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Routing-aware feature optimization for explainable autonomous driving decision-making using hybrid MCDM–AI models

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ABSTRACT

Autonomous-driving systems require reliable and explainable decision-support mechanisms for dynamic traffic environments. However, existing multi-criteria decision-making–artificial intelligence (MCDM–AI) frameworks often rely on fixed feature spaces, limited contextual integration, and evaluation settings vulnerable to routing-derived information leakage. To address these limitations, this study proposes a routing-aware selective multi-feature selection (SR-MFS) framework for explainable autonomous-driving decision support. The framework integrates routing-aware contextual prioritization, compact feature optimization, MCDM-based ranking, leakage-free AI validation, and explainable analysis within a unified architecture. Initially, 12 driving-scene descriptors are extracted from autonomous-driving datasets, after which SR-MFS reduces the feature space from 12 to 5 optimized features while preserving ranking consistency. The framework is evaluated on both BDD100K and Udacity self-driving datasets using conventional, graph-based, and transformer-inspired learning models. Experimental results demonstrate stable ranking agreement, robust cross-dataset performance, robustness under sensor-noise conditions, and interpretable decision behavior validated using SHAP/LIME analysis, ablation studies, statistical confidence intervals, and external dataset validation.

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1. INTRODUCTION

Autonomous-driving and intelligent robotic systems require decision support in uncertain traffic. Advances in perception, navigation, and transportation use deep learning, detection, segmentation, and scene analysis [1]. In parallel, multi-criteria decision-making (MCDM) approaches such as SAW, TOPSIS, VIKOR, LINMAP, and ELECTRE [2] have been widely adopted in robotic and industrial decision systems for evaluating alternatives under multiple conflicting criteria. Hybrid ranking frameworks and integrated MCDM models further improved ranking consistency and robustness in industrial robot-selection and engineering optimization problems [3]. Moreover, hybrid MCDM–machine learning frameworks and ensemble feature-selection strategies demonstrated improved explainability [4], ranking reliability [5], and adaptive decision-support capability in intelligent engineering environments [6], [7]. Deep-learning-driven perception systems have also enhanced robotic manipulation, object recognition, and autonomous-driving scene understanding [8], [9]. Semantic segmentation and pose-estimation frameworks improved

environmental perception accuracy in complex robotic environments [10], [11], while deep object-recognition systems were integrated with robotic grasping [12] and intelligent manipulation applications [13]. augmentation and feature learning improve robustness/generalization [14], [15]. Yet many frameworks prioritize detection accuracy over contextual decision-priority optimization [16], [17]. Recent studies additionally investigated context-aware optimization [18], adaptive prioritization [19], intelligent resource-allocation strategies in dynamic communication [20] and robotic environments [21]. Hybrid feature-selection approaches combining entropy weighting, statistical analysis, and machine-learning validation were also explored to reduce feature redundancy and improve computational efficiency in intelligent systems [22]. Explainable artificial intelligence (XAI) [23] frameworks further improved transparency and interpretability in intelligent robotic environments [24], while scalable explainable systems were investigated for distributed and large-scale autonomous platforms [25]. Remaining issues include static features, single-weight strategies, isolated models, weak ranking-stability, leakage-free validation, cross-dataset explainability, and limited routing-aware compact feature selection [26].

Recent autonomous-driving studies address MCDM, XAI, feature optimization, and scene analysis, but limitations remain in fixed features, single-weight strategies, routing-context integration, ranking stability, leakage-free validation, compact optimization, and cross-dataset generalizability. The proposed routing-aware selective multi-feature selection (SR-MFS) model has been designed to fill the above voids by introducing routing context-awareness, multiple weight importance, redundancy, MCDM rankings, leakage-less AI, and XAI, where 12 descriptors get reduced to 5.

The main contributions are i) routing-aware compact feature optimization, ii) six-method, multi-weight MCDM validation for ranking stability, iii) leakage-free AI excluding routing-priority scores, labels, and derived components, iv) validation on BDD100K and Udacity datasets for generalizability, and v) XAI, robustness, ablation, statistical, and runtime analyses for reliable and reproducible decision support.

2. METHOD

2.1. Problem formulation, dataset description, and preprocessing

Autonomous-driving scenes are represented using structured object-level, spatial, and contextual descriptors to construct a decision matrix for routing-aware feature optimization and ranking. The framework prioritizes scenes according to contextual importance and decision relevance. Experiments use the BDD100K dataset [27], containing diverse traffic, weather, lighting conditions, and annotations for vehicles, pedestrians, bicycles, and road signals. The Udacity Self-Driving Car Dataset [28] is used for external validation using the same 12-feature representation, routing-priority modeling, SR-MFS optimization, MCDM ranking, leakage-free AI validation, robustness, statistical analysis, and XAI evaluation.

