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Original Research Article

Smart Artificial Intelligence-Aware Traffic Prediction in Kampala City, Uganda

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Abstract: Kampala City, Uganda's capital, faces severe and escalating traffic congestion due to rapid urbanisation, population growth, and rising vehicle ownership, leading to substantial economic losses, increased emissions, and degraded quality of life. Traditional reactive traffic management systems are inadequate for addressing dynamic urban mobility patterns in resource constrained environments. This study develops an intelligent traffic congestion prediction framework using machine learning classification. A dataset of 500 observations from 15 major road segments is processed through rigorous preprocessing, domain-informed feature engineering (including capacity utilisation and flow efficiency), and ensemble classifiers to categorise congestion into four actionable severity levels: Low, Medium, High, and severe. Experimental evaluation on a stratified test set shows that XGBoost outperforms Random Forest, achieving 84.0% overall accuracy and the highest precision (0.808%), recall (0.840%), and F1-score (0.820%). Feature importance analysis highlights capacity utilisation, vehicle density, and flow efficiency as the dominant predictors, consistent with fundamental traffic flow theory. The proposed system establishes a scalable, interpretable foundation for proactive congestion management in developing cities. With future enhancements in real-world data integration and temporal-spatial modelling, it holds strong potential to support adaptive traffic control, incident response, and data-driven urban planning in Kampala and similar contexts.

Keywords: Traffic Congestion Prediction, Machine Learning Classification, Urban Traffic Management, Intelligent Transportation Systems, Kampala City.

I. INTRODUCTION, RELATED WORK, AND LIMITATIONS

Kampala, Uganda's capital and largest urban center, grapples with acute traffic congestion driven by rapid population growth, uncontrolled urbanization, and surging private vehicle ownership. Peak-hour delays impose substantial economic costs—estimated in lost productivity, excessive fuel consumption, and elevated emissions—while exacerbating commuter stress and environmental degradation in a resource-constrained setting [12]. Traditional traffic management relies on reactive measures, lacking predictive intelligence to enable proactive interventions. This project advances intelligent transportation systems (ITS) in developing contexts by developing a machine learning classification framework that forecasts congestion severity across four levels (Low, Medium, High, Severe), leveraging localised road metrics to support data-driven urban mobility planning.

Recent research has increasingly applied machine learning to urban traffic challenges, particularly in data-scarce African and developing-city environments. Notable contributions include real-time route optimization using Random Forest classifiers on Google Maps-derived features (travel time, distance, temporal variables), achieving high accuracy (92%) in predicting least-congested paths for Kampala commuters [12]. Ensemble techniques such as XGBoost, Random Forest, and LightGBM have demonstrated strong performance in shortterm congestion and crash-risk forecasting, often outperforming baselines through robust handling of non-linear patterns and feature importance analysis [14, 15]. In broader African contexts, multi-class classifiers and diversity-oriented dynamic ensemble selection (DES) methods have been explored for injury severity and congestion-related predictions, emphasizing interpretability via tools like SHAP and LIME [22]. Graphbased and deep learning

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hybrids further enhance spatialtemporal modelling in resource-limited cities [17].

These studies offer valuable methodological advances—real-time routing, ensemble robustness, and interpretable feature insights—yet reveal critical gaps for Kampala-specific applications. Few address fine-grained multi-class congestion level prediction tailored to local road dynamics. Most rely on external APIs or generalized datasets, with limited integration of domain-engineered features (e.g., capacity utilization, flow efficiency) that capture Kampala's unique saturation and incident patterns. Moreover, prior efforts often overlook ordinal class relationships and class imbalance inherent in severity-based forecasting.

These limitations—dependence on non-local data, insufficient emphasis on engineered predictors, and lack of Kampalacentric multi-class frameworks—motivate the present work.

By focusing on indigenous traffic observations and targeted feature engineering, this study bridges the gap toward a contextually relevant, deployable prediction system for proactive traffic management in Kampala.

II. PROPOSED METHODOLOGY AND DATASET

This study proposes a robust ensemble-based classification framework tailored for multi-class traffic congestion prediction in Kampala's urban environment. The pipeline integrates domain-informed data preprocessing, targeted feature engineering, and state-of-the-art gradient boosting to derive interpretable, high-performance models capable of distinguishing congestion severity levels from heterogeneous traffic observations.

