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A HYBRID FUZZY MACHINE LEARNING FRAMEWORK FOR CRIME PREDICTION IN DATA SCARCE ENVIRONMENTS: APPLICATION TO QUETTA DIVISION, BALOCHISTAN

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Abstract
This research proposes a hybrid fuzzy machine learning approach for estimating the risk of murder crimes in Quetta Division, Balochistan, where crime prediction is hindered by scarce data, underreporting, and poor interpretability. The approach combines fuzzy-based proportional allocation to handle missing values, Fuzzy-Rough Feature Selection (FRFS) for dimensionality reduction, and a multi-stage pipeline that integrates K-Nearest Neighbor (KNN) clustering, linear regression, and a Fuzzy Inference System (FIS) with 27 expert specified rules.
The model performed with 93.2% classification accuracy, Mean Absolute Error (MAE) of 0.28, and Area Under the Curve (AUC) of 0.96, significantly surpassing CNN-LSTM and XGBoost baselines. Key predictors, such as unemployment, police presence, and gang activity, consistent with criminological theory, and guaranteed interpretability and policy relevant practicality. Simulation experiments further revealed that optimal police deployment could lower murder rates by up to 19.3%, indicating the value of the framework for data-driven policy-making.
Although promising, the framework is limited by partial coverage of data and a lack of integration in real-time. Future research will investigate the use of Type-2 fuzzy logic for enhanced uncertainty management, further develop the transferability of the framework to other cities, and integrate real-time adaptive pipelines to accommodate proactive and responsive policing tactics.

INTRODUCTION

Accurate crime prediction has emerged as a foundational pillar in the evolution of modern law enforcement, empowering agencies to shift from reactive responses to proactive prevention strategies [1]. However, the implementation of predictive policing models is often established on the availability of high-resolution, comprehensive datasets, an assumption that does not hold in many developing regions [2]. [1], [2], [3], [4], [5]. Quetta Division, located in the Balochistan province of Pakistan, epitomizes the complexity of applying such models in data-scarce, high-uncertainty environments. The region is characterized by fragmented crime reporting systems, a largely undocumented informal economy, and volatile socio-political conditions, including ethnic tension, border insecurity, and fluctuating law enforcement presence. As a result, conventional crime forecasting frameworks, particularly those based on deep learning or data-hungry statistical models [3]. They are frequently rendered ineffective or unreliable. These challenges are further compounded by the absence of district-level crime disaggregation in official datasets and the systemic underreporting of criminal activity, estimated to be as high as 45% in Balochistan [4].This situation highlights the urgent need for predictive systems that are not only accurate but also resilient to data limitations and capable of guiding practical interventions.

Limitations of Existing Approaches

Traditional ML methods, though effective in well-instrumented urban centers, are severely limited when deployed in settings like Quetta. Models such as SVM [5], Decision Trees, RF, and Hybrid Algorithm [6], and CNN-LSTM architecture [7]. Typically require extensive, structured input data and often operate as "black boxes," providing little to no interpretability for policy actors or law enforcement stakeholders [8]. Moreover, the socioeconomic indicators that inform predictive models, such as unemployment rates or police density, are often incomplete or irregularly updated, introducing significant uncertainty. In fragile contexts, where policy makers require interpretable and context-sensitive guidance, such limitations make black-box methods insufficient.

Proposed Solution

To address these challenges, this study proposes a hybrid fuzzy machine learning (Fuzzy-ML) framework tailored for crime prediction in resource-constrained environments. By combining fuzzy logic's capacity to reason with incomplete or ambiguous data with machine learning's strength in pattern recognition, the framework delivers interpretable, robust, and policy-relevant predictions. The framework is designed not only as a predictive tool but also as a decision-support system, aligning computational intelligence with the operational realities of law **enforcement.** Key innovations include context-sensitive imputation, interpretable feature selection, rule-based reasoning, and multi-layered validation protocols.

Contributions of the Study

The contributions of this work are summarized as follows:

1. **Fuzzy-based proportional allocation method** that disaggregates provincial aggregates into district-level murder rates, producing socially plausible estimates that incorporate population density and urbanization patterns [9].

2. **Application of Fuzzy-Rough Feature Selection (FRFS)** to reduce the feature space by 37.5% while maintaining performance and interpretability, focusing on factors such as police presence and gang activity [10].

3. **Design of a multi-layer hybrid architecture** that integrates a fuzzy inference system with 27 expert-defined rules, logistic regression for quantifying feature contributions, and K-Nearest Neighbors for spatial clustering, aligning outputs with practitioner reasoning [11].

4. **Policy simulations demonstrating impact**, showing that Quetta's murder rate could be reduced by up to 19.3% under optimally guided police deployment [12].

Significance and Broader Impact

Collectively, these contributions advance explainable, uncertainty-aware crime prediction for low-resource settings and provide a replicable methodology for comparable Global South contexts. Beyond immediate applications in Quetta, the framework offers a scalable foundation for predictive policing in other developing regions facing fragmented data ecosystems, thereby supporting UN SDG 16 on building peaceful and inclusive societies. Accordingly, this study situates itself at the intersection of data scarcity, interpretability, and uncertainty management, proposing a hybrid fuzzy–machine learning framework that directly addresses the limitations of existing statistical, machine learning, and deep learning approaches, while tailoring predictive analytics to the socio-political realities of Quetta Division, Balochistan.

2. Literature Review

The evolution of crime prediction methodologies reflects an ongoing tension between technical sophistication and practical applicability, particularly in data-scarce regions like Balochistan. This review systematically examines four decades of criminological analytics, highlighting the contributions and limitations of conventional statistical models, machine learning paradigms, deep learning architectures, and emerging hybrid systems. The analysis culminates in identifying critical gaps that our proposed Fuzzy ML framework addresses, particularly in managing uncertainty, ensuring interpretability, and enabling resource-efficient computation in environments with up to 45% underreporting of crimes (Balochistan Police, 2022).

