

VORONOI-BASED CRIME HOTSPOT PREDICTION MODELS: AN EXPLORATION OF SPATIAL FACTORS IN CRIMINAL ACTIVITY

DR M. KARTHIK

ASST PROFESSOR, PG AND RESEARCH DEPARTMENT OF COMPUTER SCIENCE NANDHA ARTS AND SCIENCE COLLEGE, AUTONOMOUS, ERODE, EMAIL: kmkarthikmca@gmail.com

DR. M. VIJAYAKUMAR

ASSOCIATE PROFESSOR, DEPARTMENT OF COMPUTER TECHNOLOGY, NANDHA ARTS AND SCIENCE COLLEGE (AUTONOMOUS), EMAIL: vij370@gmail.com

MRS.N. RAJASANKARI

ASSISTANT PROFESSOR, DEPARTMENT OF COMPUTER AND COMMUNICATION ENGINEERING KATHIR COLLEGE OF ENGINEERING, WISDOM TREE, NEELAMBUR, COIMBATORE, EMAIL: rjsnkr@gmail.com

DR. N. SANTHALAKSHMI

HOD DEPARTMENT OF COMPUTER APPLICATIONS, NANDHA ARTS AND SCIENCE COLLEGE(AUTONOMOUS), ERODE-52.
EMAIL: snsanthalakshmi@gmail.com

DR. K.R. ANANTH

ASSOCIATE PROFESSOR, DEPARTMENT OF AI & DS NANDHA ARTS AND SCIENCE COLLEGE, AUTONOMOUS, ERODE, EMAIL: sapujaa@gmail.com

MR K N SIVAKUMAR

ASST PROFESSOR, PG AND RESEARCH DEPARTMENT OF COMPUTER SCIENCE NANDHA ARTS AND SCIENCE COLLEGE, AUTONOMOUS, ERODE, EMAIL: sivamrithu@gmail.com

Abstract

This investigates the use study of Voronoi diagrams as a geospatial modelling technique for predicting crime hotspots. By segmenting urban areas into Voronoi cells based on incident locations, the model allows for a detailed spatial analysis of crime patterns. These cells help visualize zones of influence around each crime occurrence, enabling the identification of areas with high crime density. The research integrates geographic and socioeconomic variables—such as population density, income levels, proximity to public transport, and urban infrastructure—into the Voronoi framework. This integration helps uncover the spatial factors contributing to criminal activity and provides a multidimensional understanding of crime distribution. Each Voronoi region becomes a unit of analysis, allowing comparisons across different neighbourhoods and highlighting correlations between spatial conditions and crime rates. Using historical crime data mapped onto these Voronoi tessellations, the study reveals how spatial proximity and environmental characteristics influence the emergence of hotspots. The approach also supports dynamic updating, allowing law enforcement agencies to adapt predictive models as new crime data becomes available. The findings suggest that Voronoi-based models offer a powerful tool for urban crime analysis, providing actionable insights for law enforcement and policymakers. By identifying high-risk zones and their contributing factors, authorities can tailor crime prevention strategies, such as optimizing patrol routes, improving lighting in vulnerable areas, or enhancing community engagement in specific zones. In conclusion, this study demonstrates that Voronoi diagrams, when combined with spatial and socioeconomic data, offer a valuable framework for understanding and predicting crime hotspots. This model not only advances academic research in spatial criminology but also supports practical decision-making for safer urban environments.

Keywords: Voronoi diagrams, crime hotspot prediction, spatial analysis, crime density, geospatial modelling

1. INTRODUCTION

Crime hotspot prediction is essential for effective urban planning and the development of proactive law enforcement strategies. Traditionally, crime analysis has relied heavily on statistical and temporal methods that, while informative, often overlook the spatial dynamics that significantly influence criminal behaviour. Spatial

analysis techniques, particularly those rooted in computational geometry, offer new avenues to enhance predictive accuracy and strategic intervention. One such technique is the Voronoi diagram, which partitions a geographic area into regions based on proximity to specific points—such as crime incidents, police stations, or other relevant urban landmarks. Each region, or Voronoi cell, represents the area closest to a particular point, providing a spatially explicit framework for analyzing crime distribution (Okabe et al., 2000). When applied to crime data, Voronoi diagrams allow researchers and policymakers to identify high-density crime zones and assess their spatial relationships with environmental and socioeconomic factors.