A. Dataset Description

The analysis draws on a structured dataset comprising 500 observations collected across 15 key arterial road segments in Kampala, encompassing diverse operational conditions—from free-flow traffic to severe gridlock. This size balances computational feasibility with sufficient statistical power for model training and validation, while the geographical coverage represents major commuter corridors prone to recurrent bottlenecks.

The original dataset captured 13 core variables spanning temporal, spatial, traffic flow, incident, weather, and road capacity dimensions. Through systematic feature engineering, four additional predictors were derived, yielding a final feature set of 17 variables. These engineered features incorporate traffic engineering principles to better capture saturation dynamics and flow quality—critical in Kampala's heterogeneous, incident-prone network. The complete feature inventory is detailed in Table I.

B. Data Preprocessing and Feature Engineering

To ensure model robustness and mitigate biases from noisy or incomplete observations, a rigorous preprocessing pipeline was applied. Missing values in continuous variables (e.g., speed, density) were addressed via median imputation to preserve distributional characteristics, while categorical variables (e.g., weather, incident type) employed mode imputation. Outliers in traffic metrics—common in real-world sensor or manual counts—were capped using Winsorization (typically at 5% and 95% percentiles) to reduce undue influence without information loss.

Feature engineering played a pivotal role in enhancing predictive power by embedding traffic flow theory. Four domainderived features were constructed: - *capacity utilization* (volume / capacity): Normalized measure of road saturation (range typically 0.65–1.62 in the dataset). - *time period*: Binned hour into five operationally meaningful intervals (Late Night, Morning Peak, Midday, Evening Peak, Night) to capture diurnal patterns. - *day type*: Refined temporal context by distinguishing Weekday, Friday (often transitional), and Weekend behaviours. - *flow efficiency* (speed/volume): Composite indicator of traffic health, quantifying flow degradation under increasing density.

These transformations enrich the input space, enabling models to discern subtle congestion transitions beyond raw measurements.

C. Target Variable Definition

The response variable, congestion_level, is a fourclass ordinal categorical target encoding escalating severity: - Low: Free-flow conditions with near-optimal speeds. - Medium: Emerging congestion with moderate speed reductions. - High: Substantial delays impacting travel time significantly. - Severe: Near-gridlock or complete standstill.

This graduated scale facilitates actionable outputs for traffic authorities, from monitoring to emergency response.

D. Selected Classification Algorithms

Two ensemble methods were selected for their complementary strengths in structured, tabular data: - Random Forest: Serves as a robust baseline, leveraging bagging of decision trees to handle mixed data types, non-linearity, and built-in feature importance. - XGBoost: Employed as the primary advanced model, utilizing gradient boosting with regularization, efficient missing-value handling, and superior performance on imbalanced or noisy datasets—particularly suitable for multiclass severity prediction.

Both algorithms support interpretability via feature importance scores, enabling analysis of dominant congestion drivers in Kampala's context.

III. EXPERIMENTAL SETUP AND PROCEDURE

To rigorously evaluate the proposed congestion prediction framework, a systematic experimental protocol was designed with emphasis on reproducibility, class-balanced evaluation, and multi-faceted performance assessment. All experiments were implemented in Python using the scikit-learn and XGBoost libraries, executed on a standard computing environment to ensure practical replicability.

A. Data Partitioning and Reproducibility

The dataset was divided using a stratified 70:30 traintest split, allocating 350 samples for training and 150 for independent testing. Stratification was applied with respect to the target variable (congestion_level) to preserve the original class distribution in both subsets, thereby mitigating bias from class imbalance—a known challenge in severitybased traffic classification. Reproducibility was enforced by setting a fixed random seed (random_state=42) across all random operations, including data shuffling, model initialization, and subsampling procedures.

B. Model Training and Hyperparameter Configuration

Both selected algorithms—Random Forest and XGBoost—were trained using their default hyperparameters as provided in their respective libraries, with the following key settings: - Random Forest: 100 trees, Gini impurity criterion, maximum depth unlimited, bootstrap enabled. - XGBoost: 100 boosting rounds, learning rate 0.3, maximum depth 6.

