

Introduction

Road traffic crashes remain a major **global safety issue** (WHO)

Risky behaviours such as **speeding** and **harsh braking** increase crash risk

Machine learning can classify risky behaviour, but:

- **Naturalistic driving data are highly imbalanced**
- Normal driving dominates
- High-risk events are rare

→ Leads to **biased predictions** and poor detection of critical cases

- **cGANs** generate synthetic **minority-class samples**
- Improve detection of **rare high-risk events**

Objectives

- Evaluate **cGAN augmentation** for class imbalance
- Assess **performance vs. overfitting**
- Examine impact on **interpretability (SHAP)**

☑ Support **safe use of synthetic data**

Data Collection

Dataset: Naturalistic driving data (**i-DREAMS**)

Countries: Belgium (43 drivers) & United Kingdom (26 drivers)

Duration: 4-month monitoring period

Total: 265,000+ minutes of driving

Data Acquisition:

Vehicles equipped with **OBD-II systems & Mobile sensors**

Recorded variables: Speed, Headway, Braking

Data Structure:

Driving segmented into **30-second intervals**

Classified into: Normal, Dangerous, Avoidable Accident

Methodology

Data Preparation:

- Removed **missing values**
- Applied **Min-Max normalization**
- Problem: **Binary classification** (Normal vs. **Avoidable Accident**)

Data Augmentation (cGAN):

- Generated **synthetic high-risk samples**
- Generator: Noise + **risk label** → **synthetic data**
- Discriminator: Evaluates **authenticity + class consistency**

Model Development:

- **80/20 train-validation split**
- **Stratified 5-fold cross-validation**

Models Evaluated

- XGBoost-Random Forest (**hybrid ensemble**)
- RNN + AdaBoost (**temporal patterns**)
- GAN-based classifier

Evaluation & Interpretability:

- Metrics: Accuracy, Precision, Recall, F1-score
- **SHAP analysis:**
 - Before & after augmentation
 - Assess impact on **decision patterns**

Results

Model Performance

Before Augmentation (Original Data):

- **XGBoost-Random Forest**
 - Accuracy: **>90%** (Belgium & UK)
- **RNN-AdaBoost**
 - Moderate performance
- **GAN-based classifier**
 - Lower accuracy
 - Limited **minority-class representation**

After cGAN Augmentation:

- Accuracy increased across **all models**
- **Recall improved significantly**
 - Better detection of **high-risk events**
- **GAN-based model** improved to **~90% accuracy**

Key Concern:

- Hybrid models reached **near-perfect accuracy**
- → Indicates potential **overfitting**

Dataset	Model	Accuracy	Precision	Recall	F1-score
Belgium (original dataset)	XGBOOST & RF	93%	93%	93%	93%
	RNN & AdaBoost	83%	82%	83%	82%
	GANS	76%	64%	76%	66%
UK (original dataset)	XGBOOST & RF	92%	92%	92%	91%
	RNN & AdaBoost	85%	84%	85%	84%
	GANS	79%	80%	79%	74%
Belgium (Augmented dataset)	XGBOOST & RF	100%	100%	100%	100%
	RNN & AdaBoost	100%	100%	100%	100%
	cGANS	90%	90%	90%	90%
UK (Augmented dataset)	XGBOOST & RF	100%	100%	100%	100%
	RNN & AdaBoost	100%	100%	100%	100%
	cGANS	91%	90%	91%	91%

Overfitting and Generalization

Key Observation:

- Models reached **~100% accuracy** after augmentation
- Strong indication of **overfitting to synthetic patterns**

Performance Behavior:

- **Recall improved significantly**
- **Precision improved only slightly**
- → Increased sensitivity, but limited improvement in **true positive accuracy**

Model Stability:

- Performance **varied across cross-validation folds**
- Synthetic data showed **lower variability**
- → Reduced complexity → **risk of memorization**

Implications:

- Models may learn **artificial structures**, not real behavior
- Creates a trade-off:
 - 📊 **Higher metrics**
 - vs. ⚠️ **Lower real-world reliability**

☑ Critical issue for **safety-sensitive applications**

Feature Importance and Model Interpretability

Key Predictors (Pre-Augmentation):

- **Speed-related variables** → strongest influence
 - Mean speed
 - High-level speeding indicators
- **Harsh braking** → critical for detecting *Avoidable Accidents*

Impact of Data Augmentation:

- Feature importance **shifted after GAN augmentation**
- Models relied more on **synthetic feature patterns**

Implications:

- Augmentation may **alter learned risk representations**
- Improved balance ≠ **unchanged model logic**
- Raises concerns about:
 - **Interpretability**
 - **Robustness**

Conclusions

Key Findings:

- Conditional GANs **reduce class imbalance** in risky driving data
- Improve:
 - 📊 **Recall**
 - 📊 **Overall accuracy**

Limitations:

- ⚠️ Risk of **overfitting** with synthetic data
- ⚠️ Potential **distortion of feature importance**

Interpretation:

- Near-perfect accuracy may indicate **memorization**, not generalization

Implications:

- In safety-critical systems:
 - **Robustness** and **Interpretability**
 - are as important as **Performance**

Future Research

- External validation & **transferability testing**
- Advanced **GAN-based data augmentation**
- Stronger **regularization methods**
- Simulation frameworks** for safe deployment

Acknowledgements

The present work is related to the CulturalRoad Project (Cultural, regional and societal factors to overcome barriers to connected, cooperative and automated mobility deployment). This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No. 101147397.

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