FemSafe

Data for Justice: Mapping and Predicting Femicide in Kenya

A Data-Driven Approach to proactive intervention

MEMBERS

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PROBLEM STATEMENT

- Femicide in Kenya , the gender-based killing of women , is a growing crisis.
- Often underreported or misrepresented as domestic violence.
- Media reports exist but are scattered and unstructured.
- Current interventions are reactive, not data-driven

PROJECT OVERVIEW

This project aims to analyze, map, and predict femicide cases in Kenya using data science:

• Clean and analyze publicly available femicide data

• Identify temporal, geographic, and demographic patterns

•Build machine learning models to predict risk

• Use NLP to extract insights from narrative case reports

• Deploy an interactive dashboard for stakeholder use

“History of Woman Suffrage”

“Why We Picket”

PROJECT OBJECTIVES

To prevent femicide in Kenya by identifying early warning signs, empowering at-risk individuals, and enabling timely intervention through technology, data, and community support

- To develop an AI-powered system that analyzes user-reported messages and behavior patterns to detect early signs of gender-based violence and potential femicide risk.
- To provide real-time safety features such as a panic button, emergency contact alerts, and access to support services including counseling, shelters, and legal aid
- To raise awareness and educate users on recognizing abuse, understanding their rights, and building safety plans through localized, culturally relevant content

KEY STAKEHOLDERS

who is involved ?

NGOs & Civil Society: Provide support, use risk tools, offer shelters.
Law Enforcement: Use predictive tools to prioritize protective action.
Healthcare Providers: Flag recurring injuries or delayed reporting patterns.
Judiciary & Legal: Incorporate risk indicators into legal rulings and protection
Government: Allocate resources and design GBV prevention policies.

PROJECT WORKFLOW OVERVIEW

1

Data Loading and Initial Exploration

2

Data Cleaning

3

EDA

- Class, fake/real, and age distribution plot
- Sentiment Analysis:
  - Calculate sentiment score using TextBlob
  - Plot sentiment score distribution by risk level
- Feature Correlation:
  - Plot correlation heatmap between sentiment score and meta-features

4

FEATURE ENGINEERING

- Add sentiment_score and risk_keyword_count to features
- TF-IDF + meta-features

5

Dimensionality Reduction

Apply PCA for visualizing feature space

6

MODEL BUILDING

- Logistic Regression
- BERT Transformer Model:
  - Fine-tune DistilBERT for classification
  - Save and load model

7

MODEL EVALUATION

- Classification reports & confusion matrices
- SHAP Explainability:
  - Local & global feature importance for ML models
  - SHAP applied to BERT outputs

8

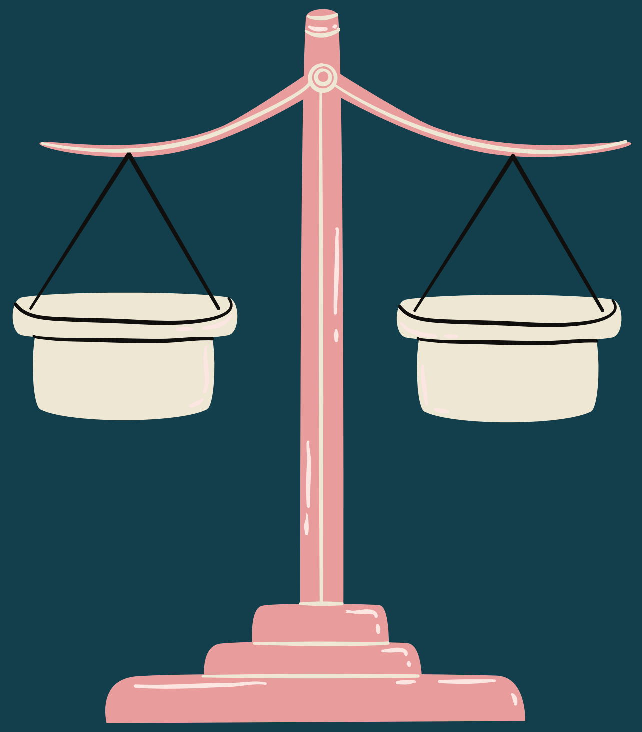
Conclusion

DATA AND METHODOLOGY

•A dataset of femicide cases in Kenya from 2016 to 2023.
•Includes columns like title, text, location, suspect relationship, Type of femicide, Mode of killing, and circumstance