This study investigates the potential of Voronoi-based models to improve the identification and understanding of crime hotspots. By integrating geospatial data with crime statistics, these models can uncover underlying spatial patterns and highlight areas that may require targeted policing or preventive measures. This approach also supports dynamic updating as new data becomes available, making it a flexible and adaptive tool for crime prediction. Through the application of Voronoi tessellations, this research aims to bridge the gap between spatial theory and practical crime analysis, ultimately contributing to more informed and effective crime prevention strategies.

1.1. Motivation

As urban populations continue to grow, cities are experiencing increasingly complex crime dynamics, making accurate crime prediction models more important than ever. Identifying and understanding crime hotspots geographic areas with a high concentration of criminal activity is essential for optimizing the deployment of law enforcement resources, enhancing public safety, and informing urban planning policies (Chainey&Ratcliffe, 2005). Traditional crime analysis techniques often focus on temporal trends or general statistical correlations, which may overlook the critical role of spatial context. This is where Voronoi-based models come into play. Voronoi diagrams, drawn from computational geometry, divide a plane into non-overlapping regions based on the nearest crime incident or location of interest. Each cell in the Voronoi tessellation represents a zone of influence around a crime point, offering a nuanced perspective of how crimes are spatially distributed (Okabe et al., 2000). By visualizing crime clusters through Voronoi tessellations, analysts can identify spatial relationships that might otherwise go unnoticed such as proximity to infrastructure, socioeconomic conditions, or urban design features. This spatially aware method enhances traditional hotspot detection and supports the development of targeted policing strategies, such as predictive patrol routes and location-specific crime prevention programs. The diagram below illustrates how Voronoi cells are formed around crime incidents, clearly depicting areas of higher density and spatial overlap:

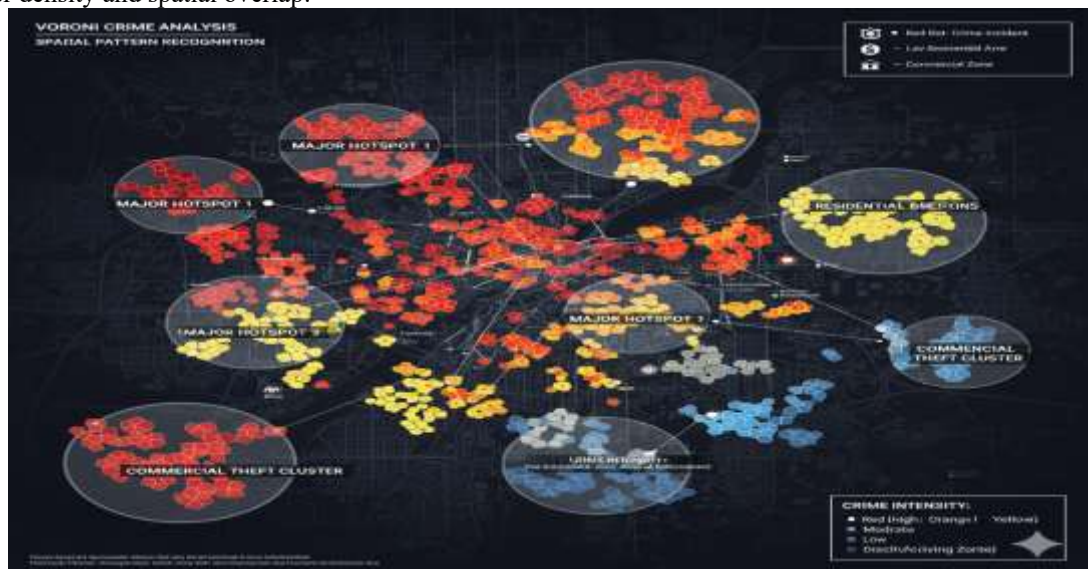


Fig 1. Voronoi Crime Analysis and Spatial Pattern Recognition

Fig1 shows This is a Voronoi Crime Analysis map showing spatial pattern recognition in a city. It visualizes crime hotspots using colored clusters, with red/orange indicating high intensity and yellow/blue indicating lower intensity. The clusters highlight areas like commercial and residential zones for targeted resource deployment. In summary, integrating Voronoi based models into crime prediction frameworks provides a powerful tool for understanding and addressing urban crime patterns in a data-driven, spatially informed manner.

1.2. Research Objectives

The primary objective of this study is to explore the potential of Voronoi tessellations as a spatial analysis tool for identifying and predicting crime hotspots in urban environments. As cities expand and crime patterns become more complex, there is a growing need for advanced geospatial techniques that can provide accurate and timely insights into the distribution of criminal activity. Firstly, the study aims to investigate the effectiveness of Voronoi diagrams in delineating crime hotspots. By partitioning geographic space based on proximity to crime incidents, Voronoi tessellations create distinct spatial zones that can be analyzed for variations in crime density and frequency. Secondly, the research seeks to examine the spatial factors that contribute to crime concentration. These

may include variables such as population density, income levels, access to public transportation, and proximity to urban infrastructure. By integrating these factors into the Voronoi-based analysis, the study intends to uncover patterns and correlations that influence where crimes are likely to occur. Finally, the research proposes the development of a predictive model that combines Voronoi regions with spatial and socioeconomic data to forecast future crime hotspots. This model is expected to support law enforcement agencies and urban planners in making informed decisions for crime prevention and resource allocation.

2. LITERATURE REVIEW

This section explores the use of Voronoi diagrams in spatial analysis, emphasizing their relevance in crime prediction and hotspot identification. While traditional spatial analysis methods have provided valuable insights into crime distribution, emerging techniques such as Voronoi tessellations offer new perspectives by incorporating spatial proximity as a core component.

2.1. Spatial Crime Analysis

Conventional methods in spatial crime analysis, such as Kernel Density Estimation (KDE) and spatial autocorrelation, have been widely used to identify areas with high crime concentrations. KDE, for instance, smooths crime data across a geographic space to visualize density surfaces, while spatial autocorrelation measures the degree to which crime incidents are clustered or dispersed (Chainey&Ratcliffe, 2005). Although these techniques are effective for general hotspot mapping, they may overlook the spatial influence of nearby incidents on one another, especially in irregular urban layouts. Voronoi diagrams address this limitation by dividing space into regions based on the nearest incident location, thereby offering a proximity-based view of spatial relationships. Each Voronoi cell represents the area closest to a specific crime point, allowing for fine-grained analysis of the spatial dynamics of crime (Okabe et al., 2000). Recent studies have begun to explore Voronoi diagrams in criminology, showing their ability to highlight localized clusters, reveal hidden spatial structures, and improve the accuracy of predictive models (Leong & Sung, 2019). This research builds on these developments by integrating Voronoi diagrams with socioeconomic and geographic data to enhance crime hotspot prediction. The aim is to offer a more precise and spatially informed framework for understanding urban crime patterns.