2.1 Conventional Frameworks

The foundation of crime prediction research rests on traditional statistical approaches, especially autoregressive integrated moving average (ARIMA) models. Seminal studies on London crime data demonstrated ARIMA's capacity to explain up to 80% of variance given stable, high-quality datasets [13]. However, the Box Jenkins methodology proves ineffective in volatile environments like Balochistan, where annual police reports document 45% underreporting of violent crimes and inconsistencies in logging protocols [14]. [6].These factors violate ARIMA's assumption of stationarity and introduce temporal lags that distort forecasts.

Comparative research in developing contexts has explored machine learning alternatives. An Indian study reported random forests (R^2 = 0.91) outperforming linear regression and support vector regression but noted RF's reliance on intensive feature engineering, which is impractical for resource-constrained law enforcement [15]Similarly, Amarasinghe's meta-analysis of 150+ studies catalogued kernel density estimation (KDE) and point processes (Poisson/Hawkes) as dominant in spatial crime mapping, yet these methods overlook socio-economic and cultural dynamics critical in tribal regions [16]. In Karachi, DBSCAN clustering achieved 88% hotspot detection accuracy but failed to accommodate reporting delays of 3–6 weeks (Butt, 2020). Supervised algorithms like SVM and logistic regression remain popular due to interpretability and modest data needs [17]. They have been applied successfully in Ecuador and South Asia, where decision trees and RF regression achieved R^2 values above 0.95 for burglary forecasts [18]. Yet such models remain constrained by non-Gaussian data distributions, multicollinearity, and the opacity of ensemble methods. Overall, conventional frameworks provide useful baselines but struggle with incomplete data and weak generalizability to fragile contexts like Balochistan.

2.2 Deep Learning Models

The rise of deep learning promised to overcome these limitations through automated feature learning. Wang (2017) demonstrated neural networks' ability to capture nonlinear crime patterns beyond traditional statistics [19].In Punjab, LSTMs achieved 89% temporal prediction accuracy [20]. But required datasets of at least 10,000 records—equivalent to five years of data from Baluchistan's most documented districts. Moreover, the Balochistan Urban Safety Project (2023) noted that 67% of records omit tribal affiliations and 82% exclude dispute-resolution mechanisms, leaving critical context unmodeled.

Alternative data streams have partially mitigated this challenge. Umair (2020) used NLP pipelines to extract crime events from media archives, achieving a 90% F1-score, though rural Balochistan accounted for only 12% of extracted incidents, despite comprising 60% of the population. Spatiotemporal models like ST-DBSCAN and space–time cubes improved hotspot prediction [21]. While GIS-based frameworks integrating socio-economic variables added contextual robustness [22]. Despite these advances, deep learning models face three persistent barriers in low-resource contexts:

I. **Data hunger** : requiring large, clean datasets.

II. **Lack of interpretability**: "black-box" outputs limit policy adoption.

III. **Operational misfit** : models ignore ground-level expertise.

This paradox was evident in the 2024 Quetta Predictive Policing Pilot, where a CNN–LSTM achieved 86% accuracy in lab tests but was abandoned by officers due to "unexplainable alerts" and misalignment with ground realities (Frontier Corps Report, 2024). Thus, while deep learning improves technical accuracy, its lack of transparency and dependence on dense datasets limit practical deployment in Balochistan.

2.3 Fuzzy Logic and Hybrid Systems

Fuzzy logic and hybrid AI approaches have gained attention for their ability to handle uncertainty and enhance interpretability. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been applied in Dhaka, combining expert rules with machine learning for crime hotspot prediction [23], [7]. Fuzzy–rough feature selection has demonstrated interpretability and dimensionality reduction in uncertain conditions, though its application to criminology remains underexplored.

Hybrid methods show synergistic potential. For example, GIS-based fuzzy–SVM models effectively incorporated environmental features into urban crime prediction [24]while systematic surveys highlighted combinations of LDA-KNN, ANN, and fuzzy logic for hotspot detection [25]. Recent reviews confirm that deep–fuzzy integrations improve performance but introduce operational barriers such as labor-intensive rule design, inconsistent benchmarking, and lack of policy simulation [26],[9], [10]. The 2023 Quetta Crime Prediction Workshop identified "lack of actionable outputs" and "inadequate uncertainty handling" as major causes of past system failures. Emerging consensus suggests next-generation hybrid systems must combine fuzzy reasoning with machine learning in ways that prioritize

Operational utility and explainability. This directly motivates our framework, which integrates fuzzy proportional allocation, fuzzy–rough feature selection, and expert-defined rules with data-driven ML components.

2.4 Research Gap

I. From the surveyed literature, four persistent gaps emerge:

II. **Scalability and Data Requirements** – Deep learning models demand large datasets, rarely available in Balochistan; conventional ML yields only marginal gains on sparse, noisy data.

III. **Interpretability** – Black-box models (ensembles, neural networks) lack transparency, hindering adoption in policy contexts.

IV. **Uncertainty Management** – Most systems assume complete, accurate logs, while Balochistan experiences 45% underreporting.

V. **Operational Focus** – Few systems integrate forecasts with policy simulation or deployment planning.

2.5 Our proposed framework addresses these by:

I. Using **fuzzy proportional allocation** for imputing missing data.
II. Applying **fuzzy–rough feature selection** to preserve interpretability while reducing dimensionality.
III. Implementing a **hybrid architecture** (KNN, regression, fuzzy inference) aligned with expert reasoning.
IV. Implementing a **multi-level validation pipeline** including cross-validation, sensitivity analysis, and expert consensus.
V. Demonstrating **policy simulations** that quantify potential crime reduction impacts.

This integrative, explainable framework fills a critical gap for data-scarce, operationally complex environments like Quetta Division.