METHODOLOGY

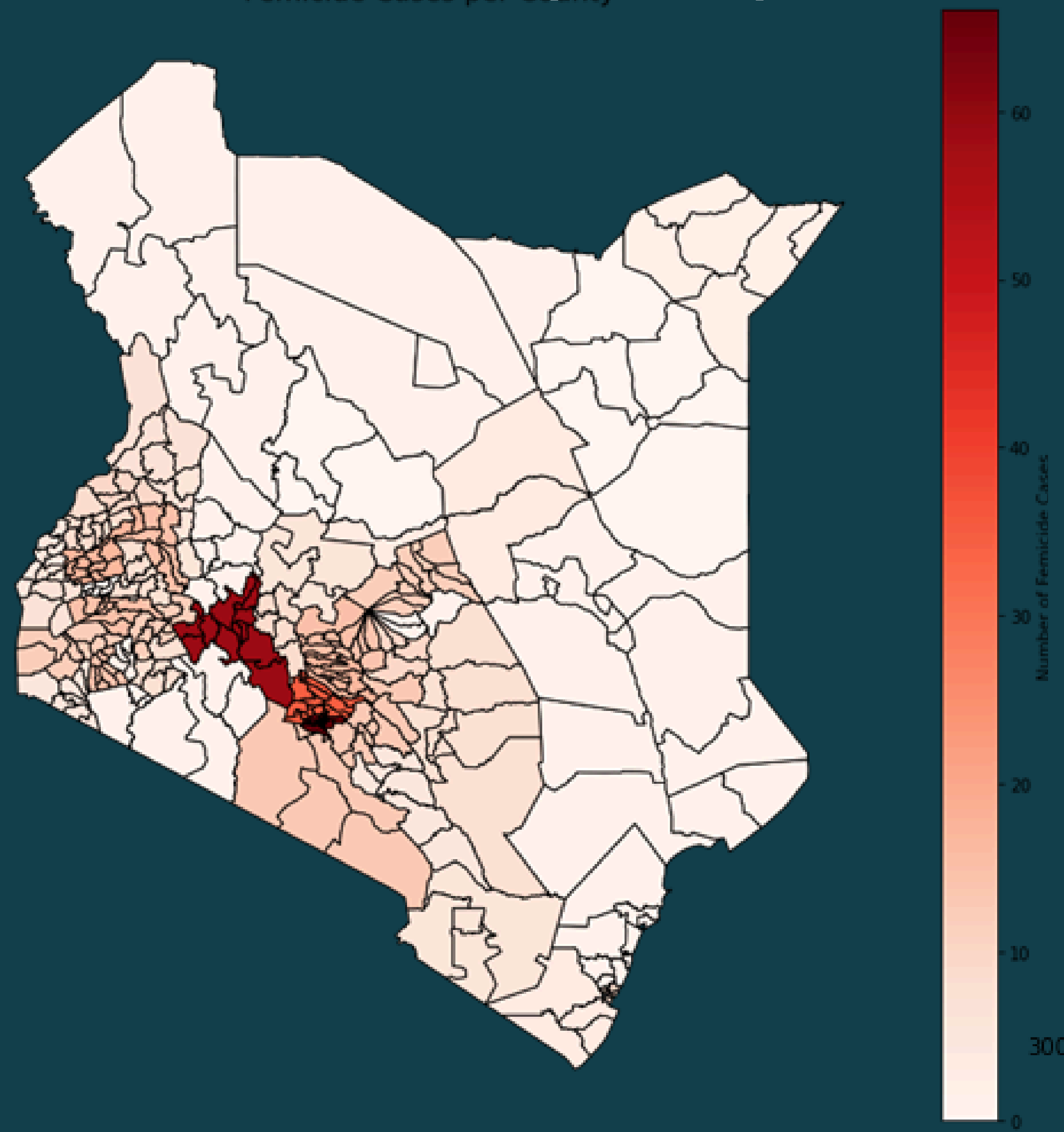
•Data preprocessing : Cleaning and preparing raw data
•Text Analysis : Using TF-IDF Vectorization and sentiment analysis
•Machine learning : Trained models like Logistic regression, RandomForest, DistilBert.



