A Machine Learning Framework for Ranking Cities Considering Crimes Against Women: A Case Study in Northeast Brazil

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Abstract. *Violence against women is a profound infringement of human rights and stands as one of the most severe public health issues globally. It is comprehensively defined as any act of physical, sexual, psychological, or property-based violence perpetrated against a woman, constituting behaviour that transgresses women's dignity, rights, and freedom. In this context, this study introduces a machine learning model aimed at classifying cities based on the potential prevalence of violence against women. The model is trained utilizing a comprehensive city database, generating classifications of cities into three levels: low, medium, and high violence. The chosen algorithm, ExtraTrees, demonstrated a noteworthy accuracy rate of 90%.*

1. Introduction

Violence against women represents a grave societal issue that transcends boundaries of social status, race, religion, and age, manifesting in various forms such as physical, sexual, psychological, economic abuse, and domestic violence. These manifestations find their roots in a patriarchal culture that reinforces gender inequality and discrimination against women [MINISTÉRIO PÚBLICO, 2022]

Addressing this issue is imperative for the well-being and safety of women, necessitating concrete actions by governments. These actions include the formulation of laws and policies criminalizing violence against women, alongside the implementation of awareness and education programs aimed at dismantling the patriarchal culture. Equally important is ensuring that victims have access to essential services like health support, legal assistance, and psychological counselling [BRASIL, 2021 & MINISTÉRIO PÚBLICO, 2022].

Concerning Brazil, violence against women constitutes a multifaceted challenge that demands a comprehensive and in-depth approach. This issue is supported by statistics highlighting cases of physical, sexual, and psychological aggression. Data indicates that gender-based violence persists across various sectors of society, transcending social classes and affecting women of all ages and backgrounds. In this context, technology emerges as a crucial ally, facilitating connections between women in distress and support resources. Additionally, technology can disseminate messages about violence against women, educating individuals about their rights and responsibilities [DE LIMA, 2017].

In this context, it becomes important to identify the most affected neighborhoods. This assessment allows for the development of effective prevention and intervention strategies, considering the specific characteristics of each community. Statistical data reveals an alarming reality, showcasing the frequency and severity of cases of physical, sexual, and psychological aggression in different areas of the country.

By identifying local patterns, a more efficient allocation of governmental resources, NGOs (non governmental organizations), and other entities involved in promoting gender equality and protecting women becomes possible. This personalized approach enables the development of strategies adapted to the specific needs of each neighborhood, ranging from awareness programs to intensified security measures.

Assessing neighborhoods with higher risk not only directs resources but also promotes community engagement. Actively involving affected communities can create synergy that strengthens prevention initiatives. Continuous monitoring and constant evaluation of adopted strategies ensure necessary adjustments and improvements in intervention effectiveness. Furthermore, by disseminating information about neighborhoods with higher violence rates, public awareness is enhanced. This awareness can trigger a shift in attitudes, fostering community vigilance and promoting a culture that does not tolerate gender-based violence.

The integration of data from various sources is fundamental in this process. Collaboration between government agencies, non-governmental organizations, and other stakeholders is essential to comprehensively address violence against women, considering social, cultural, and economic factors.

Therefore, assessing neighborhoods with a higher risk of violence against women not only reveals the extent of the problem but also provides a solid foundation for the implementation of specific and effective measures. This integrated approach aims to create safer communities, promoting gender equality, and combating the violence that affects so many women in our country.

Amid the integration of new technologies, machine learning has gained prominence in combating violence against women. Its capacity for early identification of potential risk scenarios allows for preventive measures before violence occurs. Through data analysis, machine learning enhances our understanding of factors associated with violence against women, enabling the development of effective solutions. Given the region's high incidence of diverse forms of violence against women, preventive actions are paramount.