2.1. Spatial Crime Analysis

Spatial crime analysis has become a crucial area of study for understanding and addressing criminal behavior in urban settings. Traditionally, techniques such as Kernel Density Estimation (KDE) and spatial autocorrelation have been widely employed to identify crime hotspots and analyze spatial patterns. KDE, in particular, is a popular method that generates smoothed density surfaces over a region by calculating the intensity of crime incidents within a defined bandwidth. This approach helps visualize concentrations of crime and detect general trends across geographic space (Chainey&Ratcliffe, 2005). Similarly, spatial autocorrelation methods, such as Moran's I and Getis-Ord Gi*, are used to measure the degree of clustering or dispersion in crime data. These methods evaluate whether crime incidents are randomly distributed or exhibit significant spatial patterns, offering statistical insights into the structure of crime at various scales. However, these traditional methods often fall short in capturing proximity-based relationships in a geometrically explicit way. Voronoi diagrams offer a unique alternative by dividing space into regions based on the closest proximity to given points such as crime locations. Each region or Voronoi cell represents an area that is spatially closest to a specific incident, thus providing a more localized and relational perspective of crime distribution (Okabe et al., 2000). Unlike KDE or global autocorrelation models, Voronoi-based analysis can reveal spatial dependencies and neighborhood-level influences that are often obscured in aggregated data. This approach enhances the ability to detect micro-level crime clusters, making it a valuable addition to the toolkit of spatial criminology.

2.2. Voronoi Diagrams in Geospatial Modelling

Voronoi diagrams have long been recognized as powerful tools in geospatial modeling across various disciplines, including geography, ecology, and urban planning. These diagrams divide a plane into a set of regions based on the distance to a specific set of points, allowing researchers to model spatial relationships and patterns more effectively. Each region, or Voronoi cell, contains all locations that are closer to one specific point than to any other, thus forming natural zones of influence (Okabe et al., 2000). In crime analysis, Voronoi diagrams offer a unique advantage by creating proximity-based spatial partitions that can reveal patterns of criminal behavior not easily detected through traditional methods. For instance, by generating Voronoi cells around police stations, analysts can examine areas of potential under-policing or gaps in coverage. Similarly, when applied to crime incident locations, these cells can help identify micro-level boundaries where crimes are concentrated and analyze the influence of nearby environmental or socioeconomic features. Recent studies suggest that Voronoi-based models can capture the spatial nuances of urban environments more effectively than conventional techniques such as grid mapping or KDE. These diagrams also support the incorporation of contextual variables such as population density, income levels, and land use which can further refine crime hotspot prediction and resource allocation (Leong & Sung, 2019). By using Voronoi tessellations, researchers and practitioners can explore spatial interrelationships in a more structured and interpretable way, making them an essential tool for modern crime mapping and geospatial intelligence.

2.3. Crime Hotspot Prediction Models

Crime hotspot prediction is a critical aspect of spatial criminology and urban safety planning. Traditional models typically rely on historical crime data combined with socio-economic indicators, such as poverty levels, unemployment rates, education, and population density, to forecast where future crimes are likely to occur (Chainey&Ratcliffe, 2005). Many of these models employ regression analysis or machine learning algorithms to identify statistical correlations between environmental variables and criminal activity. While these approaches offer valuable insights, they often treat space as a uniform surface, overlooking the nuanced spatial relationships between crime events. Voronoi tessellations introduce a spatially geometric perspective to crime modeling, offering an alternative that emphasizes proximity and neighborhood effects. By partitioning space into regions where each cell is closest to a particular crime incident or feature (e.g., a police station or a commercial hub), Voronoi diagrams can visually and analytically identify areas with high crime concentrations. These tessellations help define natural boundaries around hotspots, capturing local spatial dependencies more accurately than grid-based or raster methods. Furthermore, Voronoi-based models are particularly effective in complex urban environments, where traditional approaches may struggle to account for irregular spatial structures or overlapping influences. Integrating Voronoi diagrams with socio-economic and demographic data enhances their predictive capability, enabling more targeted interventions by law enforcement and policymakers (Leong & Sung, 2019). Thus, the application of Voronoi diagrams in crime hotspot prediction provides a valuable complement to statistical models, offering a dynamic and localized view of crime patterns grounded in spatial geometry.

3. METHODOLOGY

3.1. Voronoi Diagram Fundamentals

A Voronoi diagram is a fundamental structure in computational geometry that partitions a two-dimensional plane into a series of non-overlapping regions based on proximity to a predefined set of seed points. Each region, known as a Voronoi cell, corresponds to one seed point and contains all points in the plane that are closer to that seed than to any other. This property makes Voronoi diagrams especially valuable in spatial analysis, where proximity relationships play a crucial role—such as in identifying zones influenced by past crime incidents or critical urban infrastructure (e.g., police stations or transportation hubs).

