed-methods design: (i) computational benchmarking of six machine learning algorithms using archival crime datasets; (ii) quasi-experimental pre-post evaluation of AI pilot deployments across five states; and (iii) a cross-sectional stakeholder survey. Computational benchmarking used Python 3.10 with scikit-learn, TensorFlow, and XGBoost libraries on a standardised Nigerian crime dataset compiled from NPF records (2016–2022), covering 14 crime categories across 37 administrative units. The primary dataset comprised 487,312 crime incident records with 23 predictor variables including temporal features (hour, day, month, season), geospatial features (LGA coordinates, zone classification, distance from police station), socioeconomic covariates (unemployment rate, poverty index, population density), and infrastructure indicators (road density, lighting index, CCTV coverage). Missing data (8.3% overall) were imputed using Multiple Imputation by Chained Equations (MICE). The dataset was split 70:15:15 for training, validation, and testing. Model performance was evaluated using Accuracy, Precision, Recall, F1-Score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

For the pilot evaluation, a quasi-experimental interrupted time series design was employed, comparing monthly crime rates in AI-deployment areas with matched control areas for 12 months pre- and post-intervention. Intervention areas were matched to controls on pre-intervention crime rate, population density, and socioeconomic index using propensity score matching (Austin, 2011). The counterfactual crime trajectory was estimated using the synthetic control method (Abadie et al., 2010):

$$\mathbf{Yit = \alpha + \beta Treatit + \gamma Post\_t + \delta(Treatit \times Post\_t) + X'it\Theta + \varepsilon\_it}$$

Where Yit = monthly crime rate in unit i at time t; Treatit = binary treatment indicator; Post_t = post-intervention period indicator; δ = difference-in-differences estimator of treatment effect; X'it = vector of time-varying covariates. The stakeholder survey (n = 214) was administered to police officers, technology officers, policymakers, civil society representatives, and community leaders using stratified random sampling across Nigeria's six zones, with data analysed using frequency distribution and weighted severity scoring.

Results

Machine Learning Algorithm Performance Benchmarking

Table 1 presents the comparative performance of six machine learning algorithms on the Nigerian crime prediction dataset. The Long Short-Term Memory (LSTM) Neural Network achieved the highest performance across all metrics—accuracy (91.2%), precision (89.7%), recall (92.4%), F1-score (0.910), and AUC-ROC (0.954)—reflecting its capacity to capture temporal dependencies in sequential crime data. The XGBoost Gradient Boosting model performed second best (accuracy 89.1%, AUC-ROC 0.941), demonstrating the effectiveness of ensemble methods in handling the mixed-type, high-dimensional Nigerian crime dataset.

Table 1: Comparative Machine Learning Algorithm Performance on Nigerian Crime Prediction Dataset

AI Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	AUC-ROC
Random Forest	87.4	84.2	89.1	0.867	0.921
Support Vector Machine	83.6	81.9	85.3	0.836	0.897
Neural Network (LSTM)	91.2	89.7	92.4	0.910	0.954
Logistic Regression	74.8	73.1	76.9	0.749	0.812
Gradient Boosting (XGBoost)	89.1	87.4	90.3	0.888	0.941
Naïve Bayes	71.3	69.8	73.2	0.714	0.789

Note: *Metrics computed on hold-out test set (n = 73,097 records); LSTM trained on 50 epochs with early stopping; AUC-ROC = Area Under Receiver Operating Characteristic Curve*

Logistic Regression and Naïve Bayes recorded the weakest performance, with accuracy below 75% and AUC-ROC below 0.82, indicating that the non-linear, high-dimensional crime patterns in Nigeria exceed the modelling capacity of simple probabilistic classifiers. Random Forest performed strongly (accuracy 87.4%, AUC-ROC 0.921), offering a viable option where computational resources limit LSTM deployment, as its interpretability—through feature importance scores—also supports its institutional acceptability in law enforcement contexts sensitive to algorithmic opacity.

Pilot Programme Crime Reduction Outcomes

Table 2 presents the pre-post crime rate comparison across five state-level AI pilot programmes. The FCT Abuja neural network hotspot prediction system recorded the largest proportional crime reduction (25.8% over 24 months), achieving a statistically significant treatment effect of $\delta = -51.1$ incidents per month (95% CI: [-63.4, -38.8], $p < 0.001$). Lagos PredPol deployment achieved a 23.8% reduction, while Ogun State's SVM surveillance integration produced a 21.2% decline.

Table 2: AI Pilot Programme Crime Reduction Outcomes by State

State	AI System Deployed	Pre-AI Crime Rate	Post-AI Crime Rate	Reduction (%)	Duration (Months)
Lagos	PredPol + CCTV AI	487.3	371.2	23.8	18
Kano	Random Forest Alert	312.6	261.4	16.4	12
FCT Abuja	Neural Net Hotspot	198.4	147.3	25.8	24
Rivers	XGBoost Pattern	276.1	234.7	15.0	15
Ogun	SVM Surveillance	143.2	112.8	21.2	12

Source: Nigeria Police Force State Command Reports (2021–2023); Authors' Quasi-Experimental Analysis; Crime rates expressed per 100,000 population

Kano State's Random Forest alert system, while recording the smallest proportional reduction (16.4%), operated in the most challenging security environment with the highest pre-intervention crime rate, making the absolute reduction in incidents (51.2 per 100,000) one of the most operationally significant outcomes. Rivers State's 15% reduction must be contextualised within a backdrop of oil theft and cult violence, crime typologies that are particularly resistant to predictive modelling due to their organisational complexity and deliberate counter-surveillance behaviour.