Table I: Comprehensive Feature Set for Congestion Prediction

Category	Feature	Type	Description
Temporal	hour	Numerical	Hour of day (0–23)
	day week	Numerical	Day of week (1–7)
	weekend	Binary	Flag indicating weekend (1) or weekday (0)
Spatial	road name	Categorical	Identifier for road segment
Traffic Flow	volume	Continuous	Vehicle count per observation period
	speed	Continuous	Average speed (km/h)
	density	Continuous	Vehicle density (vehicles/km)
Incident	incident	Binary	Presence of incident (1) or none (0)
	inc type	Categorical	Type of incident (e.g., accident, breakdown)
Environmental	weather	Categorical	Prevailing weather condition
Road Attribute	capacity	Continuous	Maximum road capacity (vehicles/hour)
Engineered	cap util	Continuous	Capacity utilization ratio (volume / capacity)
	time period	Categorical	Time-of-day category (e.g., Morning Peak, Evening Peak)
	day type	Categorical	Day classification (Weekday, Friday, Weekend)
	flow eff	Continuous	Flow efficiency metric (speed / volume)
Target	congestion	Categorical	Congestion severity level (Low, Medium, High, Severe)

Subsample ratio 1.0, column subsample ratio 1.0, objective multi: softprob for multi-class probability output.

No extensive hyperparameter tuning was performed in this initial study to establish baseline performance and maintain comparability; future work may explore grid search or Bayesian optimization for further gains.

C. Evaluation Protocol

Model performance was assessed using a comprehensive suite of metrics suitable for multi-class classification: - Overall accuracy (proportion of correctly predicted instances). Macro-averaged precision, recall, and F1-score (unweighted averages across classes, sensitive to performance on minority classes). - Per-class precision, recall, and F1-score to reveal class-specific behavior. - Confusion matrices for detailed visualization of misclassification patterns, particularly adjacentclass errors inherent to ordinal congestion levels.

These metrics provide a balanced view of predictive power, class-wise reliability, and error typology—essential for assessing suitability in real-world traffic management where accurate detection of High and Severe states is critical.

All experiments were repeated with the fixed seed to confirm result stability, and confusion matrices were generated to support qualitative interpretation of model behaviour.

IV. RESULTS

The experimental evaluation on the held-out test set (150 samples) reveals meaningful predictive capability for the proposed multi-class congestion classification framework. XGBoost consistently outperformed Random Forest across all evaluation metrics, demonstrating superior handling of the complex, non-linear relationships inherent in Kampala's heterogeneous traffic data.

A. Overall Classification Performance

Table II presents the macro-averaged performance metrics. XGBoost achieved an overall accuracy of 84.0% (81 correct predictions out of 150), with macro-averaged precision of 0.808, recall of 0.840, and F1-score of 0.820—representing balanced improvements over Random Forest (82.7% accuracy, F1-score 0.800). These results indicate reliable classification across all four severity levels, particularly valuable for prioritizing High and Severe states in real-world traffic management.

B. Feature Importance Analysis

Feature importance analysis (gain-based from XGBoost) identifies the most influential predictors of congestion severity. As shown in Figure 1, the top-ranked features are dominated by engineered metrics: capacity_utilization (saturation ratio), vehicle_density, and flow_efficiency (speed/volume ratio). These results strongly align with traffic engineering principles, confirming that road demand-capacity imbalance and flow degradation are primary drivers in Kampala's urban network.