This paper proposes a machine learning model designed to classify cities based on their vulnerability to violence against women. Leveraging various data sources, including official public safety records, demographic and health data, and unstructured data from social networks, the model categorizes cities as high risk, medium risk, or low risk. Thus, the model becomes a valuable decision-making tool for formulating targeted strategies to mitigate violence against women in each city.

The article is structured as follows: Section 2 provides the background and context for the study, including a review of relevant literature and data sources. Section 3 details the machine learning model employed, including data preprocessing. Section 4 presents the results of the analysis, including performance metrics and city classification outcomes. Finally, Section 5 offers the conclusions, discusses the implications of the findings, and suggests directions for future research.

2. Background

The application of ML in public safety extends to the detection and prevention of violence against women, a pressing societal issue with deep-rooted historical, cultural, sociological, economic, legal, and political implications. Violence against women is a complex phenomenon influenced by gender inequality, social norms, economic disparity, and systemic discrimination. Understanding these factors is crucial for developing ML models that can effectively identify and mitigate such violence [MOHRI *et al*., 2018].

Machine Learning (ML) is a discipline focused on the scientific exploration of algorithms and computational models that leverage historical data to enhance performance in specific tasks or achieve accurate predictions. This historical data, whether identified by humans or collected through interactions with the environment, forms the foundation for ML advancements These algorithms aim to discern underlying patterns, relationships, or structures within datasets, subsequently facilitating informed decision-making, prediction, or pattern recognition [MOHRI *et al*., 2018].

The literature extensively delves into ML applications, notably in the realm of public safety. For instance, introduced an approach utilizing Support Vector Machines (SVM) to discern whether a human action captured in a video is violent. This involved employing input features derived from key points, including angles, speed, and contact detection, to investigate the efficacy of recognizing violent video behaviour [NOVA *et al*., 2019].

In another study, Alves (2018) adopted the random forest algorithm to predict and quantify the number of homicides based on urban criminal indicators. The model demonstrated a remarkable accuracy of up to 97%, with explained variance. Similarly utilizing the random forest algorithm, [Bowen *et al*., 2018] endeavored to predict areas characterized by heightened interpersonal violence, considering diverse data sources such as homicide, assault, rape, and robbery.

Addressing specific criminal activities, [Li *et al*., 2019] proposed an approach for detecting serial theft crimes by comprehending the offender's modus operandi through the integration of information from criminal case files. Employing five ML algorithms, this method aimed to classify cases and distinguish between serial and non-serial offenses, thereby enhancing police station efficiency and public safety. In a different context, [Toppi, *et al*., 2018] utilized ML algorithms to classify potential crimes in specific locations, while [Lima *et al*., 2020] identified security workers prone to long-term absenteeism, employing Support Vector Machine (SVM) and Artificial Neural Networks (ANN). These diverse applications underscore the versatility of ML in optimizing public safety measures.

Taking into consideration the studies above, ML has also proven valuable in identifying and preventing violence against women, a pervasive issue with profound social, cultural, economic, legal, and political implications. Violence against women is deeply rooted in historical and structural inequalities, shaped by cultural norms, economic conditions, and legal frameworks. The integration of ML with sociological and historical data allows researchers to uncover patterns that might otherwise remain unnoticed, aiding in the early identification of at-risk individuals and communities.

3. Machine Learning Model (MLM)

The model proposed in this study is underpinned by the novel hybrid data analysis methodology introduced by [Turet & Costa, 2022]. This innovative approach enables comprehensive examination of vast datasets comprising both structured and unstructured data. Our dataset encompasses diverse information aggregated from governmental authorities and social media platforms, notably Twitter. It encompasses a spectrum of data types, including but not limited to the characterization of criminal activities within localities, the intricacies of criminal participation, community response mechanisms, and pertinent educational indicators. The model has four distinct stages, as delineated in Figure 1.