Figure 1 illustrates the multi-dataset pipeline, where 12 descriptors are optimized to 5 features using variability, multi-weight importance, routing-context relevance, and redundancy control. The selected subset is evaluated across 24 MCDM ranking sets and validated using leakage-free AI, robustness, runtime, statistical, and XAI analyses. Before evaluation, incomplete annotations, invalid bounding boxes, and duplicates are removed; features are min–max normalized. Deterministic seeds, stratified train–test splitting, bootstrap confidence intervals, and paired significance testing support reproducibility and reliability.

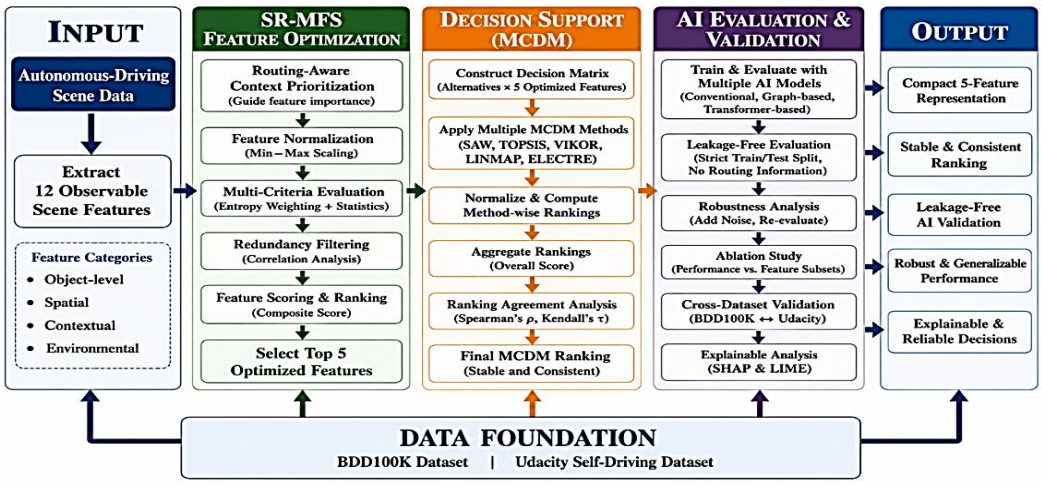


Figure 1. Architecture of the proposed routing-aware SR-MFS framework for context-driven multi-criteria decision-making in autonomous driving

2.2. Scene-to-feature transformation layer

The initial step in the suggested framework involves encoding the raw perceptions output to create a decision representation. In other words, a scene from the driving environment is converted into a feature vector that encodes information about object existence, their spatial relations, and the context complexity of the scene. Specifically, each scene $a_i$is mapped to a feature vector $x_i = [f_1, f_2, \dots, f_m]$, and generate a decision matrix X. The selected features are intended to account for the dynamics observed in real traffic situations and are classified in Table 1 into three different categories. The complete raw feature space therefore consists of 12 driving-scene descriptors combining object-level, spatial, and contextual representations. All subsequent feature-reduction experiments are performed relative to this unified 12-feature input space.

Table 1. Structured feature representation for driving scene encoding

Feature Category	Feature Name	Functional Description
Object-Level	total_objects	Overall density of detected entities
	vehicle_count	Number of vehicles present in the scene
	person_count	Number of pedestrians
	bike_count	Number of cyclists
	traffic_light_count	Number of detected traffic lights
	traffic_sign_count	Number of detected traffic signs
Spatial	avg_bbox_area	Average spatial footprint of detected objects
	max_bbox_area	Maximum object size
	avg_bbox_width	Average horizontal span of objects
	avg_bbox_height	Average vertical span of objects
Contextual	scene_complexity	Proxy for scene density and interaction level
	risk_score	Composite scene-risk descriptor used only for ranking/feature optimization

2.3. Routing-aware context injection layer

Static feature representations alone cannot capture contextual urgency in driving scenarios. Therefore, the framework introduces a priority-based context embedding layer that assigns routing weights to each scene. The values of routing coefficients are dependent on traffic density, pedestrian involvement, cycling, and scene complexity. The generated routing priority value favors interaction-intensive scenes and divides scenes based on low, moderate, and high priorities so that further decision processes may include both scene structure and relevance information.

2.4. SR-MFS: Routing-aware feature optimization

In order to remove the redundant descriptors of scenes while retaining the decision-making relevant data, a new approach called SR-MFS for selective multi-feature selection with routing-aware mechanism is proposed in this research. Unlike the traditional feature selection technique which considers only statistical significance of the features, the SR-MFS approach considers variability, multi-weight decision importance, routing awareness, and redundancy among others. Routing priority is considered only to guide the optimization of features.

