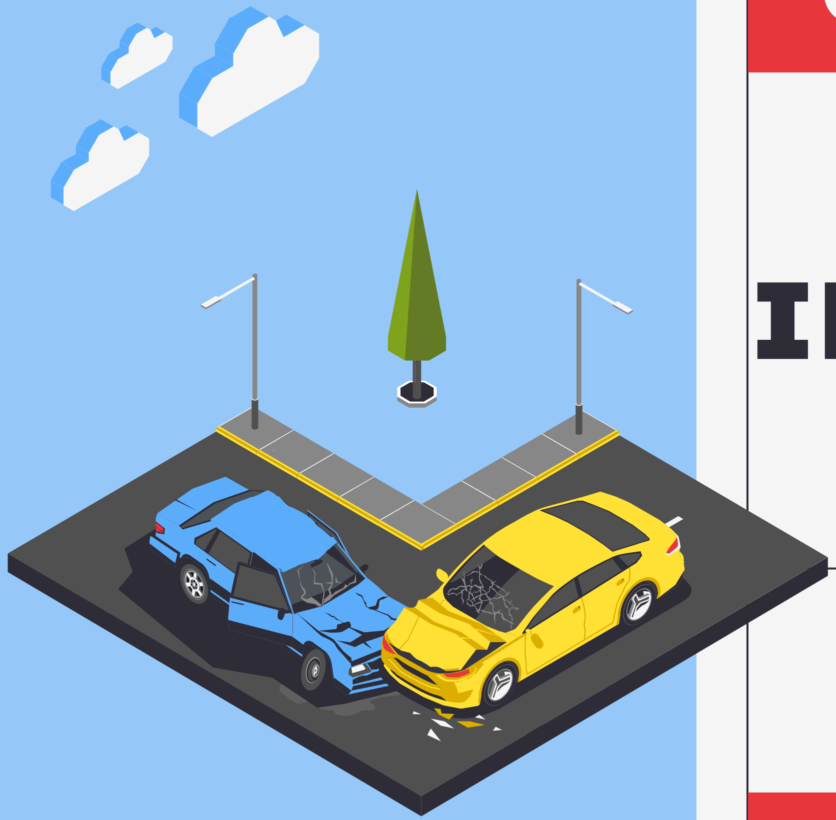
Predictive Road Safety Intelligence

UrbSafe– Mapping Risk, Saving Lives



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INTRODUCTION

UrbSafe Team

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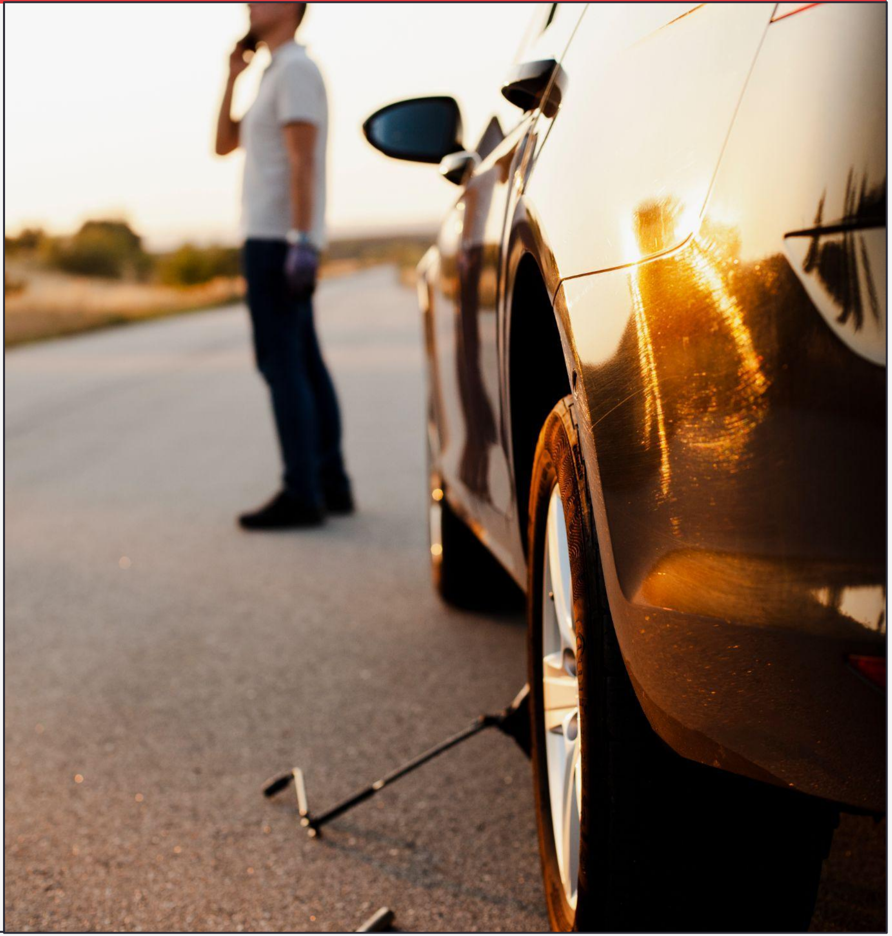
Problem Statement