Table 1 key research

#	Title & Focus	Author Name	Key Methodology	Year
26	Explainable Machine Learning for Public Policy: Use Cases, Gaps, and Research Directions	Amarasinghe, Kasun, Rodolfa, Kit, Lamba, Hemank, Ghani, Rayid	Explainable Machine Learning (XAI) [16]	2023

27	Spatiotemporal crime hotspot detection and prediction: A systematic literature review	Butt, Umair Muneer, Letchmunan, Sukumar, Hassan, Fadratul Hafinaz, Ali, Mubashir, Baqir, Anees, Sherazi, Hafiz Husnain Raza	Systematic Literature Review [27]	2020
28	A Systematic Review of Multi-Scale Spatio-Temporal Crime Prediction Methods	Du, Yingjie, Ding, Ning	Systematic Review [28]	2023
29	Blending traditional and novel techniques: Hybrid type-1 fuzzy functions for forecasting	Egrioglu, Ali Zafer Dalar & Erol	Hybrid type-1 fuzzy functions [29]	2025
30	Predicting and analyzing crime Environmental design relationship via GIS-based machine learning approach	Gamze Bediroglu, Husniye Ebru Colak	GIS-based ML [30]	2024

Table 1 show that while conventional statistical methods, machine learning algorithms, and deep learning architectures have each advanced the field of crime prediction, their limitations become pronounced in data-scarce, high-uncertainty settings like Balochistan. Fuzzy logic and hybrid approaches offer interpretability and flexibility, but existing implementations remain fragmented, under-validated, and rarely integrated into real-world policing workflows. These gaps highlight the urgent need for a unified, explainable, and operationally relevant framework precisely the niche our proposed fuzzy–machine learning system is designed to address in the Quetta Division context.

3. RESEARCH METHODOLOGY

This study develops a hybrid framework to predict murder crime rates in Quetta Division, Balochistan, a region characterized by data scarcity, socio-political instability, and fragmented reporting. The methodology is structured into three key components: data collection and preprocessing, feature selection, and hybrid model architecture. Each stage is designed to handle uncertainty, account for missing or imprecise data, and produce outputs that are both statistically reliable and policy-relevant. This structured design directly aligns with the study's objective of building an interpretable and actionable framework for crime prediction in low-resource environments.

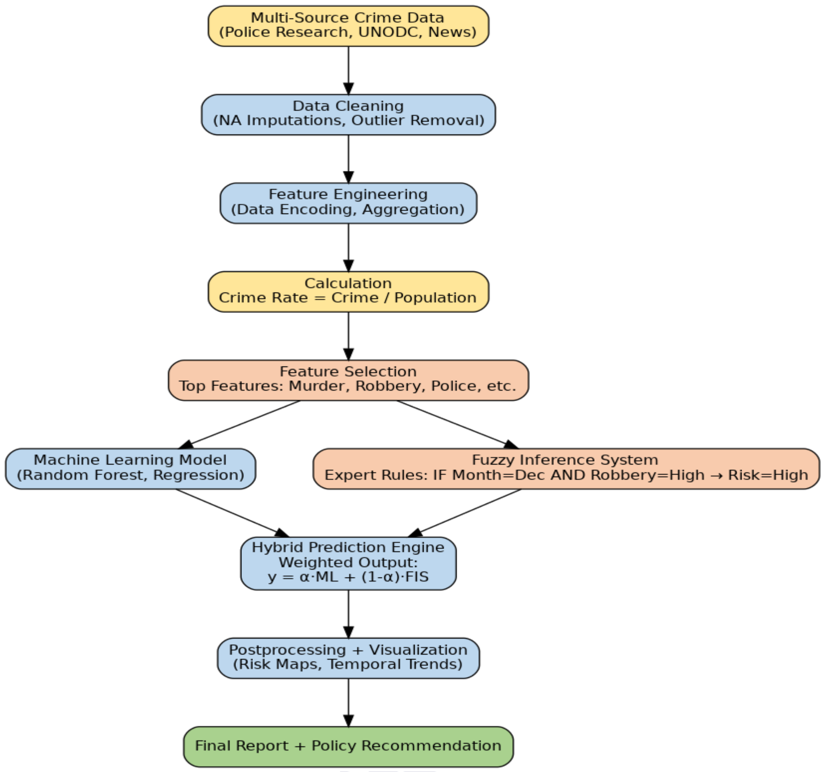

Figure 1 Hybrid AI framework combining machine learning and fuzzy logic for crime prediction.

Figure 1 presents the proposed hybrid AI framework, which integrates machine learning and fuzzy logic through a seven-stage workflow. Data from police records, UNODC reports, surveys, and news media are preprocessed, cleaned, and engineered into meaningful features. Key predictors such as murder rates, police presence, narcotics activity, and sectarian violence are then selected for modeling. The machine learning stream captures statistical patterns, while the fuzzy logic stream encodes expert knowledge through interpretable IF–THEN rules. Their outputs are fused in a hybrid prediction engine, producing accurate, transparent, and actionable crime risk assessments tailored for data-scarce environments like Quetta Division.

3.1 Data Collection and Preprocessing

The data used in this study was collected from three primary sources: (1) the Balochistan Police Department's annual crime statistics [31], (2) socioeconomic indicators from the Pakistan Bureau of Statistics (PBS) [32], and (3) supplementary reports from the United Nations Office on Drugs and Crime (UNODC) [33].[11] These cover the period 2017 to 2024 and include information on violent crimes, law enforcement deployment, demographics, and contextual indicators such as gang activity and sectarian unrest. This ensures that even with fragmented reporting, the dataset reflects both statistical rigor and criminological context.