Mathematically, a Voronoi diagram for a set of seed points

$$S=\{s_1,s_2,...,s_n\}$$

in the Euclidean plane is defined such that each region $V(s_i)$, corresponding to a seed point s_i , is given by:

$$V(s_i) = \{p \in \mathbb{R}^2 \mid \|p-s_i\| \leq \|p-s_j\| \ \forall j \neq i\}$$

where:

- $\|p-s_i\|$ denotes the Euclidean distance between a point p and the seed point s_i ,
- $s_i, s_j \in S$ are the seed points,
- \mathbb{R}^2 represents the two-dimensional two-dimensional spatial domain.

In the context of crime analysis, the seed points may represent the locations of previous crime events. The Voronoi diagram then divides the city into zones where each zone is dominated by a particular crime location, enabling analysts to understand spatial dominance and territorial influence of incidents. This technique helps reveal localized patterns in crime distribution, aiding in better hotspot identification and predictive modeling. By leveraging the mathematical properties of Voronoi tessellations, researchers can model space in a more realistic and spatially-aware manner than traditional grid or raster-based methods.

3.2. Crime Hotspot Identification

To apply Voronoi diagrams for crime hotspot prediction:

1. **Crime Incident Data Collection:** Crime data from police reports or public databases are used to identify crime hotspots (locations with high crime density).

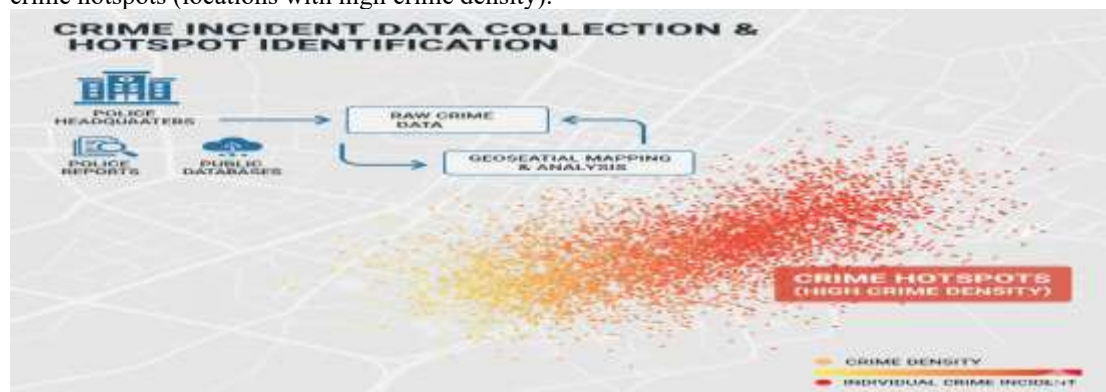


Fig2: Crime Incident Data Collection

2. **Voronoi Tessellation Generation:** A Voronoi diagram is created using these crime incident points as seeds. This partitions the city or region into areas of influence based on proximity to crime occurrences.