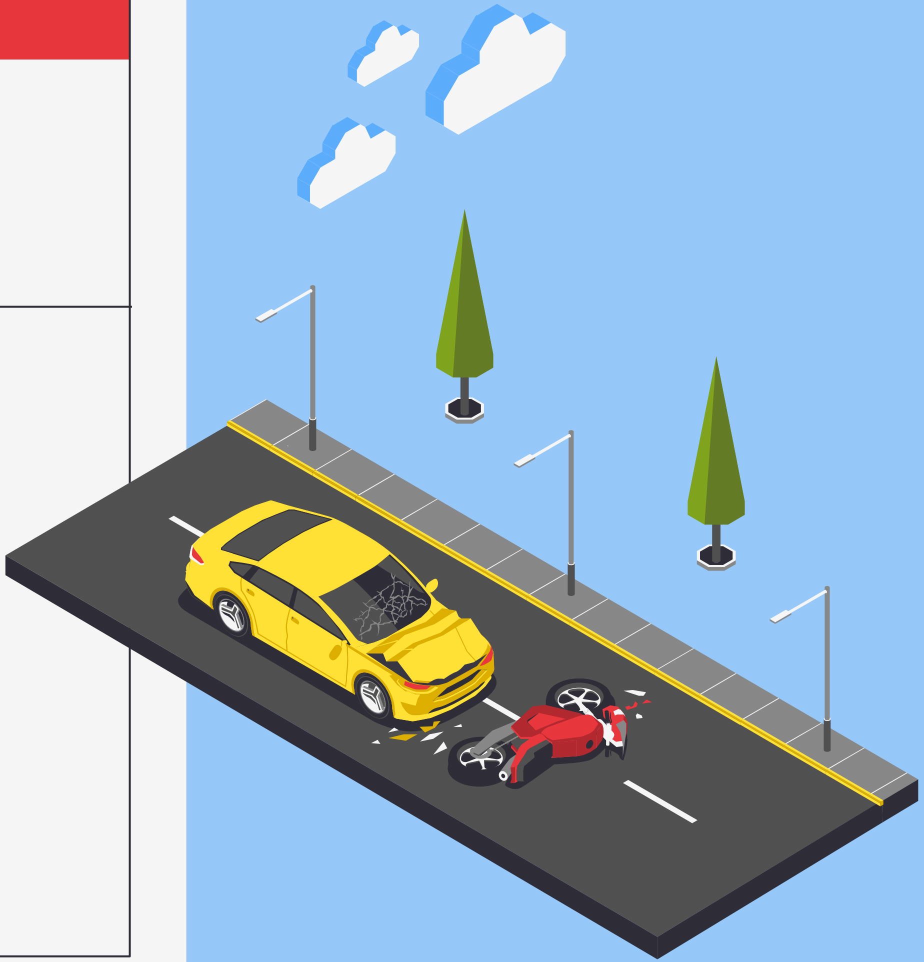
- High road traffic fatality rate: 27 per 100,000 (above global average)
- Lack of real-time, actionable road safety data
- Current interventions are reactive, not data-informed
- City planning often blind to hotspots and patterns



UrbSafe Solution

AI-powered smart road safety analytics platform

- Map crash hotspots with risk severity scores
- Predict where future crashes are likely to occur
- Recommend targeted safety interventions
- Enable public reporting of hazards via mobile
- Provide open access dashboards and analytics for stakeholders