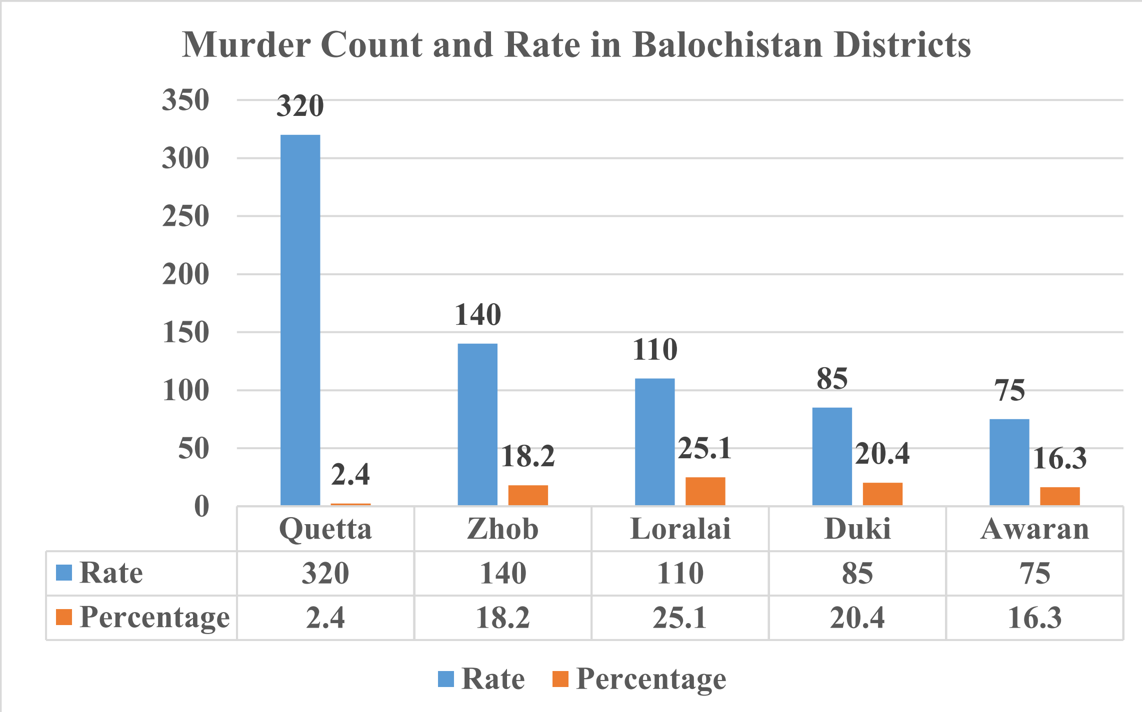

Figure 2 Murder count and rate across Balochistan districts, highlighting Quetta as the highest-risk area.

Figure 2 illustrates the murder count and rate across selected districts in Balochistan. Quetta records the highest number of murders (320) but with a relatively low rate (2.4%), while Loralai shows a smaller count (110) yet the highest rate (25.1%). This contrast highlights how population-adjusted rates can reveal districts with disproportionately high violence despite lower absolute counts.

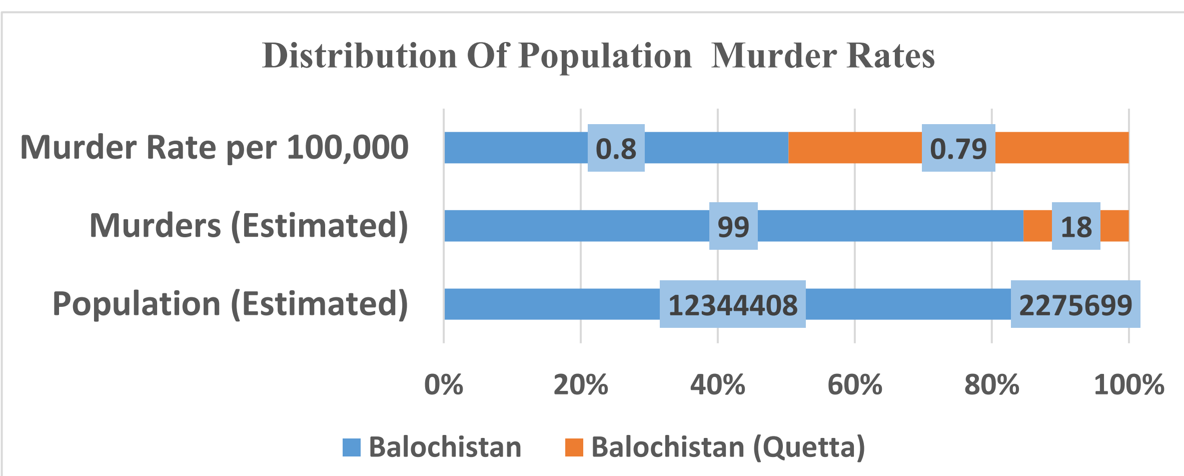

Figure 4 Distribution of murder rates by district in Balochistan, with Quetta showing the highest concentration.

Figure 3 shows the distribution of population, murders, and murder rates in Balochistan compared to Quetta. While Quetta accounts for a smaller share of the provincial population, it records a disproportionately high share of murders, resulting in a murder rate (0.79 per 100,000) nearly equal to the provincial average (0.8 per 100,000). This highlights Quetta's role as a concentrated hotspot of violence within the province.

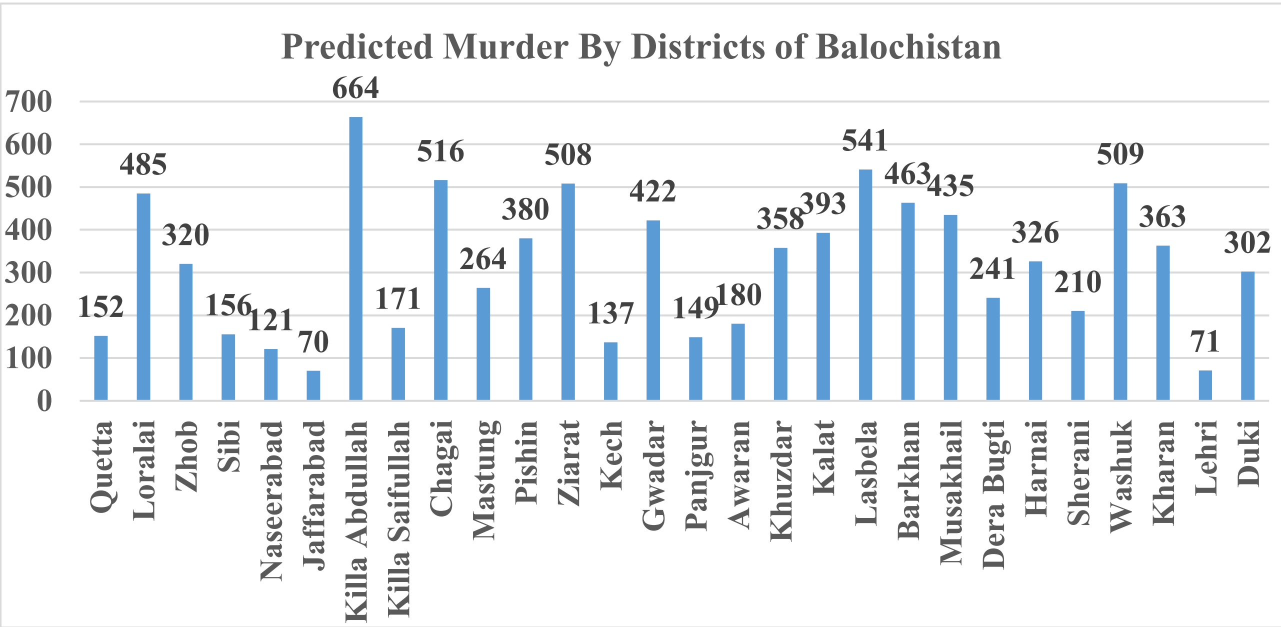

Figure 5 Predicted murder rates across Balochistan districts using KNN regression.