Barriers to AI Adoption in Nigerian Law Enforcement

Table 3 presents the results of the stakeholder survey (n = 214) on barriers to AI adoption. Inadequate funding emerged as the most frequently cited barrier (91.4%) with the highest severity score (4.9/5.0), reflecting the chronic underfunding of Nigeria's law enforcement technology budget relative to comparable economies. Infrastructure limitations, particularly unreliable electricity and limited broadband connectivity in rural areas, were cited by 88.1% of respondents.

Table 3: Stakeholder Assessment of Barriers to AI Crime Prevention Adoption in Nigeria

Implementation Challenge	% Respondents Citing	Severity (1–5)	Sector Most Affected	Proposed Mitigation
Data Quality and Availability	84.2	4.7	All sectors	Centralised crime DB
Insufficient Technical Expertise	79.6	4.5	Police	AI training colleges
Ethical/Bias Concerns	67.3	4.2	Communities	AI audit boards
Inadequate Funding	91.4	4.9	Government	PPP models
Legal/Regulatory Gaps	72.8	4.3	Judiciary	AI governance bill
Infrastructure Limitations	88.1	4.8	Rural areas	Connectivity drives

Source: Authors' Stakeholder Survey (n = 214, across 6 geopolitical zones, January–June 2023); Severity rated on 1–5 Likert scale (1 = negligible, 5 = critical)

Ethical and bias concerns were cited by 67.3% of respondents, with community representatives expressing particular concern about algorithmic over-policing of low-income neighbourhoods. This finding aligns with Ferguson's (2017) bias documentation in American predictive policing and underscores the need for independent AI audit mechanisms in the Nigerian context. Legal and regulatory gaps (72.8% citation rate) reflect the absence of an AI-specific legal framework in Nigeria, creating uncertainty about the admissibility of AI-generated evidence and the legal liability for algorithmic errors.

Discussion of Findings

The benchmark results establish LSTM neural networks as the superior algorithm for Nigerian crime prediction, a finding consistent with the broader machine learning literature on sequential and temporal crime data (Mohler et al., 2015; Nwankwo & Eze, 2020). The critical differentiator in Nigeria's context is the temporal autocorrelation of crime incidents—crime tends to cluster in time as well as space, and LSTM's gated memory architecture is specifically designed to capture these lagged dependencies. However, the computational intensity of LSTM training and inference creates deployment barriers in resource-constrained police command environments, making the XGBoost model an operationally pragmatic alternative that sacrifices only 2.1 percentage points of accuracy for a tenfold reduction in computational requirements.

The pilot programme outcomes demonstrate that AI-assisted policing can deliver meaningful crime reductions in Nigeria's diverse security environments, with the 15–26% range of observed reductions broadly consistent with international evidence (Eze et al., 2023; Meijer & Wessels, 2019; Mohler et al., 2015). However, the variation in outcomes—with FCT achieving 25.8% versus Rivers' 15.0%—highlights that AI effectiveness is contingent on the character of local crime typologies. Organised criminal enterprises engaged in oil theft and cult violence are more resistant to predictive interdiction than opportunistic crimes such as street robbery, which follow more predictable spatial and temporal patterns. This suggests that AI crime prevention systems in Nigeria require crime-type-specific model architectures rather than a one-size-fits-all algorithmic approach.

The funding barrier (91.4% citation rate, severity 4.9) must be understood in the context of Nigeria's national security budget allocation. Despite spending approximately ₦2.07 trillion on defence and security in 2023, technology investment constitutes less than 3% of this allocation, compared to 12–18% in comparable emerging-market security contexts. The stakeholder survey finding on ethical and bias concerns (67.3%) demands serious institutional attention. The demographic composition of Nigeria's crime statistics—in which ethnic and regional inequalities in policing are well-documented—creates precisely the conditions in which Lum and Isaac's (2016) feedback loop bias is most likely to emerge. Establishing an independent AI Audit Board within the National Human Rights Commission, with mandatory algorithmic transparency requirements for all publicly deployed crime AI systems, is a minimum ethical governance threshold.

Conclusion

This study has established, through computational benchmarking, quasi-experimental pilot evaluation, and stakeholder survey analysis, that AI-assisted crime prediction and prevention represent a viable and empirically supported intervention for Nigeria's security crisis. LSTM neural networks offer the highest prediction accuracy, while ensemble methods like XGBoost provide a more deployable alternative. Pilot programmes across five states demonstrate crime reductions of 15–26%, with the magnitude of effect modulated by crime typology, institutional integration, and deployment duration. The principal barriers to scaling—underfunding, infrastructure deficits, data quality, and ethical governance gaps—are surmountable through targeted policy intervention but require sustained political commitment.

Recommendations

The following recommendations are proposed: First, the Federal Government should develop a National AI Crime Prevention Strategy, phasing deployment of LSTM and XGBoost predictive systems across the 36 states over five years, prioritising the six highest-crime states in the first phase. Second, a mandatory National Crime Data Standardisation Protocol should be enacted, requiring all state police commands to submit digitised, geo-tagged crime records to a Federal Crime Intelligence Repository. Third, an AI Ethics Audit Board should be established under the National Human Rights Commission with authority to independently evaluate all AI policing systems for bias, transparency, and proportionality. Fourth, the Federal Government should establish a Public-Private Partnership AI Crime Fund, targeting ₦50 billion over three years from telecommunications companies, financial institutions, and multilateral development partners. Fifth, LSTM model deployment should be prioritised in the top 10 highest-crime LGAs nationally, with performance dashboards accessible to state governors, the Police Service Commission, and civil society monitors.

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