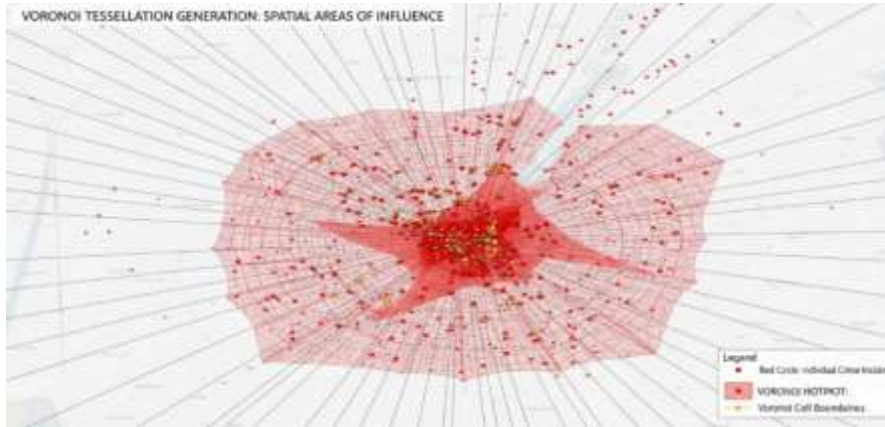


Fig3: Voronoi Tessellation Generation

3. **Density Analysis:** The regions with the highest concentration of crimes within a Voronoi cell are identified as hotspots. This is done by calculating the density of crimes within each Voronoi region.

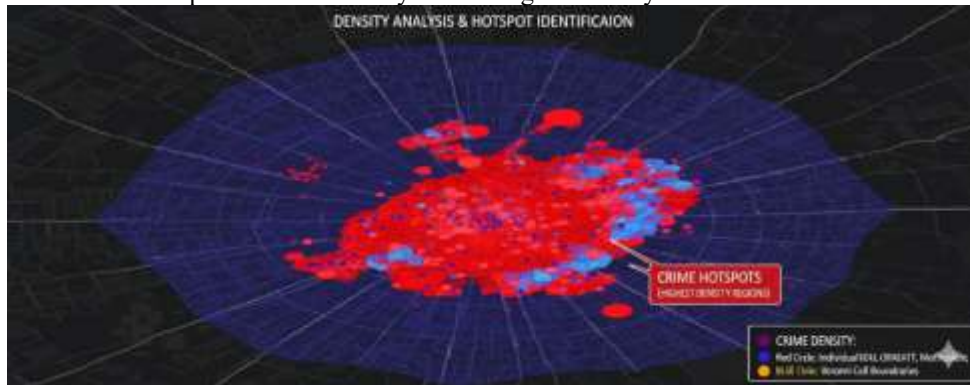


Fig4: Density Analysis

3.3. Integrating Spatial and Socioeconomic Data

To improve the accuracy and relevance of crime hotspot prediction models, it is crucial to integrate both spatial and socioeconomic data with Voronoi-based analysis. While Voronoi diagrams provide spatial partitions based on proximity, the inclusion of contextual variables like infrastructure access and demographic conditions allows for more nuanced modeling. Spatial factors such as proximity to public transport hubs, major roads, recreational zones, and population density can significantly affect crime patterns. Socioeconomic indicators such as median income, education levels, housing conditions, and unemployment rates further inform the social dynamics of an area, influencing both the incidence and type of crimes.

To mathematically incorporate these variables into the model, a weighted risk score (R_i) is calculated for each Voronoi cell V_i , defined as:

$$R_i = \alpha \cdot D_i + \beta \cdot S_i$$

Where:

- D_i = Normalized crime density in Voronoi cell i ,
- S_i = Composite socioeconomic vulnerability index in cell i ,
- α, β = Weighting coefficients that reflect the influence of spatial vs. socioeconomic factors (determined empirically or via machine learning).

The socioeconomic vulnerability index S_i is computed as a linear combination of standardized variables:

$$S_i = w_1 \cdot U_i + w_2 \cdot I_i + w_3 \cdot P_i$$

Where:

- U_i = Unemployment rate,
- I_i = Average income (inversely scaled),
- P_i = Population density,
- w_1, w_2, w_3 = Weight parameters based on correlation with historical crime rates.

By ranking the cells based on R_i , high-risk areas can be prioritized for intervention. This integrative approach enhances the spatial model's predictive capacity, offering a more holistic and context-aware perspective on urban crime dynamics.