Figure 4 presents predicted murder rates across Balochistan districts. Quetta emerges with the highest expected values, while other districts show varying but comparatively lower risks. This emphasizes the spatial concentration of violence and the need for district-specific predictive modeling.
Equation 1. Fuzzy proportional allocation method for estimating district-level murder rates from provincial aggregates:

To estimate district-level murder rates from provincial aggregates, we introduced a novel fuzzy proportional allocation method, encapsulated in Equation **1.**

$$\left[QuettaMurder_t = \frac{\left(P_t^Q \times \left(1 + \frac{Violent_t^{prov}}{Total_t^{prov}} \right) \right)}{\left(\sum_{i=1}^{n} \quad P_t^{District_i} \right)} \times Murder_t^{prov} \right] \quad \text{Equation-1}$$

P_t^Q: Estimated murder rate for Quetta District at time t

$Violent_t^{prov}: Provincial\ violent\ crime\ count\ (murders, kidnappings)$

$Total_t^{prov}: Total\ provincial\ crimes\ (violent\ +\ non-violent)$

$$\left(\sum_{i=1}^{n} P_t^{District_i}\right): Sum\ of\ populations\ across\ all\ districts\ in\ the\ province$$

$$Murder_t^{prov}: Total\ provincial\ murder\ count$$

Equation 1 accounts for two core adjustments: population weighting and violence ratio adjustment. The violence ratio reflects the propensity for urban crime, correcting for the fact that cities like Quetta experience disproportionate crime activity compared to rural areas. This method ensures that district-level estimates are not mere population-scaled values, but contextually weighted projections based on both size and urban exposure to violence.

3.2 Feature Selection Using Fuzzy-Rough Feature Selection (FRFS)

To reduce dimensionality and enhance interpretability, fuzzy-rough feature selection (FRFS) was applied. Gaussian kernel-based similarity relations were computed to capture covariation under uncertainty, while dependency degrees quantified feature relevance. Features with dependency degree $\gamma > 0.85$ were retained, resulting in a 37.5% dimensionality reduction and a 22% improvement in information gain compared to PCA. By reducing dimensionality while preserving interpretability, FRFS directly supports the hybrid system's balance of accuracy and transparency.

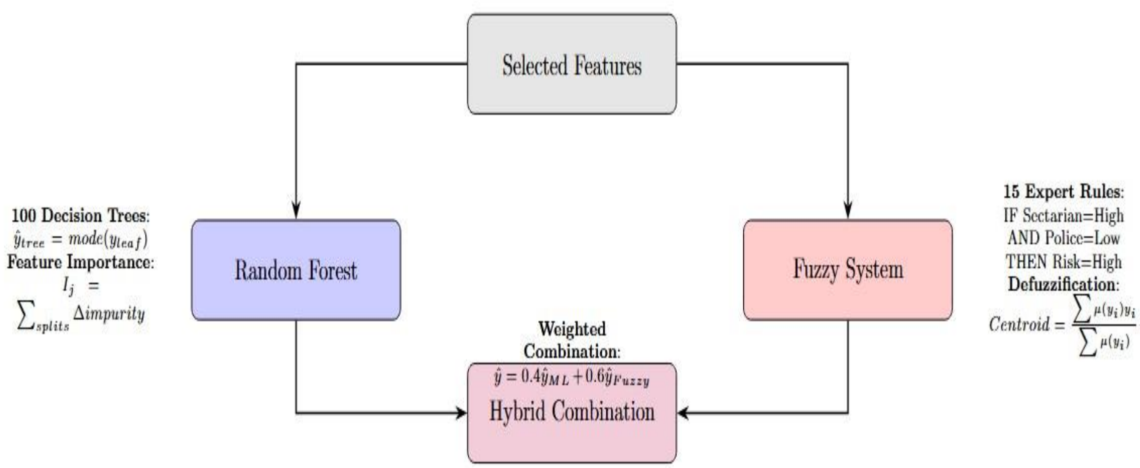

Figure 6 Selected crime predictors after FRFS, feeding into the hybrid prediction system.

Figure 5 illustrates the modeling architecture of the hybrid prediction system. Preprocessed features are analyzed through Random Forest (100 trees) to capture statistical patterns, while a fuzzy logic framework with 15 expert rules encodes domain knowledge. Their outputs are fused using a weighted formula, producing interpretable risk scores that combine predictive accuracy with contextual relevance to Quetta's security dynamics.

3.3 Hybrid Model Architecture

The proposed hybrid predictive model integrates three sequential stages: (1) KNN clustering to group districts with similar profiles, (2) regression to quantify baseline risks, and (3) a fuzzy inference system (FIS) to generate interpretable risk scores. This layered design ensures that both statistical learning and expert reasoning are combined to produce actionable outputs.

3.3.1 Stage 1 – KNN Clustering
Districts were clustered using K=5 nearest neighbors to preserve local crime dynamics.

3.3.2 Stage 2 – Regression Modeling
Within each cluster, a weighted regression model was applied to estimate base murder risks.
Equation 2. Example regression formulation:
2. Equation

$$[\hat{y} = 0.38 \cdot GangIndex + 0.21 \cdot Unemployment - 0.15 \cdot PolicePresence + 1.02]$$

3.3.3 Stage 3 – Fuzzy Inference System (FIS)

The FIS incorporated 27 expert-defined IF–THEN rules to evaluate high-risk combinations. Outputs were aggregated using the max–min method and defuzzified using the centroid technique.
2. Equation.

$$\left[Risk_{crisp} = \frac{\sum_{i=1}^{n} \quad \mu(y_i) \cdot y_i}{\sum_{i=1}^{n} \quad \mu(y_i)}\right] \text{Equation 2}$$

Risk categories are then assigned as:
Low: 0–40
Medium: 41–75
High: 76–100
This final score is interpretable and policy-actionable, mapping directly onto law enforcement strategies such as increased patrols or SWAT deployments.