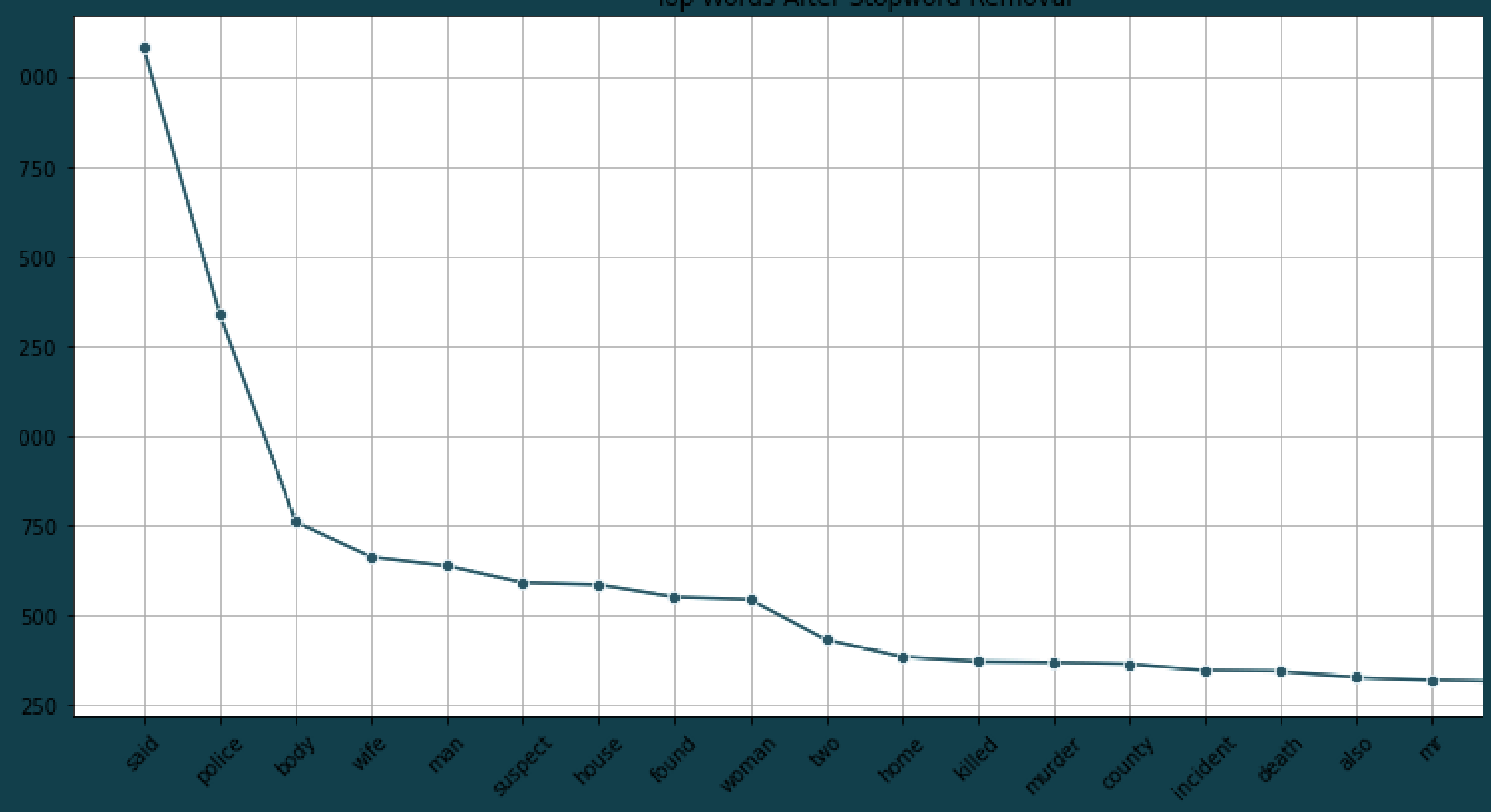
FINDINGS

•Geographic Patterns: Cases are disproportionately concentrated in major urban centers and their surrounding areas.
•Relationship Dynamics: A significant majority of victims were killed by a current or former intimate partner.
•Common Killing Modes: The most frequent methods identified were stabbings and strangulation.
Missing Data: A notable number of cases lacked information for key fields like label, femicide_type, and circumstance, highlighting a challenge in data collection