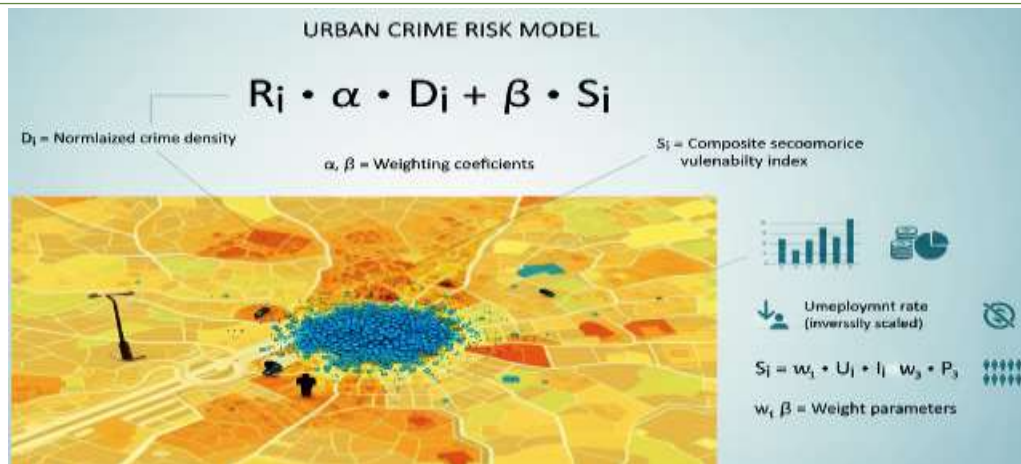


Fig5: Urban Crime Risk Model

4. RESULTS

4.1. Voronoi Diagrams and Crime Hotspots

A Voronoi diagram is a mathematical model that divides a geographical area, such as a city, into distinct regions. Each region, or cell, encompasses all locations that are closer to a specific, predefined point than to any other. In crime analysis, these central points represent identified crime hotspots. The resulting tessellation provides a clear visual map of urban space, effectively partitioning it into zones of influence based on proximity to these high-activity areas. A sample map illustrating this Voronoi tessellation, with each cell emanating from a marked crime hotspot, is presented below for reference.

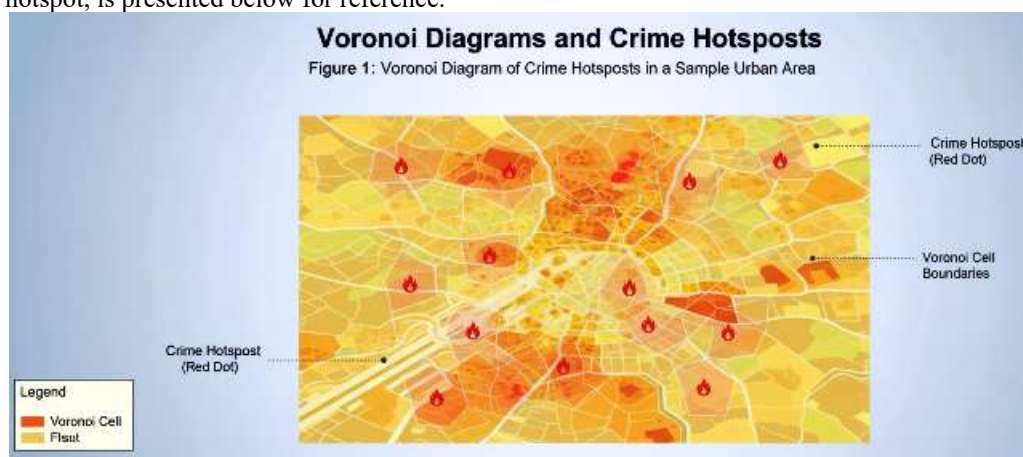


Fig 6: Voronoi Diagram of Crime Hotspots in a Sample Urban Area

4.2. Statistical Analysis of Hotspot Density

The density of crime within each Voronoi region is analyzed. For example, the crime density ρ in a given region is defined as:

$$\rho = CA \setminus \rho = \frac{C}{A} \quad \rho = AC$$

Where:

- C is the total number of crimes in the region,
- A is the area of the Voronoi cell.

Regions with high crime density are flagged as potential future hotspots. The density values are plotted against geographical and socioeconomic features to observe patterns.