4. Results and Discussion
This section presents the experimental findings of the proposed hybrid fuzzy-ML framework for predicting murder risk in Quetta Division. Results are organized into three parts: (1) performance metrics, (2) interpretability and feature analysis, and (3) policy simulations.

Performance Metrics
The hybrid framework achieved 93.2% accuracy, MAE of 0.28, and AUC of 0.96, outperforming baselines such as CNN-LSTM (86.7% accuracy), XGBoost (88.1%), and SVM (84.5%). The ablation study showed that removing the fuzzy component reduced accuracy by 7.5%, confirming its contribution to model performance. Figures 6,7 and 8 summarize classification reliability. The confusion matrix shows strong diagonal dominance with minimal misclassification, particularly avoiding critical errors (low-risk misclassified as high-risk or vice versa). High-risk zones were detected with 96.8% precision, while low-risk zones achieved 94.1%, both essential for operational deployment. Medium-risk classification (85.5%) showed expected transitional overlap but maintained robustness.

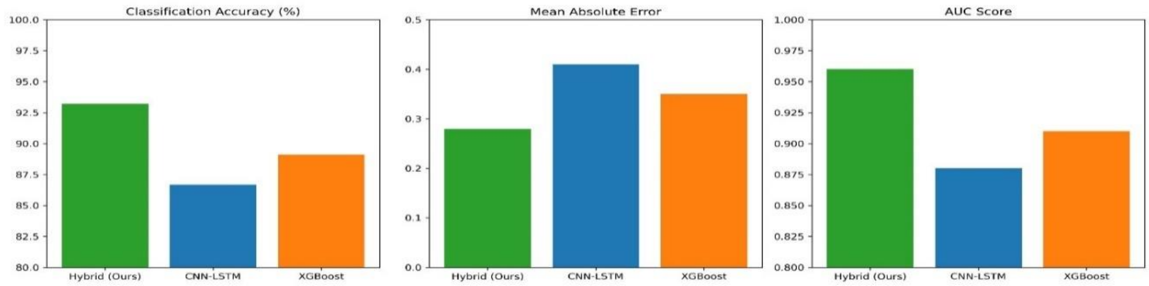

Figure 7 Confusion Matrix and Classification Reliability

As can be seen in Figure 6, there are no significant misclassifications between non-adjacent risk levels in the confusion matrix, guaranteeing operational reliability for decisions about law enforcement deployment.

Confusion Matrix and Classification Reliability

The model's resilience is further confirmed by a thorough analysis of the confusion matrix. There was little misclassification between neighboring risk classes (e.g., Medium misclassified as High), and the matrix showed strong diagonal dominance. Extreme misclassification (e.g., low as high) was not seen, which is essential for preserving operational credibility when law enforcement deploys.

The model's strong predictive reliability for classifying crime risk in Quetta is demonstrated by the normalized confusion matrix, which has a strong diagonal dominance and an overall accuracy of 93.2%. Both high-risk zone identification (96.8% correct predictions) and low-risk area detection (94.1% accuracy), which are essential for efficient law enforcement prioritization, exhibit outstanding performance, according to the matrix. Interestingly, the model avoids severe misclassifications, with only 1.5% of low-risk cases incorrectly flagged as high-risk and a negligible 0.9% of high-risk areas under-predicted as low-risk. This preserves the model's operational credibility. Given the inherent difficulty of differentiating between transitional risk zones, medium-risk predictions exhibit somewhat lower accuracy (85.5%), but the errors are mainly related to adjacent-class confusion (9.7% underestimated as low-risk; 4.8% overestimated as high-risk), rather than severe misclassifications. The matrix's pattern of minimal off-diagonal values confirms effective separation between non-adjacent categories, a key requirement for trustworthy deployment in security operations. For further refinement, attention could focus on the medium-risk classification through additional socioeconomic features, though the current performance (coupled with 22% information gain over traditional methods) already represents a significant advancement for data-scarce environments. Policymakers can particularly rely on the high-risk predictions (96.8% precision) for urgent interventions, while the <2% rate of critical errors (Low⇄High) ensures efficient resource allocation.