OBJECTIVES

- ❑ What are the high-risk crash hotspots across the city, based on location and time patterns?
- ❑ What is the crash severity based on day, hour, and other contextual features?
- ❑ Can we build an interactive web app that allows users to input a date and time and receive high-risk location predictions and safety recommendations

DATA UNDERSTANDING

SOURCE

- ❑ World popular Kenyan Twitter account @Ma3Route
- ❑ Dataset maps 30,000+ road crashes in Nairobi (2013–2022)
- ❑ Collected from OB records, police forms, and news reports

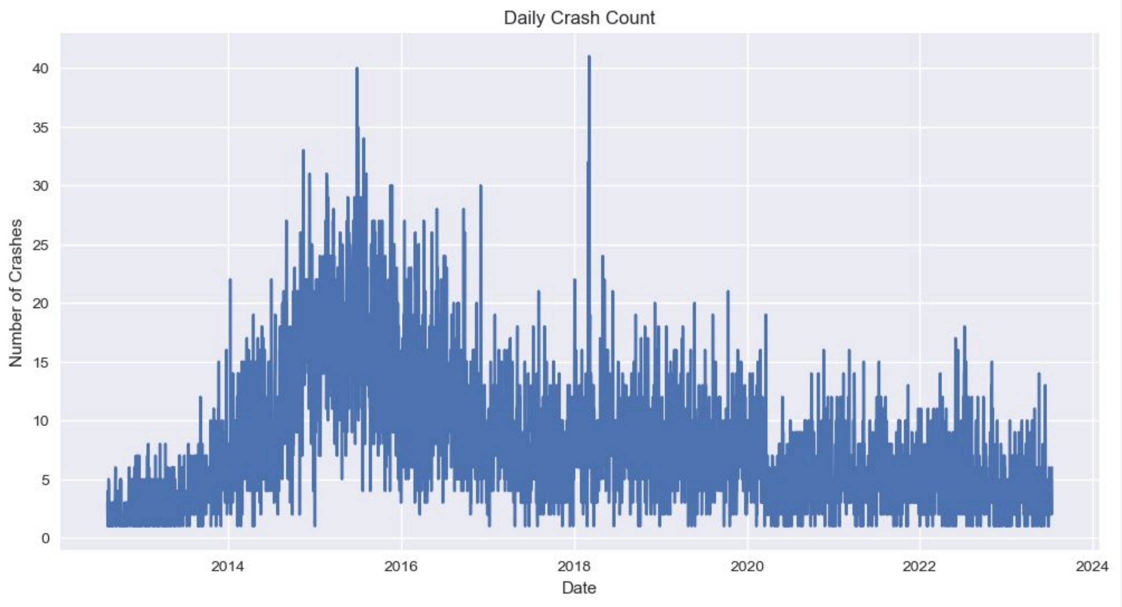
WHY?

- ❑ Offers the most detailed spatial crash map of Nairobi to date
- ❑ Enables hotspot detection, trend analysis, and risk-based planning
- ❑ Forms the baseline training data for UrbSafe's AI models

