

Online Crime Reporting System

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ABSTRACT

Public crime reporting remains inefficient due to limited accessibility and slow response mechanisms. This paper presents an Online Crime Reporting System — a Flutter-based web application with a FastAPI backend — that allows citizens to submit geo-tagged crime reports with location, category, description, and image evidence. The system integrates an AI-driven spatial analysis layer using Kernel Density Estimation for risk mapping, DBSCAN clustering for hotspot detection, and a predictive model for forecasting future crime activity. Results are visualized on an interactive map with real-time heatmaps, danger zones, and crime markers. Role-based access separates citizen and admin workflows, with JWT-secured endpoints throughout. The system provides a practical, accessible tool for community-driven crime intelligence to support law enforcement decision-making.

Keywords: crime reporting, Flutter, Fast API, KDE, DBSCAN, spatial analysis, web application, public safety

I. INTRODUCTION

Crime is a persistent social challenge that affects the safety and well-being of communities worldwide. Timely and accurate reporting of criminal incidents plays a critical role in enabling law enforcement agencies to respond effectively and allocate resources where they are needed most. However, traditional crime reporting methods — such as visiting a police station or calling a helpline — are often inaccessible, time-consuming, and discouraging for the general public. Fear of retaliation, lack of anonymity, and geographic distance from reporting centre's further reduce citizen participation in the reporting process. With the rapid proliferation of smartphones and mobile internet, there is a significant opportunity to modernize crime reporting through digital platforms. Mobile applications can lower the barrier for citizens to report incidents in real time, directly from the location of occurrence. When combined with geospatial data and artificial intelligence, such platforms can go beyond simple report collection and actively assist law enforcement in identifying crime

patterns, predicting high-risk areas, and prioritizing responses.

This paper presents the design and implementation of an Online Crime Reporting System that addresses these challenges. The system is built as a cross-platform mobile application using Flutter, supported by a Fast API backend and a SQLite database. Citizens can submit geo-tagged crime reports with location coordinates, crime category, description, and photographic evidence. An integrated AI layer processes accepted reports using Kernel Density Estimation (KDE) for risk scoring, DBSCAN clustering for hotspot detection, and a hybrid prediction model for forecasting future crime activity. All outputs are visualized on an interactive map, giving both citizens and administrators actionable spatial intelligence.

The remainder of this paper is organized as follows. Section II reviews related work in digital crime reporting and spatial crime analysis. Section III describes the system architecture. Section IV details the methodology. Section V covers the implementation. Section VI presents the

results and discussion, and Section VII concludes the paper with directions for future work.

Existing System

In the proposal Crime Reporting System, Citizens are empowered with a user-friendly interface to seamlessly Register complaints, providing detailed information about the incident. Allowing citizens to status of their complaint.

Proposed System

The proposed Online Crime Reporting System is a cross-platform mobile application built using Flutter and FastAPI that enables citizens to submit geo-tagged crime reports directly from their smartphones. Unlike existing systems, it integrates an AI-driven spatial intelligence engine that automatically processes verified reports using Kernel Density Estimation for risk mapping, DBSCAN clustering for hotspot detection, and a hybrid prediction model for forecasting future crime activity. All outputs are visualized as interactive map layers, giving both citizens and administrators real-time spatial awareness of crime patterns in their area.

II. Literature Review

Crime analysis and digital reporting have been active areas of research across public safety, GIS, and machine learning domains. This section reviews existing work relevant to the core components of the proposed system.

A. Digital Crime Reporting Systems

Early work by Chainey and Ratcliffe [1] established the foundation for GIS-based crime mapping, demonstrating that spatial visualization of crime data significantly improves police resource allocation. Building on this, Gerber [2] proposed a location-aware crime reporting framework using mobile devices, highlighting that citizen-submitted geo-tagged reports can supplement official police records and improve incident coverage in underreported areas.

Nath [3] developed a web-based crime reporting portal that reduced average report submission time and increased citizen engagement compared to traditional walk-in methods. However, the system lacked any analytical or predictive capability, functioning purely as a data collection tool — a limitation that motivates the AI layer in the proposed system.