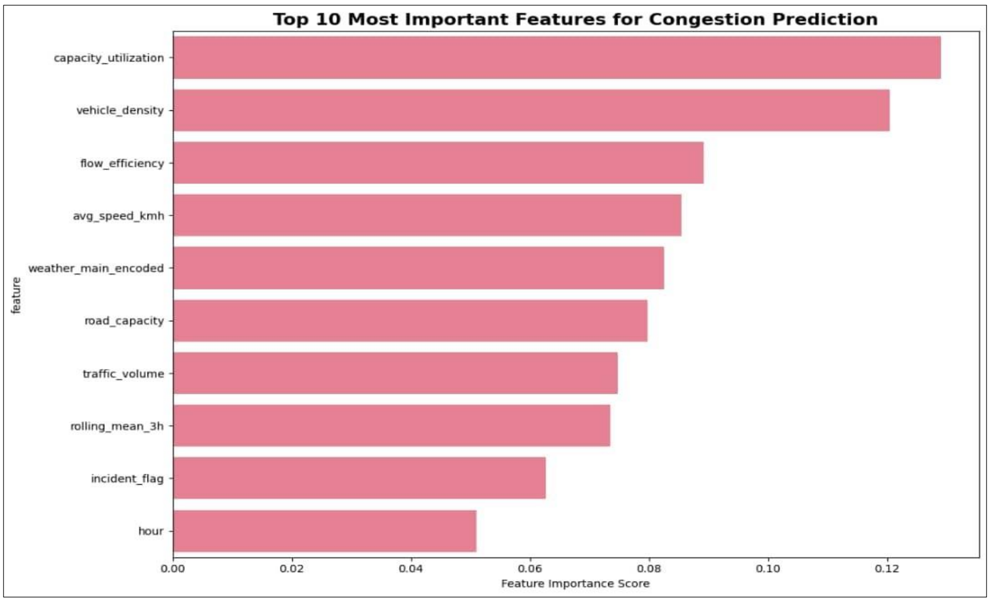

Fig. 1: Top 10 feature importance scores from the XGBoost model (gainbased). Engineered features related to road saturation and flow quality dominate, highlighting the value of domain-informed engineering

V. ANALYSIS AND DISCUSSIONS

A. Model Performance Superiority

XGBoost's consistent outperformance over Random Forest (higher accuracy, precision, recall, and F1-score) stems from its core algorithmic advantages: sequential error correction via gradient boosting, built-in L1/L2 regularization to prevent overfitting, and efficient handling of non-linear interactions and feature interactions. These properties are particularly well-suited to Kampala's complex traffic patterns, which involve heterogeneous road usage, frequent incidents, variable weather, and temporal peaks—factors that create intricate, non-linear dependencies beyond what bagging-based Random Forest can fully capture.

Table II: Overall Classification Performance on the Test Set (Macro-Averaged Metrics)

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	82.7%	0.880	0.827	0.800
XGBoost	84.0%	0.808	0.840	0.820

B. Interpretation of Feature Importance

The feature importance analysis (gain-based from XGBoost) reveals strong alignment with established traffic flow theory.

The dominance of capacity_utilization (saturation ratio = volume / capacity) as the top predictor confirms that road demand exceeding supply is the primary congestion trigger. vehicle_density ranks second, underscoring physical occupancy as a direct driver of flow breakdown. The engineered flow_efficiency (speed / volume) emerges as a valuable complementary metric, quantifying flow degradation under density—offering better discrimination than raw speed or volume alone. These insights validate the domain-informed feature engineering approach and provide urban planners with actionable priorities: targeting capacity bottlenecks and density hotspots could yield the greatest congestion relief.

C. Error Patterns and Classification Challenges

Confusion matrix analysis shows that misclassifications are predominantly between adjacent severity levels (e.g., Medium High, High Severe). This pattern is characteristic of ordinal classification problems, where congestion evolves continuously rather than in discrete jumps—models struggle with precise boundary thresholds but successfully capture overall degradation trends. The underrepresented Low class (due to class imbalance in the dataset) exhibits lower recall, a common challenge in severity-based tasks where ”normal” states are less frequent in urban data. Despite this, XGBoost’s stronger performance on the critical Severe class highlights its utility for high-stakes applications, where accurate detection of gridlock enables prioritized interventions.

D. Implications for Proactive Traffic Management

Overall, the framework effectively captures congestion trends in a developing-city context like Kampala, where data scarcity and heterogeneity are prevalent. The modest accuracy gains, combined with interpretable features and ordinal-aware behavior, position this approach as a practical foundation for intelligent transportation systems. It supports proactive strategies—such as dynamic signal timing, incident response prioritization, or traveler information systems—potentially reducing economic losses, emissions, and commuter frustration.