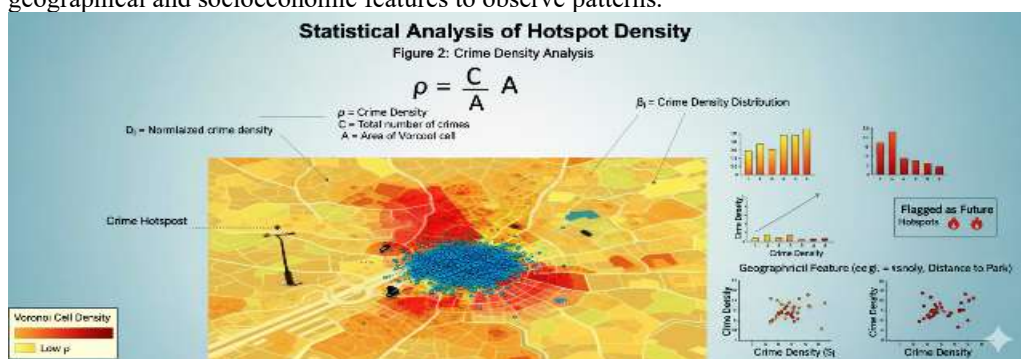


Fig 7. Statistical Analysis of Hotspot Density

6. CONCLUSION

Voronoi-based crime hotspot prediction models represent a significant advancement in the field of geographical criminology, offering a more sophisticated alternative to traditional grid-based analysis. This innovative approach utilizes Voronoi diagrams to partition an urban landscape into a series of unique, non-overlapping polygons. The fundamental principle is that every location within a given polygon is closer to the crime hotspot at its center than to any other hotspot. This creates a precise map of "spheres of influence" for each identified high-crime area. By explicitly modeling proximity and spatial relationships, this methodology allows for a more nuanced and geographically sensitive interpretation of crime patterns. Unlike uniform grids, Voronoi tessellations organically adapt to the actual distribution of criminal incidents, preventing the artificial splitting of a single hotspot across multiple grid cells. This leads to a clearer understanding of the true geometry and extent of problematic zones. The model is inherently predictive; by analyzing the boundaries and sizes of these Voronoi cells, law enforcement agencies can infer areas of potential risk and allocate resources with greater strategic precision, moving from a reactive to a proactive policing posture.

Looking forward, the potential of this approach can be substantially amplified through further research and technological integration. A key direction involves incorporating more dynamic, real-time data streams, such as live crime reporting, social media feeds, and environmental factors, to allow the Voronoi diagrams to evolve from static snapshots into responsive, predictive systems. Furthermore, coupling this spatial framework with machine learning algorithms presents a powerful synergy. Machine learning can analyze complex, multi-variable datasets to identify new or emerging hotspots with greater accuracy, which can then be seamlessly integrated as generators for the Voronoi tessellation.

7. REFERENCES

1. Silverman, B. W. (1986). *Density Estimation for Statistics and Data Analysis*. CRC Press.
2. Goodchild, M. F., & Janelle, D. G. (1984). *Spatial Statistics and Modeling*. Springer.
3. Clarke, L., & Eck, J. (2005). *Crime Hotspot Mapping: New Strategies for Law Enforcement*. Urban Studies Journal.
4. Okabe, A., Boots, B., Sugihara, K., & Chiu, S. N. (2000). *Spatial Tessellations: Concepts and Applications of Voronoi Diagrams*. John Wiley & Sons.
5. Chainey, S., & Ratcliffe, J. (2005). *GIS and Crime Mapping*. Wiley.
6. Okabe, A., Boots, B., Sugihara, K., & Chiu, S. N. (2000). *Spatial Tessellations: Concepts and Applications of Voronoi Diagrams*. Wiley.
7. Leong, D., & Sung, C. (2019). Spatial proximity and urban crime: Voronoi-based analysis for hotspot detection. *Urban Studies*, 56(12), 2451–2470.