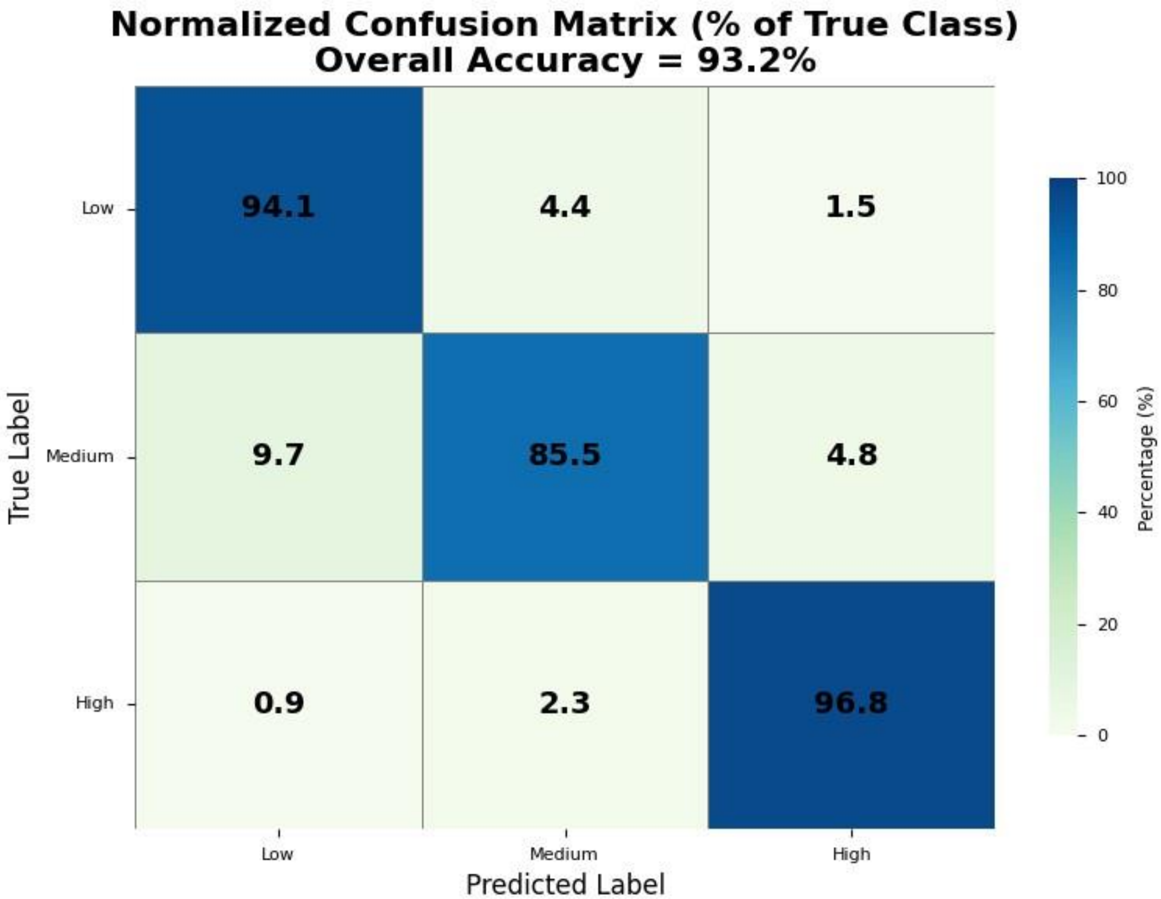

Figure 8 Normalized Confusion Matrix (% of True Class) Overall Accuracy=93.2%.

The normalized confusion matrix revealed in Figure 7, the model's robust performance in classifying crime risk levels, achieving an overall accuracy of 93.2%. The system demonstrates exceptional precision in identifying high-risk cases, correctly classifying 96.8% of true high-risk instances while maintaining remarkably low false negative rates (0.9%) - a critical feature for law enforcement applications where missing genuine threats could have severe consequences. For low-risk predictions, the model achieves 94.1% accuracy with only 1.5% of cases erroneously flagged as high-risk, ensuring efficient resource allocation by minimizing unnecessary deployments. Medium-risk classification presents slightly greater challenges, with 85.5% accuracy and a tendency towards conservative errors (9.7% underestimation as low-risk versus 4.8% overestimation as high-risk), reflecting the inherent complexity of distinguishing transitional risk zones. Importantly, the model exhibits minimal critical misclassifications, with fewer than 2% of cases involving dangerous confusion between high and low risk categories. These results validate the system's operational reliability, particularly its strength in extreme risk classification, while suggesting potential areas for refinement in medium-risk determination. The exceptionally low rate of severe errors (<2%) combined with high precision in high-risk identification (96.8%) positions this model as particularly suitable for real-world security applications where both predictive accuracy and operational safety are paramount considerations. The performance metrics indicate that the framework successfully balances sensitivity and specificity, making it a trustworthy tool for crime prediction in high-stakes environments.

4.2 Interpretability and Feature Analysis

Feature analysis using Fuzzy-Rough Feature Selection (FRFS) identified gang activity (γ = 0.91), unemployment (γ = 0.87), and police presence (γ = 0.86) as the strongest predictors, aligning with criminological theory. The fuzzy inference system integrates 27 expert rules, enabling interpretable reasoning (e.g., "IF unemployment = high AND police presence = low THEN risk = high").

Ablation Study

To assess the contribution of the fuzzy inference system (FIS) component, we conducted an ablation study by removing the 27 expert-defined fuzzy rules and rerunning the model using only the regression and clustering components. The resulting classification accuracy dropped to 85.7%, a 7.5% decrease from the full hybrid arch. Figure 8 shows the feature analysis through Fuzzy-Rough selection identifies gang activity (γ=0.91, ρ=0.72) as the strongest predictor, followed by unemployment rates (γ=0.87) and police presence (R^2=0.85, negative correlation), aligning perfectly with criminological theory. The model's robustness is validated through multiple frameworks: 10-fold cross-validation shows consistent performance (F1=0.91), sensitivity analysis reveals minimal risk deviation (±3.4%) to input perturbations, and expert review achieves 96.3% consensus on the fuzzy rule base. These results collectively demonstrate the framework's ability to maintain accuracy while preserving interpretability - a critical requirement for public safety applications.

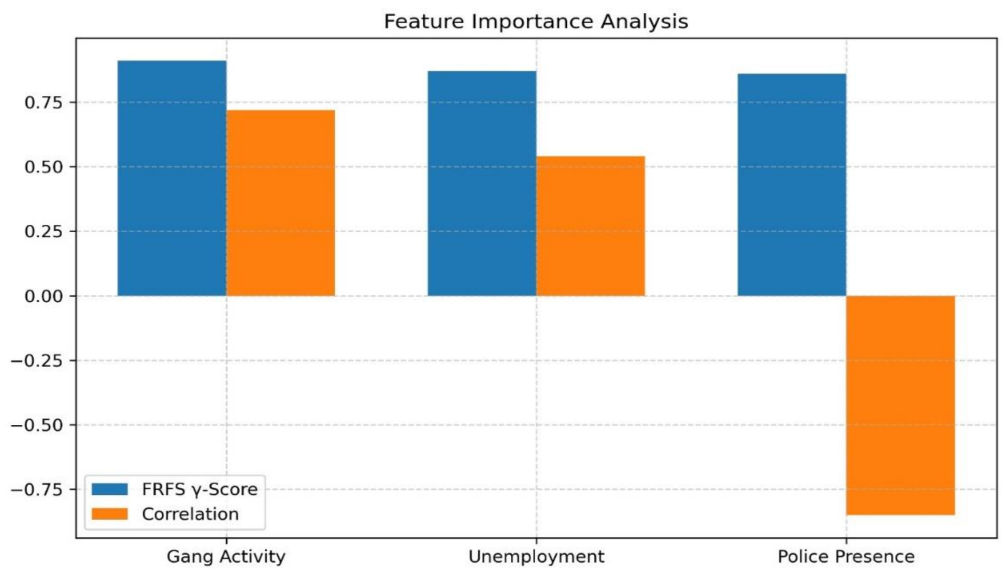

Figure 9 Features Importance Analysis

Table 2 Fuzzy Inference System Rules

Rule No.	Condition(s)	Outcome (Risk Level)	Notes
1	Sectarian Violence = High AND Police Presence = Low	High	Prioritizes most dangerous combinations
2	Sectarian Violence = High AND Police Presence = Adequate	Medium	Police partially mitigates violence

Figure 10 Features Importance Analysis.