YEARLY EVALUATION

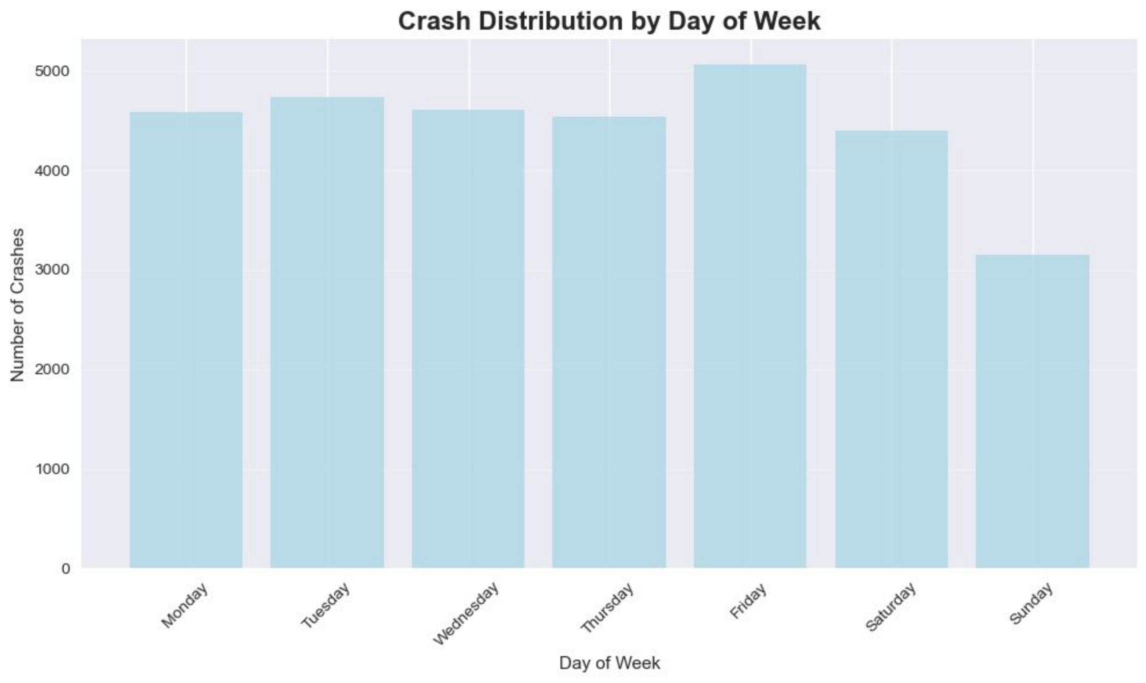
- Decrease after 2015 may reflect reduced use of @Ma3Route rather than an actual drop in crash occurrences.

- Sharp decline in March 2020 due to COVID-19 lock-down or fewer people on the roads to report incidents.



WEEKLY EVALUATION

- Friday: highest likely due to increased traffic as people wrap up the workweek, begin social activities, or drive while fatigued.
- Monday-Thursday: Consistently high crash numbers, reflecting typical commuter and school-related traffic.
- Sunday: Lowest due to lighter traffic, limited movement, and more relaxed driving behavior.