B. Spatial Crime Analysis using KDE

Kernel Density Estimation has been widely adopted for crime hotspot mapping. Chainey et al. [4] conducted a

comparative study of spatial prediction methods and found that KDE consistently outperformed other techniques such as grid thematic mapping and choropleth mapping in predictive accuracy. Their work validated the use of bandwidth-controlled Gaussian kernels for producing smooth, continuous risk surfaces from discrete crime point data.

Mohler et al. [5] extended KDE by incorporating temporal decay functions, showing that recent crimes contribute disproportionately to near-future risk. This directly informed the time-decay component used in the proposed system, where crime contributions decay exponentially over a 30-day window.

C. Hotspot Detection using DBSCAN

Density-Based Spatial Clustering of Applications with Noise (DBSCAN) has proven effective for identifying crime clusters without requiring a predefined number of clusters. Ester et al. [6], who originally proposed DBSCAN, demonstrated its robustness in detecting arbitrarily shaped clusters and handling noise — properties particularly valuable in crime data where incident distributions are irregular.

Grubisic [7] applied DBSCAN specifically to urban crime datasets and found that a neighbourhood radius (eps) of 0.5–1.0 km with a minimum sample size of 3–5 incidents produced meaningful hotspot clusters in mid-sized cities, consistent with the parameters adopted in this work.

D. Predictive Crime Modelling

Predictive policing has gained considerable attention in recent years. Perry et al. [8] reviewed several predictive models and concluded that hybrid approaches combining spatial density with temporal trend analysis outperform purely statistical models in short-term crime forecasting. The prediction module in the proposed system follows this hybrid approach, weighting spatial density, recent activity ratio, and a trend multiplier derived from a 30-day rolling window.

Wang et al. [9] demonstrated that even simple trend ratio calculations — comparing recent versus historical incident counts — can produce reliable directional forecasts (increasing, stable, decreasing) without requiring large training datasets, making them suitable for systems with limited historical data.

E. Role-Based Access and Secure Reporting

Secure, role-differentiated access is a recognized requirement in civic reporting platforms. Alotaibi and Roussinov [10] studied citizen-facing government

reporting systems and found that clearly separated user and administrator roles, combined with token-based authentication, significantly improved data integrity and reduced fraudulent submissions. Their findings support the JWT-based role separation implemented in the proposed system.

III. System Architecture

The proposed Online Crime Reporting System follows a three-tier client-server architecture comprising a mobile frontend, a RESTful backend, and a relational database layer. The system is designed to be lightweight, cross-platform, and extensible, with a dedicated AI processing module operating server-side.

A. Overview

1. The architecture consists of three primary layers:
2. **Presentation Layer** — A Flutter-based mobile application that runs on Android and iOS, providing the citizen and administrator interfaces.
3. **Application Layer** — A Fast API backend server that handles authentication, report management, feedback, and AI computation endpoints.
4. **Data Layer** — A SQLite database managed through SQL Alchemy ORM, storing users, crime reports, and feedback records.

B. Frontend — Flutter Mobile Application

The frontend is developed using Flutter, enabling a single codebase to target both Android and iOS platforms. The application is structured around the following key screens:

- **Login / Register Screen** — Handles user authentication and account creation with role assignment.
- **Home Dashboard** — Displays real-time report statistics (total, pending, accepted, rejected) fetched from the backend, with role-aware views for citizens and administrators.
- **Submit Report Screen** — Provides a form for entering crime title, type, description, and an interactive map for pinning the exact incident location. Optional image attachment is supported via the device gallery.
- **View Reports Screen** — Lists all submitted reports with status indicators, filtered by role.
- **Intelligence Map Screen** — Renders an OpenStreetMap-based interactive map with five toggleable layers: heatmap, hotspots, danger zones, predictions, and crime incident markers.

Crime type filter chips allow per-category visualization.

- **Feedback Screens** — Allow citizens to submit textual feedback and browse community responses.