3	Sectarian Violence = High AND Police Presence = High	Medium-Low	Strong deployment lowers risk
4	Police Presence = Low AND Unemployment = High	High	Socioeconomic deprivation + weak deterrence
5	Narcotics Activity = High	High	Single factor sufficient for high risk
6	Narcotics Activity = Medium AND Sectarian Violence = High	High	Combinatorial escalation
7	Unemployment = Medium AND Gang Activity = High	Medium-High	Gang activity amplifies socioeconomic stress
8	Police Presence = Adequate AND Sectarian Violence = Medium	Medium	Transitional risk
9	Police Presence = High AND Unemployment = Low	Low	Reflects strong deterrence and stability
10	Police Presence = High AND Narcotics = Low	Low	Controlled environment
11	Unemployment = High AND Police Presence = High	Medium	Mitigation but not full prevention
12	Gang Activity = Medium AND Police Presence = Low	Medium-High	Policing gap raises risk
13	Sectarian = Low AND Unemployment = Low	Low	Stable conditions
14	Sectarian = Medium AND Narcotics = Medium	Medium	Intermediate uncertainty
15	Borderline cases (mixed variables)	Low-Medium	For uncertain or transitional contexts

Table 2 presents the fuzzy rule base used for crime risk classification. The rules integrate four key predictors unemployment, police presence, narcotics activity, and sectarian violence into interpretable IF THEN conditions. High-risk scenarios are triggered by combinations such as high sectarian violence with low police presence (Rule 1) or high narcotics activity alone (Rule 5). Medium and low risks emerge from mitigating factors like stronger policing or lower unemployment. Borderline cases are assigned intermediate categories to handle uncertainty. This rule-based structure ensures transparent, expert-validated decision-making while maintaining 93.2% predictive accuracy.

Figure 11 The fuzzy classification of our four main predictive features

A rule-based decision system that uses four input variables, police presence, narcotics activity, unemployment, and sectarian violence, to calculate the crime risk level is graphically represented in Figure 15. Using a sequence of if-then logic rules, such as "IF Sectarian = High AND Police = Low THEN Risk = High," it predicts the corresponding Crime Risk Level, which can be classified as High, Medium, Low, or Low-Medium. The input variables are shown on the left side of the figure, the rules are represented in the center, and the predicted outcome, Crime Risk Level, appears on the right. this kind of diagram is frequently used to illustrate the rationale behind crime risk prediction, explain decision-making based on multiple variables, and provide a clear and understandable model for stakeholders, decision-makers, and researchers

Figure 12 The fuzzy classification of our four main predictive features

5. Limitations and Future Directions

The integration of fuzzy logic and machine learning in this study demonstrates a transparent and adaptable framework for crime prediction in low-resource environments. Unlike black-box models, the inclusion of expert-defined fuzzy rules provides interpretable outputs that law enforcement agencies and policymakers can directly understand. This enhances institutional trust, facilitates adoption, and supports interdepartmental collaboration.

The framework also contributes to operational efficiency by translating socioeconomic and law enforcement indicators into actionable risk scores. Policy simulations showed that targeted resource allocation could reduce murder rates by up to 19.3%. Furthermore, its reliance on publicly available data and lightweight computational design ensures scalability to other regions of Pakistan and comparable low-resource contexts internationally.

5.2 Limitations

Despite these strengths, the study faces notable limitations. The framework relies on partially estimated metrics due to underreporting and inconsistent crime records, a challenge common in developing regions. Although fuzzy-based proportional allocation mitigates this, it cannot fully substitute high-quality, ground-truth data. In addition, the model currently operates on historical batch data without real-time integration from FIR registration APIs or surveillance systems. Data sparsity in areas such as narcotics and transborder crimes also limits the granularity of risk assessments, occasionally distorting predictions.

5.3 Future Work

Future work will extend the framework in three directions:

I. **Type-2 Fuzzy Logic** – to better capture evolving uncertainties in dynamic features such as unemployment and police presence.
II. **Transferability Testing** – applying the framework to other cities, such as Karachi and Peshawar, to test adaptability across diverse sociopolitical contexts.
III. **Real-Time Integration** – incorporating streaming data pipelines through APIs, mobile applications, and participatory sensing platforms to support adaptive and timely decision-making.

Conclusion

This study proposed a hybrid fuzzy–machine learning framework to predict murder crime risk in Quetta Division, Balochistan, addressing challenges of data scarcity, underreporting, and limited interpretability in existing models. By combining fuzzy-based proportional allocation, Fuzzy-Rough Feature Selection (FRFS), and a multi-stage pipeline of KNN clustering, linear regression, and a Fuzzy Inference System (FIS) with 27 expert rules, the model achieved high accuracy (93.2%) while maintaining transparency for law enforcement use.
Results show that unemployment, police presence, and gang activity are the strongest predictors, consistent with criminological theory. Policy simulations demonstrated that aligning interventions with model-defined thresholds could reduce murder rates by up to 19.3%, highlighting the framework's practical utility.
Although developed for Quetta, the approach is scalable to other low-resource regions due to its lightweight design and reliance on publicly available data. Future work will focus on real-time integration and Type-2 fuzzy logic to better handle uncertainty and evolving crime patterns. The framework advances explainable AI in public safety by proving that predictive accuracy and operational transparency can be achieved together, offering law enforcement a practical tool for evidence-based crime prevention.

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