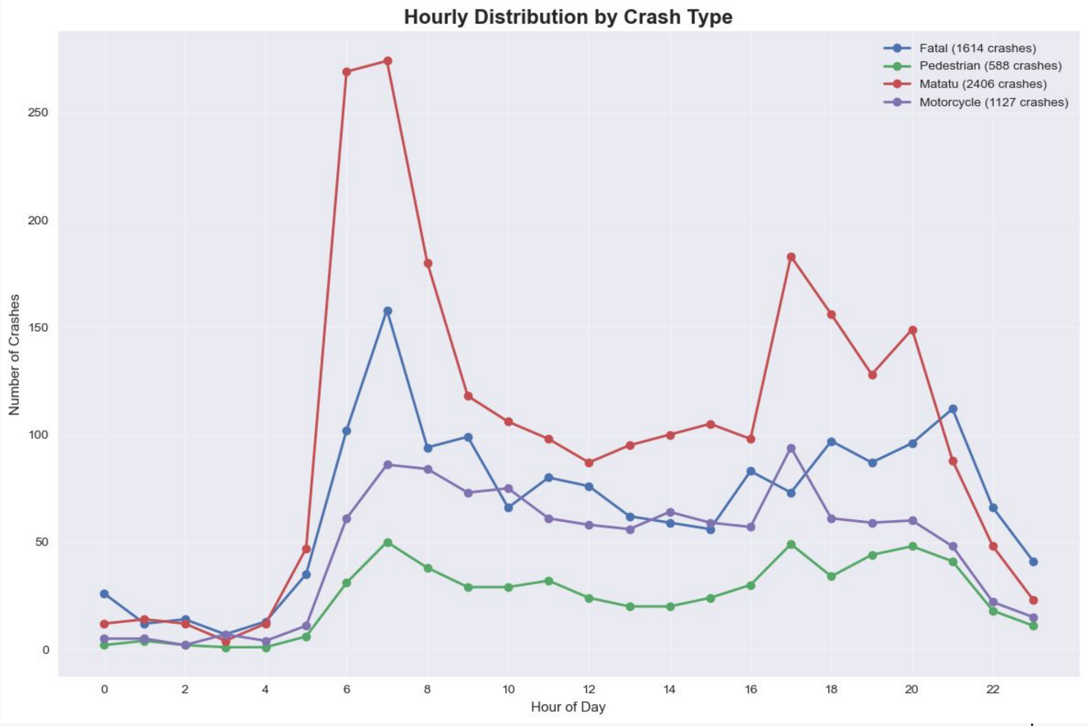


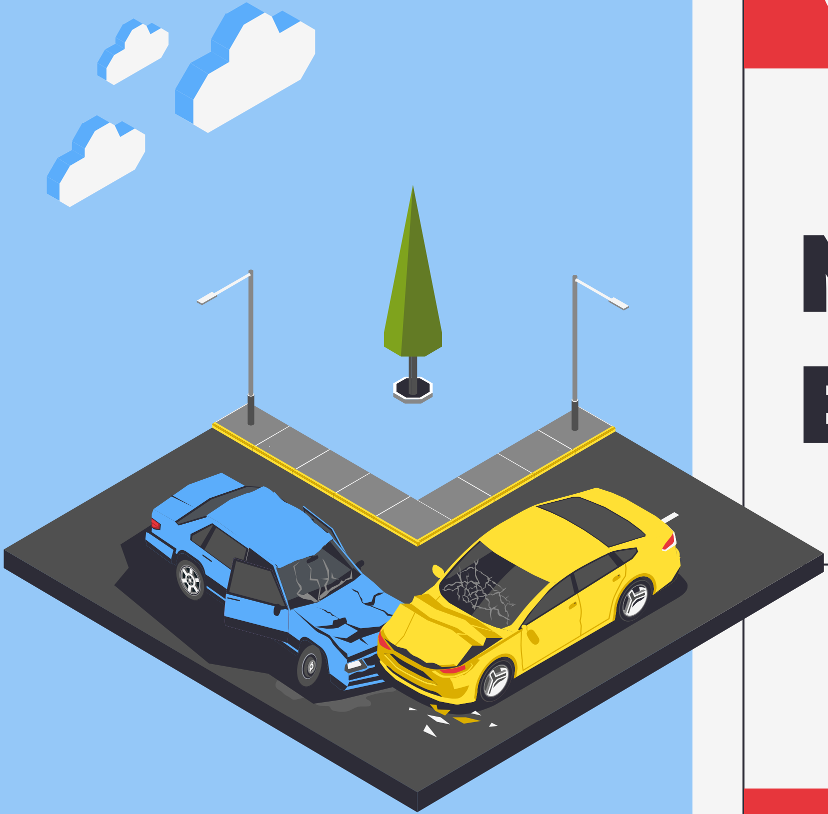
HOURLY EVALUATION

- Peak during morning (6–9 AM) and evening (4–7 PM) rush hours, coinciding with high traffic volumes.

- Overnight hours (12–5 AM) are few but fatal due to factors like fatigue or impaired driving.

- This underscores the need for targeted safety interventions during high-risk periods.





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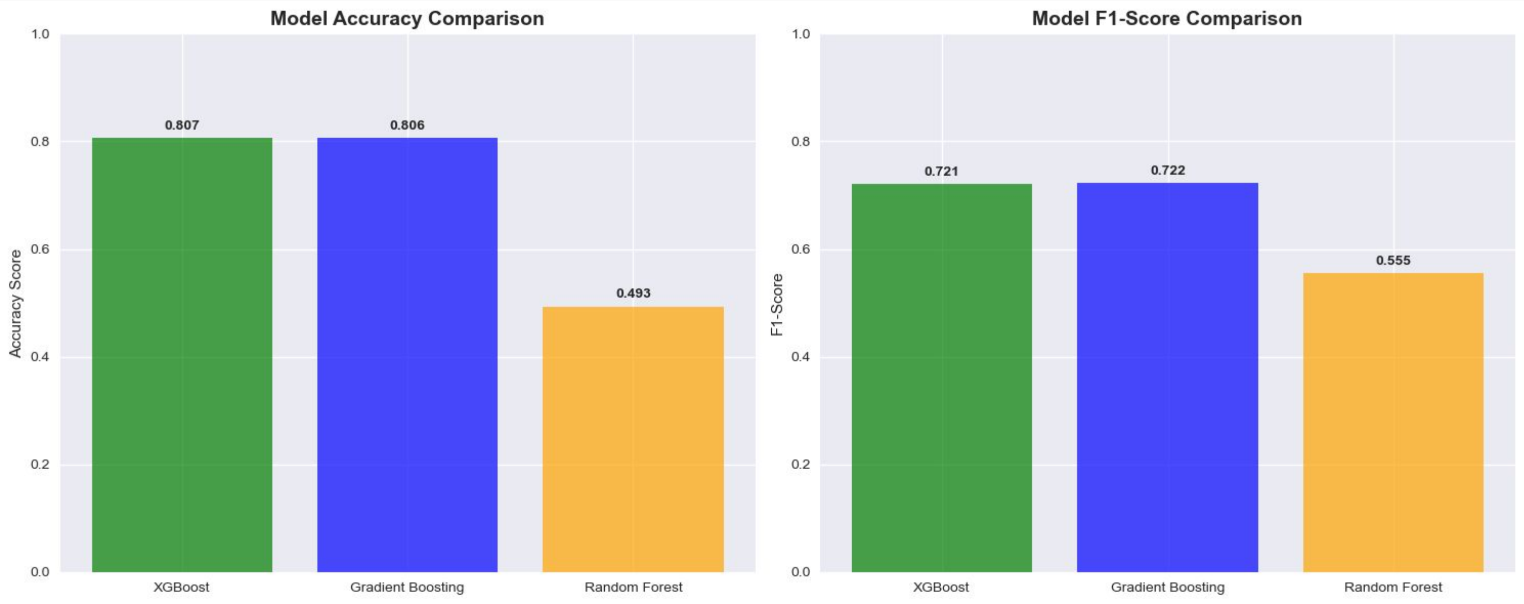
MODELLING & EVALUATION