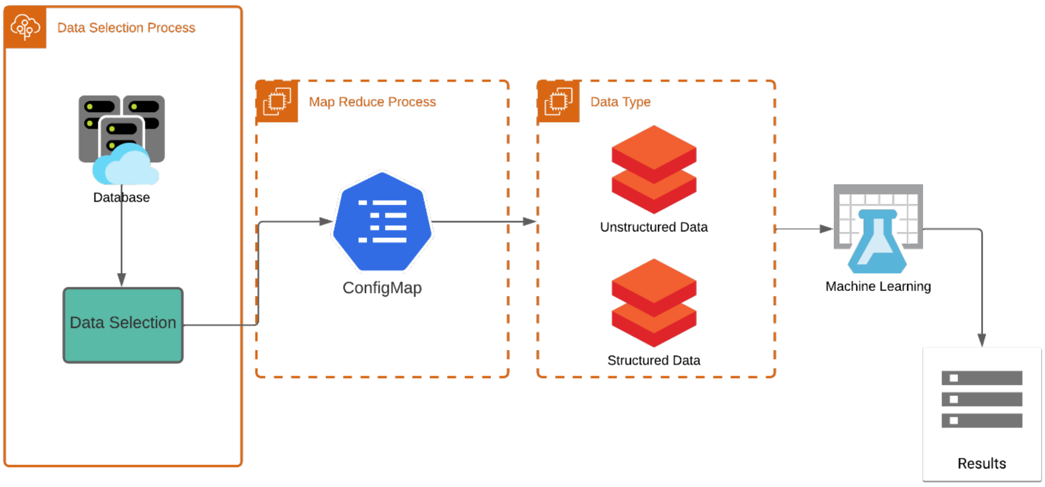

Figure 1: Machine Learning Model

Data Selection Process: The initial phase of the study involves meticulous scrutiny of the associated database, encompassing verification procedures to ensure data integrity, as well as an assessment of data types prevalent within the repository. This preliminary analysis aims to delineate between structured and unstructured data components, laying the groundwork for subsequent analytical endeavours.

MapReduce Process: The MapReduce framework assumes a pivotal role in the data processing pipeline, orchestrating the exploration of intricate data structures to discern underlying patterns while concurrently streamlining data manipulation operations. Primarily, the MapReduce paradigm operates by partitioning the dataset into manageable segments, employing parallelized computation techniques to facilitate pattern identification, and subsequently aggregating results to effectuate database optimization.

Data Type: The heterogeneous nature of data necessitates tailored analytical methodologies to extract meaningful insights effectively. Structured data, characterized by well-defined schemas, lends itself to conventional extraction and analysis techniques, leveraging standardized data measurement scripts for processing. Conversely, unstructured data poses a unique set of challenges, requiring a systematic approach to decipher latent patterns and transform raw information into structured formats. Herein, the hybrid methodology advanced by Turet and Costa (2022) assumes prominence, delineating a logical sequence of analytical procedures aimed at synthesizing unstructured data into a cohesive, structured repository.

Machine Learning Integration and Results: Building upon the foundation of meticulously curated and analysed data, machine learning algorithms are harnessed to augment the analytical capabilities of the study. Specifically, these algorithms are tailored towards the task of neighbourhood classification, with a specific focus on identifying and mitigating crimes against women. Through the amalgamation of data-driven insights and algorithmic prowess, machine learning techniques afford a data-driven approach towards enhancing societal safety measures and fostering proactive intervention strategies.

4. Results

Based on the methodology presented in the previous section, a case study was conducted in the state of Pernambuco to classify cities considering violence against women. This is predictive analysis. This ranking can happen in real-time, while its result can be changed daily.