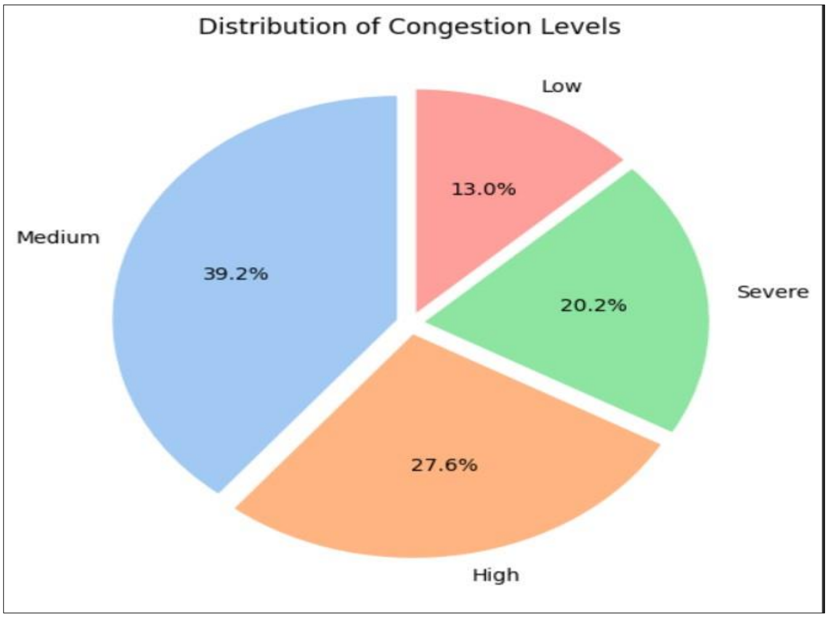

Fig. 2: Distribution of Congestion Levels in the Dataset (Pie Chart). This visualization shows the proportional representation of each congestion severity class, highlighting potential class imbalance issues

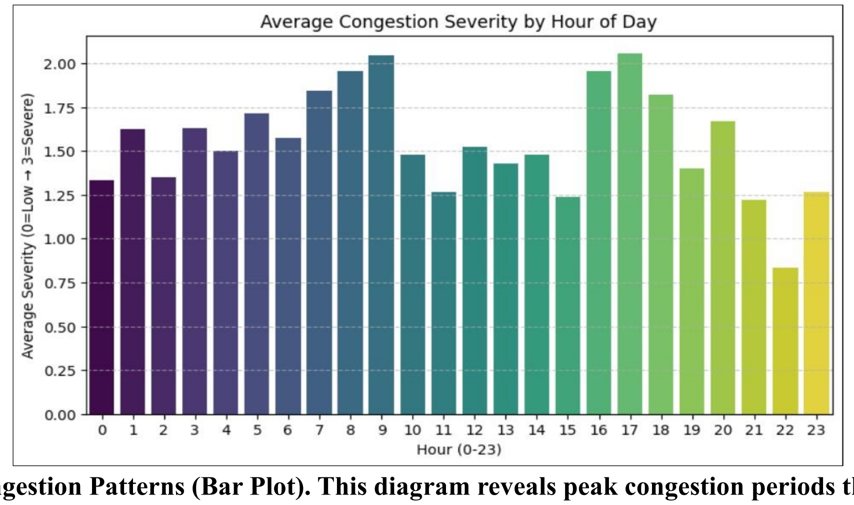

Fig. 3: Hourly Congestion Patterns (Bar Plot). This diagram reveals peak congestion periods throughout the day, identifying morning and evening rush hours as critical times

Future enhancements could address limitations through classbalancing techniques (e.g., SMOTE), ordinal-specific losses, or integration of temporal/spatial dependencies via LSTM or graph models to further refine boundary discrimination and generalizability.

VI. GRAPHS AND DIAGRAMS

This section presents a comprehensive set of visualizations derived from the dataset analysis and model evaluation. These diagrams illustrate key data patterns, model performance, and interpretive insights, facilitating a deeper understanding of traffic congestion dynamics in Kampala. The figures include distributions, temporal patterns, correlations, feature importance, and performance metrics, providing multifaceted views of the prediction framework.

These visualizations collectively demonstrate the model's interpretability through feature rankings, reveal data characteristics via distributions and patterns, and assess performance using standard diagnostic tools. They underscore the framework's potential for real-world deployment while identifying areas for refinement, such as addressing class imbalance in visualizations like the confusion matrices.