MODEL SELECTION

- XGBoost outperforms Gradient Boosting and Random Forest in both accuracy (~0.4) and F1-score (~0.855), making it the best model for this task.



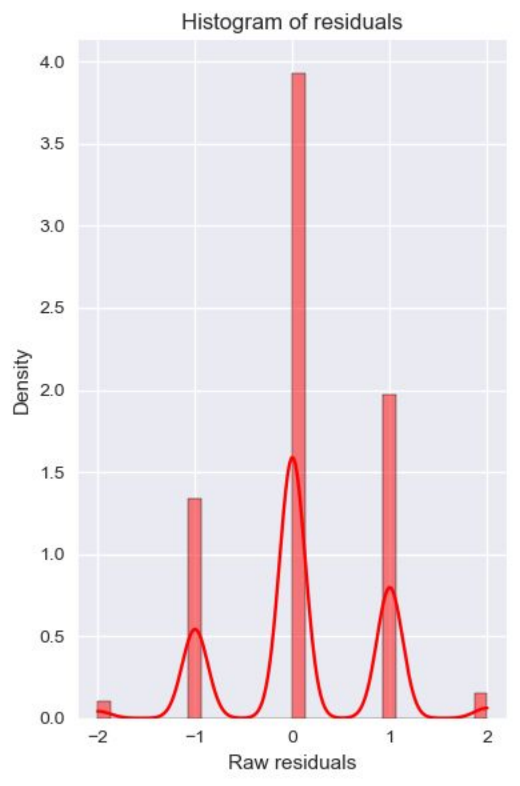
RESIDUAL PLOT

- Sharp peak at 0 means many predictions were correct — the predicted class matched the actual class.

- The spikes at -1 and +1 indicate that when the model was wrong, it often misclassified by just one class step (e.g., predicting "No_Injury" instead of "Moderate" or vice versa).