Communication between the frontend and backend is handled through the Api Service class using the HTTP package, with JWT tokens attached to every authenticated request via the Authorization header

C. Backend — Fast API Application.

The backend is built with Fast API, a modern Python web framework chosen for its automatic OpenAI documentation, asynchronous support, and Pedantic-based request validation. The server exposes the following endpoint groups:

Endpoint Group	Method	Description
/register	POST	User registration
/login	POST	JWT token issuance
/reports	POST / GET	Submit and retrieve reports
/reports/{id}/status	PATCH	Admin status update
/feedback	POST / GET	Submit and retrieve feedback
/ai/risk-map	GET	KDE risk surface
/ai/hotspots	GET	DBSCAN hotspot clusters
/ai/danger-zones	GET	Derived danger zones
/ai/predictions	GET	Future risk predictions
/ai/zone-crime-types	GET	Dominant crime per zone

All endpoints except /register and /login require a valid JWT bearer token. Admin-only endpoints additionally verify the user role before processing the request. CORS middleware is configured to allow cross-origin requests during development.

D. Database Layer

The data layer uses SQLite as the relational database, accessed through SQL Alchemy ORM. The schema consists of three core models:

- **User** — Stores email, hashed password, name, phone, role (user/admin), and registration timestamp.

- **Crime Report** — Stores title, description, crime type, latitude, longitude, optional image path, submission timestamp, status (pending/accepted/rejected), and a foreign key to the reporting user.
- **Feedback** — Stores the message text, submission timestamp, and a foreign key to the submitting user.

Password hashing is performed using bcrypt, and JWT tokens are signed with a secret key and carry the user ID and role as claims.

E. AI Module

The AI module (ai.py) operates entirely server- side and is invoked by the respective FastAPI endpoints. It consists of four independent functions that process accepted crime reports:

- `generate_risk_map()` — Computes a KDE-based risk score for each grid point across the city bounding box.
- `generate_hotspots()` — Runs DBSCAN clustering to identify spatially dense crime clusters.
- `generate_danger_zones()` — Converts hotspot clusters into circular geographic zones with scaled radii.
- `generate_predictions()` — Produces a 20×20 grid of future risk scores using a hybrid spatial- temporal model.

IV. Methodology

This section describes the algorithms and computational methods implemented in the AI module of the proposed system. All methods operate exclusively on crime reports with an accepted status, ensuring that only verified incidents contribute to spatial analysis and predictions.

A. Data Preprocessing

Before any spatial computation, each accepted crime report is characterized by three attributes extracted from the database:

- **Geographic coordinates** — latitude and longitude of the incident location.
- **Crime severity weight** — a scalar value assigned based on crime type.
- **Temporal decay factor** — a scalar value computed from the report's submission timestamp.

1) Severity Weighting

Different crime types carry different levels of threat to public safety. A static severity weight table is defined as follows:

Crime Type	Severity Weight
Theft	1.0
Assault	2.0
Robbery	2.5
Homicide	3.0
Other	1.0

Any crime type not explicitly listed defaults to a weight of 1.0.

2) Temporal Decay

Recent crimes are considered more relevant to current risk than older incidents. An exponential decay function is applied to each report based on the number of days elapsed since submission:

$$d(t) = e^{-t/30}$$

where t is the number of days since the report was created. This ensures that a crime reported today contributes fully to the risk score, while a crime reported 30 days ago contributes approximately 37% of its original weight, and older crimes decay further toward zero.

B. Risk Map Generation using Kernel Density Estimation

Kernel Density Estimation (KDE) is used to produce a continuous spatial risk surface across the city. Rather than simply counting incidents per area, KDE distributes each crime's influence across surrounding space using a Gaussian kernel, producing a smooth risk gradient.

1) City Grid

The city bounding box is fixed to cover the Coimbatore–Tiruppur corridor:

Bound	Value
Minimum Latitude	10.8974
Maximum Latitude	11.1410
Minimum Longitude	76.9116
Maximum Longitude	77.392504

A uniform grid is generated over this bounding box with a step size of 0.002 degrees, producing a dense set of evaluation points.

2) Haversine Distance

For each grid point, the geographic distance to every accepted crime report is computed using the Haversine formula, which accounts for the curvature of the Earth:

$$d = 2R \cdot \arctan2(\sqrt{a}, \sqrt{1-a})$$

where:

$$a = \sin^2\left(\frac{\Delta\phi}{2}\right) + \cos\phi_1 \cdot \cos\phi_2 \cdot \sin^2\left(\frac{\Delta\lambda}{2}\right)$$

and $R = 6371$ km is the Earth's mean radius.