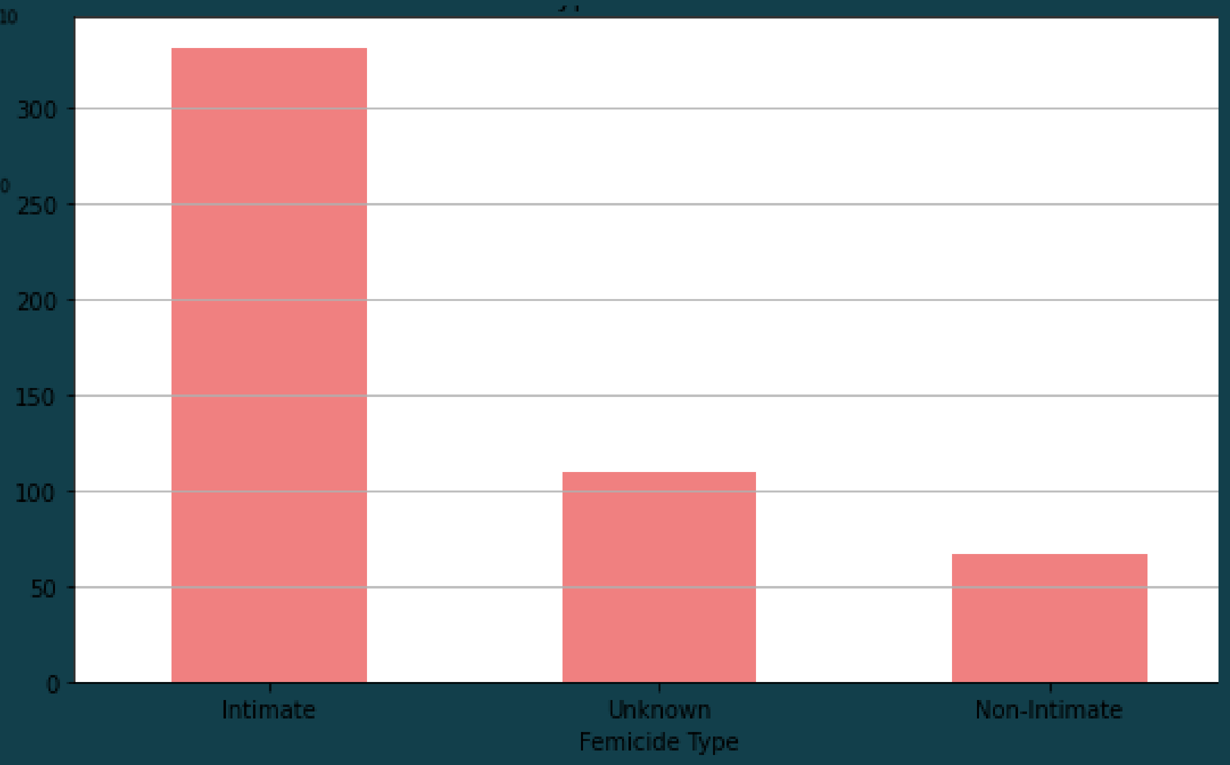
Femicide by county



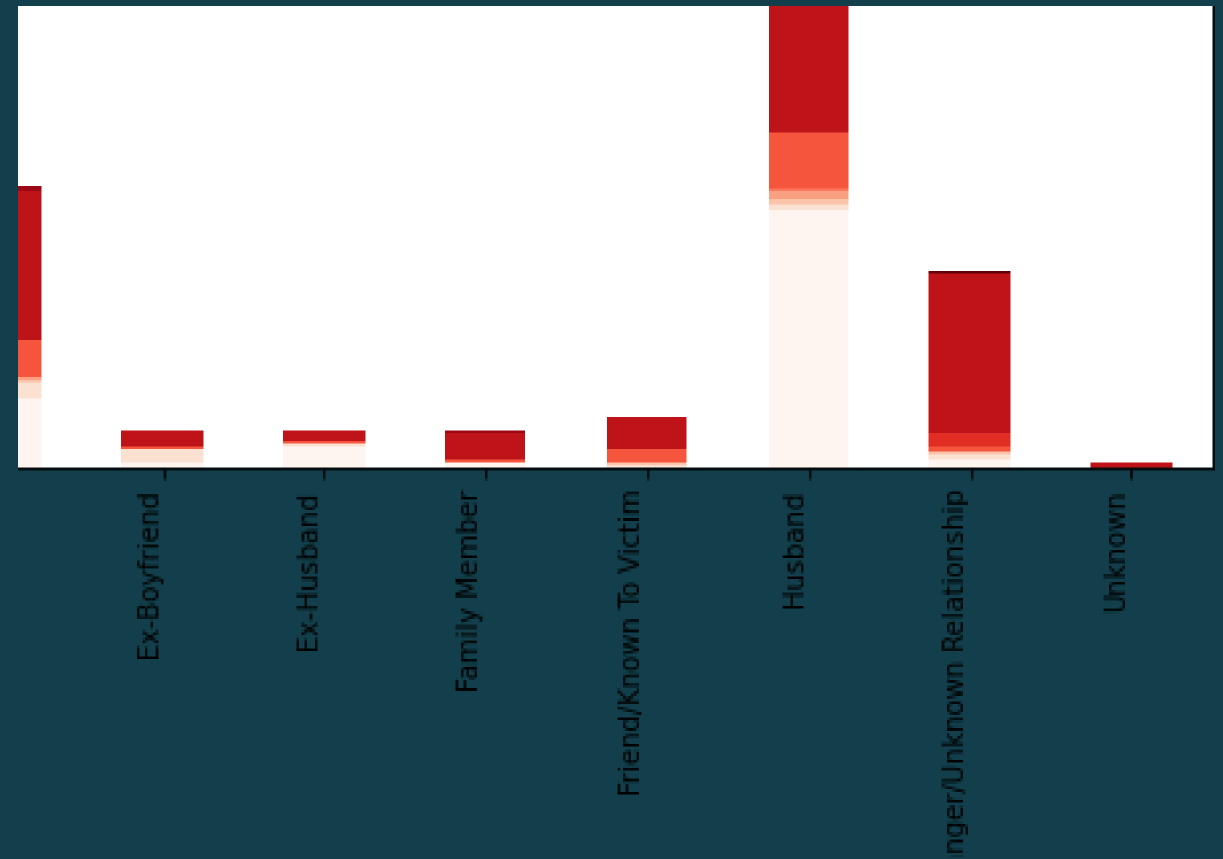
TOP words



Type of femicide



Circumstance by suspect relationship



MODELING

Baseline Model - Logistic Rgression

How we used it:
TF-IDF vectorization for text
Train-test split
Measured metrics: Accuracy, Precision, Recall, F1
Results Example:
Accuracy: 78%
F1: 0.76

Advanced Model - DistilBERT

Why BERT?

- Transformer-based model that understands context in text better than traditional methods
- Pre-trained on large text corpus → fine-tuned for our data

What we did:

- Used DistilBERT (lightweight BERT) for efficiency
- Fine-tuned with our dataset
- Used Hugging Face Transformers library

MODEL EVALUATION

MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
LOGISTIC REGRESSION	97	100	91	95
DISTILBERT	97	97	97	97

Your paragraph text

DEPLOYMENT

- The model was deployed to make it usable for others

How it was deployed:

- Saved model with save_pretrained()
- Streamlit app for predictions
- Allows users to input a text narrative and get risk prediction instantly

LIMITATIONS

- Limited dataset size
- Model overfitting risk
- Ethical concerns around misclassification

RECOMMENDATIONS

Translating Data Into Action

•Create Integrated Platforms: Develop a central platform where NGOs, police, and healthcare providers can securely share and access risk-assessment data.
Develop Training Programs: Educate law enforcement and social workers on how to use the predictive tools and dashboards effectively.
Implement a Pilot Program: Launch the risk detection system in a specific, high-risk region to test its efficacy and gather feedback for improvements..

NEXT STEPS

The Road Ahead

•**Model Refinement**: Continuously update and retrain the model with more diverse and real-time data to improve accuracy.

•**Ethical Oversight**: Establish a dedicated ethics committee to oversee the deployment and use of the predictive system.

•**Expand Data Sources**: Integrate additional data, such as call center logs, social media data (with consent), and court records to enhance the model's predictive power.

•**Public Awareness**: Launch public campaigns to inform communities about the new system and how they can report potential cases of GBV.

CONCLUSION

A shift from Reactive to Proactive

- Data reveals clear temporal, demographic, and relationship-based risk patterns.
- Logistic Regression, Random Forest, and DistilBERT effectively identified high-risk cases.
- SHAP provided transparency and interpretability.
- Shifts response from reactive crisis management to proactive prevention and protection.
- Emphasizes privacy, bias mitigation, and human oversight.