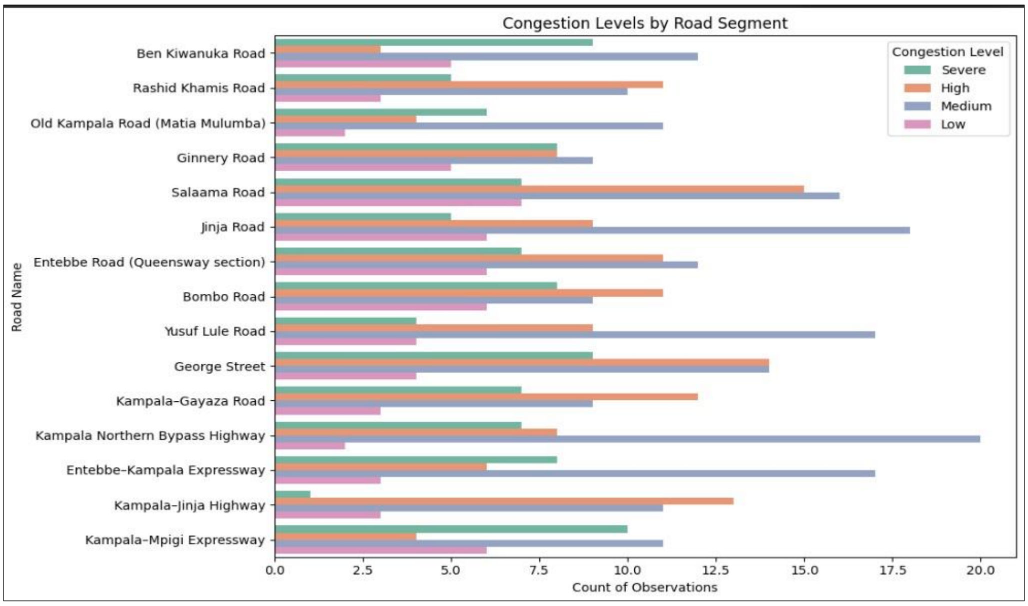

Fig. 4: Road-wise Congestion Distribution (Bar Plot). This figure compares congestion levels across different Kampala road segments, pinpointing highrisk arterial routes

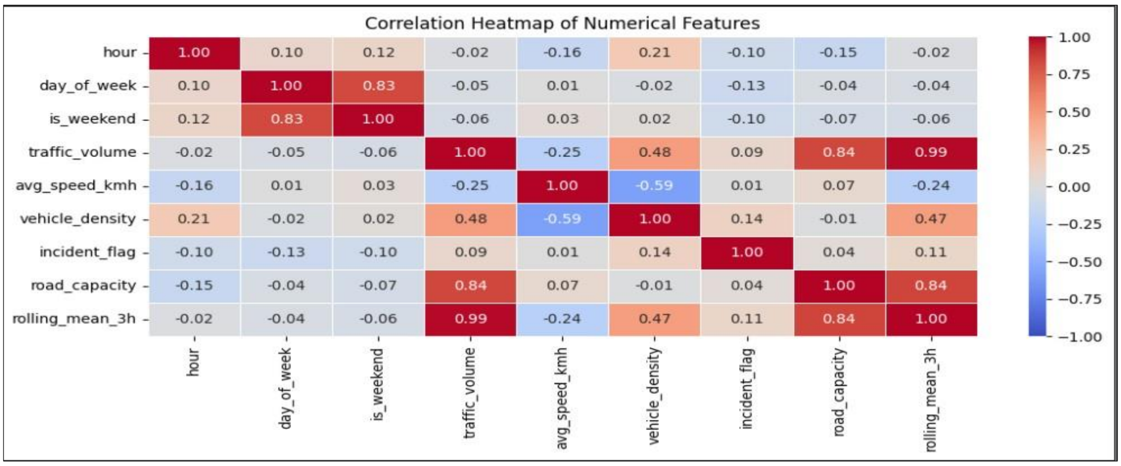

Fig. 5: Feature Correlation Heatmap. This heatmap displays pairwise correlations between numerical features, aiding in the identification of multicollinearity and key relationships (e.g., speed vs. density)

VII. LIMITATIONS

While the developed congestion prediction framework demonstrates promising results in a Kampala-specific context, several important limitations must be acknowledged. These constraints provide valuable guidance for future improvements and realistic interpretation of the current findings.

1. Limited Dataset size and Synthetic Nature

The analysis relies on only 500 observations, which, while sufficient for initial model development and proofof-concept, is relatively small compared to typical realworld traffic datasets. Additionally, the data is synthetically generated rather than collected from live traffic sensors or cameras. This synthetic origin may not fully capture the complete range of real-world variability, noise, and rare events characteristic of Kampala's heterogeneous, incident-prone, and weather-sensitive traffic environment. Consequently, the model's generalizability to actual operational conditions remains uncertain and should be validated with larger, real-world data in subsequent work.

2. Static Classification Approach

The current methodology treats each observation as an independent instance and applies static multi-class classification. This approach completely disregards the inherently temporal and sequential nature of traffic flow (e.g. congestion build-up and dissipation over time) as well as the spatial dependencies between adjacent road segments. Real traffic congestion is a dynamic, interconnected phenomenon — ignoring these temporal and spatial relationships represents a significant simplification that limits the model's ability to capture evolving patterns and network-wide effects.