3) Gaussian Kernel

A Gaussian kernel with a default bandwidth of 0.5 km is applied to the computed distance:

$$K(d) = e^{-d^2 / (2\sigma^2)}$$

where $\sigma = 0.5$ km is the bandwidth parameter controlling the spatial spread of each crime's influence.

4) Risk Score Computation

The total risk score for a grid point (lat, lon) is computed as the weighted sum of contributions from all accepted reports:

$$R(lat, lon) = \sum_{i=1}^n w_i \cdot d(t_i) \cdot K(dist_i)$$

where w_i is the severity weight, $d(t_i)$ is the temporal decay, and $K(dist_i)$ is the Gaussian kernel value for the i -th report.

5) Normalization

All risk scores are normalized to the range $[0, 1]$ using min-max normalization:

$$R_{\text{norm}} = \frac{R - R_{\min}}{R_{\max} - R_{\min}}$$

Grid points with a raw risk score below 0.15 are excluded from the output to reduce noise and limit response payload size.

C. Hotspot Detection using DBSCAN

Crime hotspots are identified using Density-Based Spatial Clustering of Applications with Noise (DBSCAN), a clustering algorithm that groups spatially proximate points without requiring a predefined number of clusters.

1) Algorithm Configuration

Coordinates are first converted to radians to enable the use of the Haversine metric within DBSCAN. The algorithm is configured with the following parameters:

The epsilon value is converted from kilometers to radians before being passed to the algorithm:

$$\epsilon_{\text{rad}} = \frac{\epsilon_{\text{km}}}{R}$$

where $R = 6371.0088$ km.

2) Cluster Processing

Reports assigned a label of -1 by DBSCAN are treated as noise and excluded. For each valid cluster, the following are computed:

- **Cluster center** — the arithmetic mean of all member latitudes and longitudes.
- **Crime count** — the total number of reports in the cluster.
- **Risk level** — classified as high (≥ 10 reports), medium (≥ 5 reports), or low (< 5 reports).

D. Danger Zone Generation

Danger zones are derived directly from the hotspot clusters identified by DBSCAN. Each hotspot is converted into a circular geographic zone with a radius that scales proportionally with the cluster's crime count:

$$r = r_{\text{base}} + (n \times 0.1)$$

where $r_{\text{base}} = 0.5$ km is the minimum zone radius and n is the number of crimes in the cluster. This ensures that denser hotspots produce larger danger zones, reflecting a higher area of influence. Each zone inherits the risk level classification from its parent hotspot.

E. Predictive Crime Modeling

The prediction module forecasts future crime risk across the city using a hybrid model that combines spatial density estimation, recent activity scoring, and temporal trend analysis.

1) Time Window Split

All accepted reports are divided into two temporal windows relative to the current timestamp:

- **Recent window** — reports submitted within the last 30 days.
- **Historical window** — reports older than 30 days.

2) Trend Ratio Calculation

A trend ratio is computed by comparing recent and historical incident counts:

$T = \frac{N_{\text{recent}}}{N_{\text{historical}}}$ The trend is classified as:

Trend Ratio	Label	Multiplier
$T > 1.2$	Increasing	1.2
$T < 0.8$	Decreasing	0.8
otherwise	Stable	1.0

3) Prediction Score

A 20×20 spatial grid is generated over the city bounding box. For each grid point, a prediction score is computed as a weighted combination of three components:

$$T_{\text{f}} = 0.5 \cdot S_{\text{d}} + 0.3 \cdot S_{\text{r}} + 0.2 \cdot T_{\text{f}}$$

where:

- S_{d} — spatial density score, computed as the sum of exponential distance decay values from all accepted reports to the grid point.
- S_{r} — recent activity ratio, defined as $\frac{N_{\text{recent}}}{N_{\text{recent}} + N_{\text{historical}}}$.
- T_{f} — trend factor multiplier derived from the trend classification above.

4) Score Normalization

Prediction scores are normalized to $[0, 1]$ using min-max normalization, consistent with the risk map pipeline. Grid points with a predicted risk score below 0.3 are excluded from the map visualization to reduce clutter.