The attributes utilized for the machine learning (ML) model would likely encompass a diverse set of features derived from the different data sources mentioned, including:

1. ***Official Public Safety Records:***
    - Frequency and types of reported crimes against women (e.g., domestic violence, sexual assault, stalking).
    - Spatial and temporal patterns of incidents.
    - Severity levels and outcomes of reported offenses.
    - Effectiveness of law enforcement responses and interventions.
2. ***Demographic and Health Data:***
    - Socioeconomic indicators such as income levels, education attainment, employment status, and housing conditions.
    - Gender-specific demographic characteristics such as the proportion of female residents, age distribution, and marital status.
    - Access to healthcare services, including availability of domestic violence shelters and support programs.
3. ***Unstructured Data from Social Networks (e.g., Twitter):***
    - Sentiment analysis of tweets related to violence against women, capturing public perceptions, concerns, and discussions.
    - Identification of influential topics, hashtags, or user communities discussing gender-based violence.
    - Geospatial analysis to map the distribution of relevant social media content across different cities.

To conduct this study, the ExtraTrees algorithm was employed, yielding notable performance metrics including an F1-Score of 91% and an Accuracy test of 90%, as depicted in Table 1. These results signify a substantial achievement in the realm of machine learning-based classification tasks. ExtraTrees, a variant of the Random Forest algorithm, distinguishes itself by employing a distinctive strategy during the decision tree construction process (Table 1).

Unlike conventional decision tree algorithms that select the optimal decision node for each split based on specific criteria like information gain or Gini impurity, ExtraTrees adopts a randomized approach. Specifically, it utilizes a predefined number of random decision nodes for splitting at each tree node, rather than exhaustively searching for the best candidate. This strategy introduces a controlled level of randomness into the model, which serves multiple purposes.

Firstly, the incorporation of randomness during the split selection process helps mitigate the risk of overfitting, a common challenge encountered in complex machine learning models. By introducing diversity among the individual decision trees comprising the ensemble, ExtraTrees reduces the likelihood of individual trees memorizing noise or idiosyncrasies present in the training data, thus enhancing the generalization capability of the model.

Secondly, the use of random decision nodes promotes diversity among the constituent trees, leading to a broader exploration of the feature space. This diversified exploration facilitates the discovery of potentially informative feature interactions and patterns that may remain undiscovered in traditional decision tree models. Consequently, the resulting ensemble model exhibits enhanced robustness and adaptability, particularly in scenarios characterized by high-dimensional or noisy data.

Furthermore, the randomized nature of ExtraTrees fosters computational efficiency, as the absence of an exhaustive search for optimal splits reduces computational overhead during model training. This attribute renders ExtraTrees particularly suitable for large-scale datasets and real-time applications where computational resources are constrained.

Table 1: Algorithm Performance

Algorithm	**Acuracy**	**F1 - Score**
ExtraTrees	0.900	0.910
Random Forest	0.823	0.875
Decision Tree	0.856	0.840

To ensure the integrity of the model, cross-validation techniques were applied by splitting the dataset into multiple partitions to assess the robustness of the results. Additionally, a bias analysis was conducted to ensure that the model did not favor or disadvantage specific regions or socioeconomic profiles. This included checking class distribution, balancing the dataset using techniques such as SMOTE, and analyzing feature importance to detect potential distortions.

Regarding the cities, they will be divided into three main categories: the probability of high incidence of crimes against women (represented by dark red color); probability of medium incidence of crimes against women (represented by light red color); probability of low incidence against women (represented by white color). The types of crimes that are taken into consideration are bodily injury; threat for domestic violence; mistreatment; insult and Defamation (Table 2).

Table 2: Classification Process

Classification	What is taken into consideration?
High incidence of crimes	For all three cases, the following are taken into consideration:
Medium incidence of crimes	History of the location concerning crime; Types of crimes against
Low incidence of crime	Social factors of the region (HDI, population income); Other types of crimes.