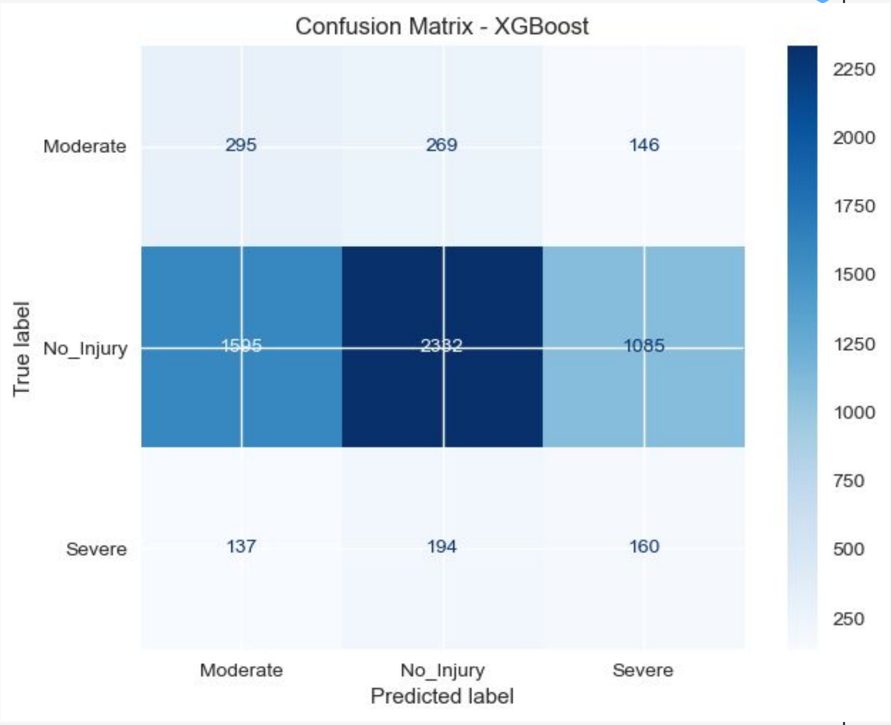
- Very few residuals fall beyond ±1, which implies that large classification errors (e.g., predicting "Severe" instead of "Moderate") are rare.

- The symmetry of the distribution suggests the model isn't biased toward overpredicting or underpredicting a particular class.



CONFUSION MATRIX

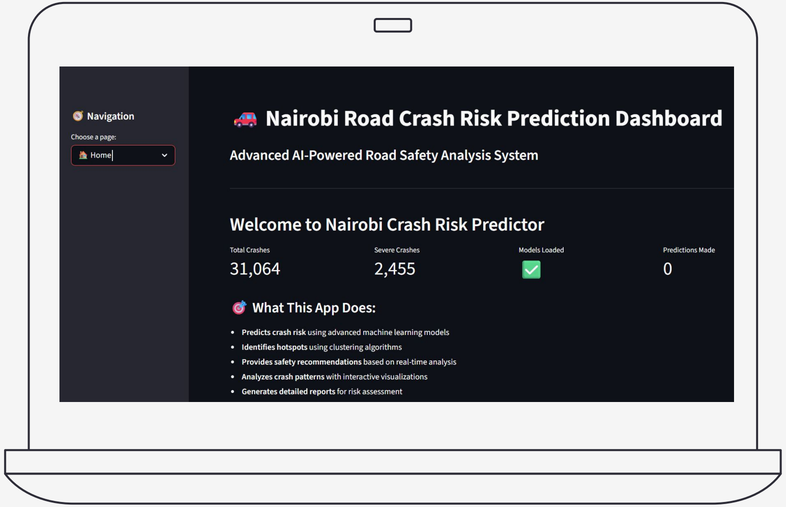
- The model excels at predicting 'No_Injury', with a strong concentration of correct predictions.
- Misclassifications are common for 'Moderate' and 'Severe', often confused with 'No_Injury'.
- The prediction pattern reflects class dominance, indicating the model is influenced by the majority class.
- Correct hits across all categories show the model has some capacity to distinguish between severity levels.



OUR PLATFORM

- The Nairobi Crash Risk Predictor is an advanced AI-powered system designed to predict and analyze road crash risks in Nairobi, Kenya.

- Using machine learning algorithms and historical crash data, it provides real-time risk assessments and safety recommendations.”



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NEXT STEPS & CONCLUSION

NEXT STEPS

- ❑ **Retrain with class balancing techniques** and compare macro-averaged metrics.
- ❑ **Engineer new features** from spatial clustering, time context (e.g. pre- vs. post-rush hour), and external data sources.
- ❑ **Run hyperparameter tuning** on both XGBoost and Gradient Boosting variants.
- ❑ **Present updated results** using ROC curves, residual histograms, and confusion matrices to stakeholders with a focus on safety-critical class detection.

CONCLUSION

- The model demonstrates strong potential, especially in learning from patterns that predict No_Injury crashes accurately.
- Model underperforms in identifying critical crash categories like severe.
- With improved feature representation, targeted balancing, and refined evaluation methods, the model can evolve into a powerful tool for predicting and mitigating high-risk traffic incidents in Nairobi.

THANKS!

DO YOU HAVE ANY QUESTIONS?

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