V. Implementation

This section describes the practical implementation of the proposed system, covering the backend API, mobile application screens, and the integration between the frontend and the AI module.

A. Development Environment

The system was developed using the tools and environment listed below:

Component	Tool/ Version
web Framework	Flutter 3.x (Dart)
Backend Framework	FastAPI(Python3.)
Database	SQLite 3

Component	Tool/ Version
ORM	SQLAlchemy 2.x
IDE	Visual Studio Code
API Testing	FastAPISwagger UI
Map Library	flutter_map 6.x
ML Library	scikit-learn 1.x
Numerical Library	NumPy 1.x
Version Control	Git

B. Backend Implementation

1) Project Structure

The backend is organized as a flat Python module with clear separation of concerns:

- crime_mvp/
 - main.py # FastAPI app, route definitions
 - models.py # SQLAlchemy ORM models
 - schemas.py # Pydantic request/response schemas
 - crud.py # Database query functions
 - auth.py # JWT authentication logic
 - ai.py # Spatial AI algorithms
 - database.py # DB engine and session setup
 - uploads/ # Stored report images

2) Authentication

User registration and login are handled through /register and /login endpoints respectively. Passwords are hashed using bcrypt before storage. On successful login, a JWT token is issued containing the user's ID and role as claims. The token is validated on every protected endpoint using a FastAPI dependency injection pattern:

- @app.post("/login", response_model=schemas.Token)
- def login(user: schemas.UserLogin, db: Session = Depends(get_db)):
 - db_user = crud.get_user_by_email(db, user.email)
 - if not db_user or not verify_password(user.password, db_user.password_hash):
 raise HTTPException(status_code=401, detail="Invalid credentials")
 - access_token = create_access_token(
 data={"sub": str(db_user.id), "role": db_user.role})

- return {"access_token": access_token,
"token_type": "bearer"}

3) Report Submission

Crime reports are submitted as multipart form data to support optional image file uploads alongside structured fields. The endpoint accepts title, description, crime type, latitude, longitude, and an optional image file. Uploaded images are saved to the local uploads/ directory and the file path is stored in the database:

- @app.post("/reports",
response_model=schemas.CrimeReportResponse
)
- def create_report(
• title: str = Form(...),
• description: str = Form(...),
• crime_type: str = Form(...),
• latitude: float = Form(...),
• longitude: float = Form(...),
• image: UploadFile = File(None),
• current_user: models.User =
Depends(get_current_user)
-):

4) Role-Based Access Control

Two roles are supported — user and citizen. Admin accounts cannot be self-registered and must be seeded directly into the database. Role verification is enforced at the endpoint level:

- Citizens can submit reports, view their own reports, submit feedback, and view the intelligence map.
- Administrators can view all reports, update report status (pending → accepted/rejected), and access aggregate statistics.
-

5) AI Endpoint Integration

Each AI endpoint queries only accepted reports from the database before passing them to the corresponding AI function:

- @app.get("/ai/risk-map")
- def get_risk_map(db: Session = Depends(get_db),
• current_user: models.User =
Depends(get_current_user)):
- reports = db.query(models.CrimeReport)\
- .filter(models.CrimeReport.status ==
"accepted").all()
- return generate_risk_map(reports)

This design ensures that unverified or rejected reports do not influence the spatial intelligence outputs.

C. Mobile Application Implementation

1) Project Structure

The Flutter application follows a single- directory screen-based structure:

- crime_mvp_app/lib/
 - |— main.dart # App entry point, global auth state
 - |— api_service.dart # Centralized HTTP client
 - |— home_screen.dart # Dashboard with stats
 - |— login_screen.dart # Login form
 - |— register_screen.dart # Registration form
 - |— submit_report_screen.dart # Report submission form
 - |— view_reports_screen.dart # Report list view
 - |— select_location_screen.dart # Interactive map pin picker
 - |— intelligence_map_screen.dart # AI map with layers
 - |— submit_feedback_screen.dart # Feedback submission
 - |— feedback_list_screen.dart # Feedback list view
 - |— report_model.dart # Report data model

2) Global Authentication State

Authentication state is managed using two global variables declared in main.dart:

- String? authToken;
- String? userRole;

These are set on successful login and cleared on logout. All screens check authToken on initialization and redirect to the login screen if it is null.