For a clearer and more objective classification of cities based on the incidence of crimes against women, the following criteria were established:

- High incidence of crimes: Cities reporting more than 100 incidents of violence against women per 100,000 inhabitants annually. These locations also exhibit a high volume of negative sentiment related to gender-based violence on social media platforms, and tend to have a Human Development Index (HDI) below 0.600.
- Medium incidence of crimes: Cities with between 30 and 100 reported incidents per 100,000 inhabitants annually. These areas show moderate social media activity discussing violence against women and have an HDI ranging between 0.600 and 0.750.
- Low incidence of crimes: Cities reporting fewer than 30 incidents per 100,000 inhabitants annually. These locations have low or negligible social media mentions of violence against women and generally present an HDI above 0.750.

This classification approach integrates quantitative crime statistics, social media sentiment, and socioeconomic indicators to provide a comprehensive and nuanced ranking of cities with respect to violence against women.

It is noticeable that some cities are with a more accentuated red. These cities, historically, tend to have violence against women in a short period considering bodily injury; threat for domestic violence; mistreatment; insult and defamation (Figure. 2)

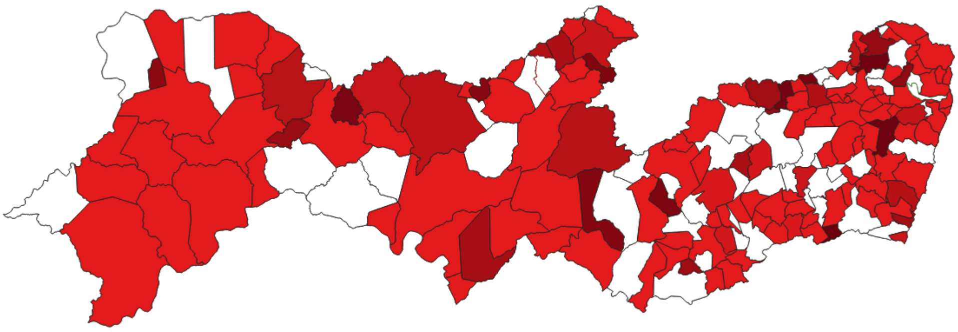

Figure 2: Classification Process (Pernambuco State – Brazil)

5. Conclusions

This study has introduced a machine learning model designed to address the critical issue of violence against women by classifying cities based on this parameter. The model serves as a pivotal tool for facilitating comprehensive insights necessary for the strategic planning and implementation of targeted interventions by pertinent authorities.

Of paramount importance is the model's capacity to provide an overall understanding, empowering relevant departments to orchestrate proactive control measures and preventive actions against such crimes. These actions encompass a spectrum of initiatives, including the establishment of dedicated police stations, community awareness campaigns, mobile patrolling units, and optimized policing routes tailored to the dynamics of complex localities. The model's versatility extends across multiple dimensions, offering nuanced analyses pertinent to both neighborhood-level and city-wide assessments.

The integration of machine learning techniques imbues the model with the capability to operate in real-time, thereby enabling the continuous monitoring and evaluation of outcomes. This dynamic feedback loop ensures the timely adaptation of interventions in response to evolving trends and emerging challenges, thereby enhancing the efficacy and responsiveness of crime mitigation efforts.

As a prospective avenue for further research, the exploration of alternative algorithms presents an intriguing opportunity to delve deeper into the comparative performance landscape. Conducting a systematic evaluation of diverse algorithmic approaches could yield valuable insights into the efficacy, scalability, and robustness of the model across varied contexts. Such endeavors would not only enrich our understanding of algorithmic suitability but also foster advancements in predictive modeling techniques tailored to the multifaceted domain of crime prevention and public safety.

The persistent and multifaceted nature of violence against women demands a sustained, interdisciplinary response that extends beyond data-driven models. While predictive analytics offer powerful tools for anticipating and mitigating risks, they must be integrated within broader societal efforts that include legal reform, cultural change, and community engagement. Addressing such a deeply rooted social issue requires collaboration across institutions and continuous reflection on ethical considerations such as privacy and fairness. Ultimately, this research underscores the potential of machine learning as part of a comprehensive strategy to enhance public safety and promote gender equity, while reminding us of the need for vigilance and adaptability in confronting evolving challenges.

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