3. Class Imbalance and Representation of Low Congestion States

The dataset exhibits noticeable imbalance, with fewer observations of the *Low* (free-flow) congestion class.

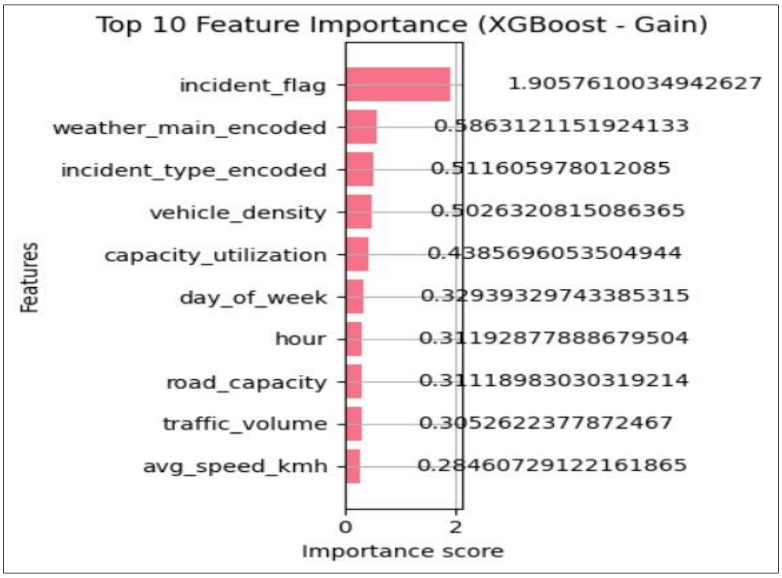

Fig. 6: XGBoost Confusion Matrix (Heatmap). This matrix shows classification accuracy per class and common misclassification patterns, particularly between adjacent severity levels

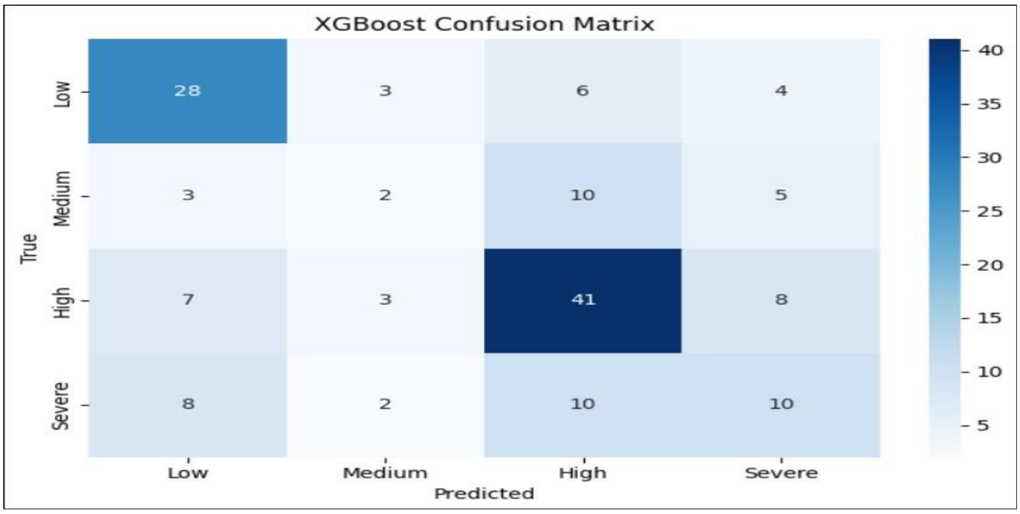

Fig. 7: Random Forest Confusion Matrix (Heatmap). Similar to the XGBoost matrix, this highlights comparative performance and error distributions across classes

Compared to higher severity levels. This imbalance adversely affects model performance on the minority class, resulting in reduced recall and precision for *Low* congestion detection. In practical terms, this means the system may be less reliable at confidently identifying normal traffic conditions — an important state for avoiding unnecessary interventions.

4. Lack of External Validation and Deployment Testing

The evaluation has been conducted solely on the internal train-test split of the synthetic dataset. No external validation using completely unseen real-world data from different time periods, locations, or traffic conditions has been performed. Furthermore, the framework has not yet been tested in a real-time deployment scenario, where prediction latency, data streaming quality, and integration with traffic management systems become critical factors.