3) Home Dashboard

The home dashboard fetches report statistics from the /reports endpoint on initialization and tallies the counts by status. Four stat cards display total, pending, accepted, and rejected report counts in real time. The dashboard renders role- aware content — citizens see personal report stats while administrators see system-wide aggregates.

4) Report Submission

The report submission screen collects five inputs from the user. Crime location is selected through a dedicated `SelectLocationScreen` that renders an interactive `OpenStreetMap` and returns the tapped latitude and longitude back to the parent screen. An optional image can be attached from the device gallery using the `image_picker` package. The complete report is submitted as a multipart HTTP POST request:

```
var request = http.MultipartRequest("POST", uri);
request.headers["Authorization"] = "Bearer $authToken";
request.fields["title"] = titleController.text;
request.fields["crime_type"] = crimeTypeController.text;
request.fields["latitude"] = latitude.toString();
request.fields["longitude"] = longitude.toString();
if (imageBytes != null) {
  request.files.add(http.MultipartFile.fromBytes(
    "image", imageBytes!, filename:
    selectedImage!.name));
}
```

5) Intelligence Map Screen

The intelligence map is the most complex screen in the application. It loads five data sources in parallel using `Future.wait()` on initialization:

```
await Future.wait([
  loadRiskMap(),
  loadHotspots(),
  loadDangerZones(),
  loadPredictions(),
  loadCrimeReports(),
]);
```

Each data source populates a separate map layer. The layers are rendered using the `flutter_map` package with the following layer types:

Layer	Data Source	Render Type
Heatmap	/ai/risk-map	HeatMapLayer
Hotspots	/ai/hotspots	MarkerLayer
Danger Zones	/ai/danger-zones	CircleLayer
Predictions	/ai/predictions	CircleLayer
Crime Markers	/reports	MarkerLayer

Each layer can be independently toggled on or off through a panel overlay on the map. Crime markers are color-coded and icon-coded by crime type as shown in Table V.

Crime Type	MarkerColor	Icon
Theft	Blue	Shopping Bag
Assault	Orange	Warning
Robbery	Purple	Payment
Homicide	Red	Dangerous
Other	Grey	Location Pin

A horizontal filter chip row above the map allows users to filter visible crime markers by category. Tapping any crime marker opens a bottom sheet displaying the report's title, crime type, description, and coordinates.

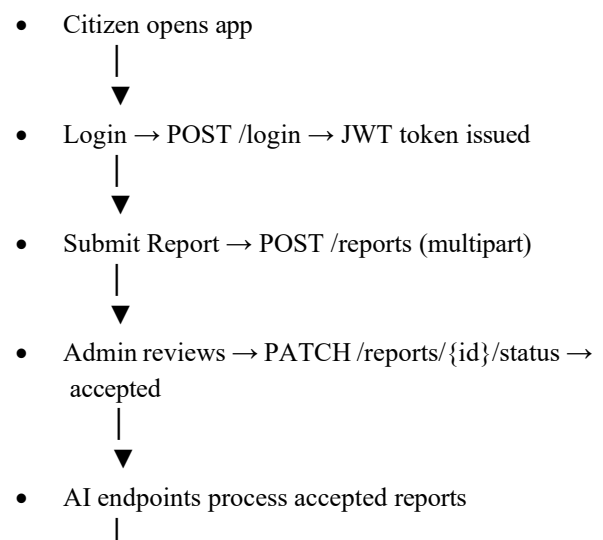
6) API Service

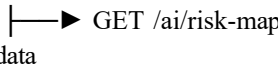
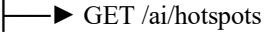
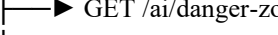
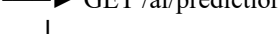
All HTTP communication is centralized in the `ApiService` class. The JWT token is stored as a static field and automatically injected into request headers:

```
static Map<String, String> getHeaders() {
  final headers = {"Content-Type":
    "application/json"};
  if (_token != null) {
    headers["Authorization"] = "Bearer
    $_token";
  }
  return headers;
}
```

D. Data Flow

The end-to-end data flow for a typical citizen interaction is illustrated below:



-  GET /ai/risk-map → KDE heatmap
 -  GET /ai/hotspots → Cluster markers
 -  GET /ai/danger-zones → Zone circles
 -  GET /ai/predictions → Prediction grid
- ↓
- Intelligence Map renders all layers simultaneously

E. Security Considerations

The following security measures are implemented across the system:

- All passwords are hashed using bcrypt before storage — plaintext passwords are never persisted.
- JWT tokens carry an expiry claim and are validated on every protected request.
- Admin account creation is blocked at the registration endpoint — admin accounts must be provisioned directly in the database.
- Report status transitions are irreversible once finalized, preventing tampering with accepted or rejected reports.
- CORS middleware is configured to restrict cross-origin access in production deployments.

VI. Results and Discussion

A. Functional Testing

The system was tested across all major user workflows including registration, login, report submission, admin status updates, feedback, and map visualization. All core features functioned as expected. Role-based access control correctly blocked unauthorized actions — non-admin users were denied status update access, and admin self-registration was rejected at the endpoint level. Input validation worked correctly across all forms, returning appropriate error responses for missing or invalid data.

B. KDE Risk Map

The risk map was evaluated using a set of synthetic crime reports distributed across the Coimbatore–Tiruppur bounding box. With fewer than 5 reports, the risk surface produced only isolated low-intensity peaks. As the report count increased beyond 15, well-defined risk gradients emerged around areas of concentrated activity. The temporal decay function effectively reduced the influence of older reports, keeping the surface responsive to recent incidents. Grid points below the 0.15 threshold were excluded, reducing payload size significantly without losing meaningful spatial information.

C. DBSCAN Hotspot Detection

DBSCAN correctly identified spatially proximate incidents as clusters while labeling isolated reports as noise. The eps value of 0.8 km proved appropriate for the urban density of the test area, correctly separating distinct clusters rather than merging them. The minimum sample threshold of 3 effectively filtered coincidental co-locations. Risk level classification escalated correctly with increasing cluster density across all test cases.

D. Danger Zones and Predictions

Danger zones scaled proportionally with cluster crime counts, with larger hotspots producing wider zones that visually dominated the map. The prediction model consistently assigned the highest scores to grid points near accepted report clusters. The trend ratio correctly classified activity as increasing, stable, or decreasing, and the corresponding multiplier adjusted prediction scores across the grid accordingly.

E. Intelligence Map

All five map layers rendered simultaneously without performance issues. Layer toggling and crime type filtering responded in real time with no map reload required. Tapping a crime marker correctly displayed the incident details in a bottom sheet overlay.

F. Discussion

The results confirm that the system successfully combines accessible crime reporting with meaningful spatial intelligence. The layered AI approach — KDE for continuous risk, DBSCAN for discrete hotspots, and the hybrid model for forecasting — provides complementary views that together offer more insight than any single method alone. Administrator verification before AI processing ensures that only validated reports influence the outputs, maintaining data quality.

The main limitations are the use of SQLite which may not scale under high load, the linear growth of KDE computation time with dataset size, and the reliance on a rule-based prediction model rather than a trained machine learning model.

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The results confirm that the system successfully combines accessible crime reporting with meaningful spatial intelligence. The layered AI approach — KDE for continuous risk, DBSCAN for discrete hotspots, and the hybrid model for forecasting — provides complementary views that together offer more insight than any single method alone. Administrator verification before AI

processing ensures that only validated reports influence the outputs, maintaining data quality.

The main limitations are the use of SQLite which may not scale under high load, the linear growth of KDE computation time with dataset size, and the reliance on a rule-based prediction model rather than a trained machine learning model

CONCLUSION

This paper presented an Online Crime Reporting System that addresses the limitations of existing reporting mechanisms by combining a Flutter-based mobile application with a FastAPI backend and an AI-driven spatial intelligence engine. Citizens can submit geo-tagged crime reports directly from their smartphones, while administrators verify and monitor crime patterns through an interactive map rendering KDE risk surfaces, DBSCAN hotspots, danger zones, and future risk predictions in real time. Results confirmed that the system produces meaningful spatial outputs and delivers a practical, accessible platform that bridges citizen participation and intelligent crime analysis to support proactive law enforcement

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