These limitations are characteristic of early-stage applied machine learning research in resource-constrained environments. They do not invalidate the core contributions of the work — namely the demonstration of effective feature engineering and the superior performance of gradient boosting for this task — but they clearly delineate the boundary of current results and highlight the most important directions for future enhancement.

VIII. CONCLUSION

This project successfully demonstrates the feasibility and value of applying machine learning classification techniques to predict traffic congestion severity in Kampala City — a

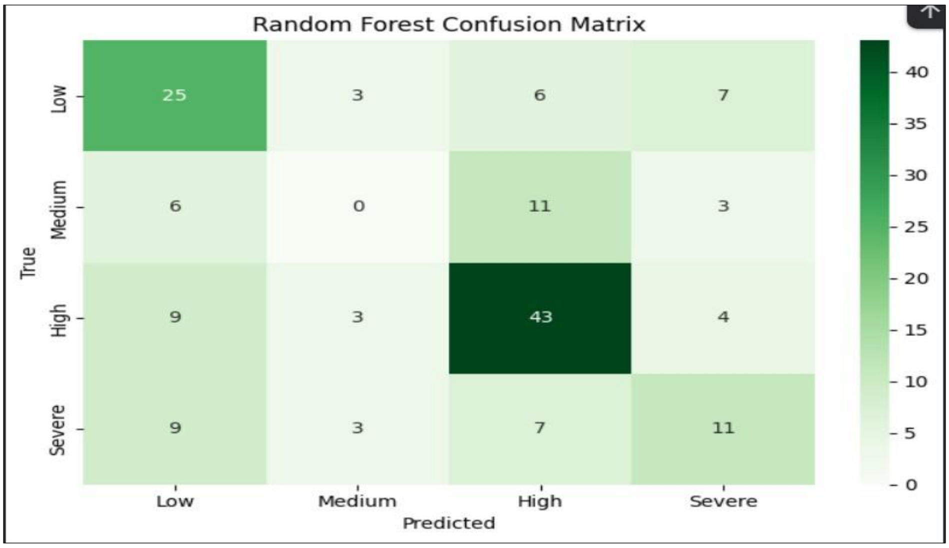

Fig. 8: Multi-Class ROC Curves for XGBoost. This plot evaluates the model's ability to distinguish between classes, with AUC values indicating discrimination power for each severity level

Rapidly urbanizing African metropolis facing acute mobility challenges. By developing a complete end-to-end framework that integrates domain-informed feature engineering with ensemble classifiers, the work establishes a practical classification system capable of categorizing congestion into four actionable levels: Low, Medium, High, and Severe.

The XGBoost classifier emerged as the superior performer, achieving 84.0% overall accuracy and the highest macro-averaged precision (0.808), recall (0.840), and F1score (0.820) on the held-out test set. More importantly, feature importance analysis revealed that engineered predictors — particularly capacity utilization (volume/capacity ratio), vehicle density, and flow efficiency (speed/volume ratio) — dominate decision-making. These findings strongly align with fundamental traffic flow theory and provide urban planners and traffic authorities with interpretable, high-impact insights into the primary drivers of congestion in Kampala's heterogeneous road network.

Although the modest accuracy reflects challenges inherent to the small synthetic dataset, class imbalance, and static modeling approach, the framework nonetheless captures meaningful congestion trends and demonstrates the clear superiority of gradient boosting over traditional ensembles for this structured, tabular prediction task. The developed system lays a solid foundation for intelligent transportation systems (ITS) in resource-constrained developing cities, offering a scalable, interpretable classification pipeline that can be readily extended and deployed.

Future enhancements should prioritize: - Acquisition and integration of larger, real-world traffic datasets from sensors, GPS traces, or KCCA feeds - Incorporation of temporal modeling (e.g., LSTM, GRU) and spatial dependencies (e.g., graph neural networks) to capture dynamic congestion propagation - Application of imbalance-aware techniques (e.g., SMOTE, focal loss, class-weighted training) and ordinal-specific losses - Real-time deployment testing, including API integration with traffic management dashboards and evaluation of prediction latency.

By addressing these directions, the proposed approach holds strong potential to evolve into a proactive, data-driven tool that supports adaptive signal control, incident prioritization, traveler information systems, and long-term urban mobility planning — ultimately contributing to reduced congestion, lower emissions, improved economic productivity, and enhanced quality of life for Kampala's residents.

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