Algorithm 1. Routing-aware selective multi-feature selection (SR-MFS)
Input: Scene features, routing weights, feature count (K=5), redundancy threshold
Output: Optimized feature subset and reduced feature matrix

1. Extract 12 scene descriptors from each driving scene.
2. Compute routing-based contextual priority for each scene.
3. Normalize all scene features.
4. Evaluate feature variability, importance, and contextual relevance.
5. Compute final SR-MFS score for each feature.
6. Rank features according to SR-MFS scores.
7. Remove highly correlated redundant features.
8. Select the top 5 optimized features.
9. Construct the reduced feature matrix using selected features.
10. Perform MCDM ranking, AI validation, robustness analysis, and XAI evaluation.
11. Exclude routing-derived variables during final AI validation to avoid leakage.
    All features were normalized using min–max scaling before feature evaluation.

2.5. Multi-weight feature selection and MCDM evaluation

To prevent the reliance on just one criterion for importance, SR-MFS uses mean weight, standard deviation weight, entropy weight, and preference selection index, which represent uniform contribution, statistical variance, information entropy, and sensitivity to change in the decision process, respectively. The formula for calculating the feature importance score is (1).

$$S(f_j) = \frac{1}{K} \sum_{k=1}^{K} [V(f_j) \times w_k(f_j)] \quad (1)$$

where $w_k(f_j)$ represents the weight assigned to feature f_j under method k, and K as the number of methods for assigning weights. The roles of these weighting approaches are presented in Table 2.

Table 2. Multi-weight integration strategies within SR-MFS

Weighting Method	Underlying Principle	Role in Feature Optimization
Mean Weight	Uniform contribution	Provides baseline reference
SDV Weight	Statistical dispersion	Captures variability-driven importance
Entropy Weight	Information theory	Quantifies information content
PSI Weight	Preference deviation	Highlights sensitivity to decision changes

To prevent the reliance on just one criterion for importance, SR-MFS uses mean weight, standard deviation weight, entropy weight, and preference selection index, which represent uniform contribution, statistical variance, information entropy, and sensitivity to change in the decision process, respectively. The formula for calculating the feature importance score is (2).

$$S_{SAW}(a_i) = \sum_{j=1}^{m^*} w_j \cdot x'_{ij} \quad (2)$$

where higher scores indicate preferable alternatives. TOPSIS ranks alternatives according to their relative proximity to ideal and negative-ideal solutions.

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (3)$$

LINMAP, VIKOR, ELECTRE, and NFM provide complementary ranking perspectives, collectively improving decision stability, robustness, and reliability across multiple evaluation strategies.

2.6. Learning, explainability, and validation layer

The optimized SR-MFS feature space is evaluated based on decision tree, random forest, XGBoost, and neural network classifiers, and their performance is compared with respect to accuracy, precision, recall, and Macro F1. Explanability analysis is performed using random forest feature importance and SHAP/LIME. Additional validation includes ablation analysis, six MCDM methods with four weighting strategies producing 24 ranking sets, and XAI-based identification of influential leakage-free features.

3. RESULTS AND DISCUSSION

3.1. Experimental setup, evaluation, and reproducibility

The routing-aware SR-MFS framework models each driving scene as a multi-criteria decision problem and applies contextual feature optimization instead of the baseline full-feature approach. Six MCDM methods—SAW, TOPSIS, LINMAP, VIKOR, ELECTRE, and NFM—were evaluated using mean, entropy, SDV, and PSI weights. Udacity validation selected five compact features, achieving Spearman/Kendall agreement of 0.9936/0.9932 and Macro-F1 of 0.919–0.976. Decision tree, random forest, XGBoost, neural network, extra trees, HistGradientBoosting, graph kNN, and lightweight tabular transformer were tested using deterministic seeds, regularization or early stopping, and leakage-free validation in Python 3.12 with Scikit-learn, XGBoost, NumPy, Pandas, SHAP, and Matplotlib.

3.2. Feature optimization analysis

The results indicate that the SR-MFS module effectively compresses the feature space more than fifty percent while still keeping only the most useful attributes. However, this is more than simply feature space compression; rather, it can be considered as a feature selection process. Using both the variance and

multi-weight assessment of attributes, the SR-MFS algorithm selects only those features that are essential in making decisions. As such, not only does the feature space get compressed, but it also becomes much easier to analyze and understand, which aligns well with the nature of the decision problem at hand. In fact, it can be said that the optimized set of features obtained through this algorithm forms the basis of further MCDM assessments.

Figure 2 illustrates the extent of dimensionality reduction performed by the proposed SR-MFS model reduces the original 12-feature representation to 5 optimized features in both datasets, achieving a consistent dimensionality reduction of 58.33% while preserving decision-relevant information for ranking and AI validation.

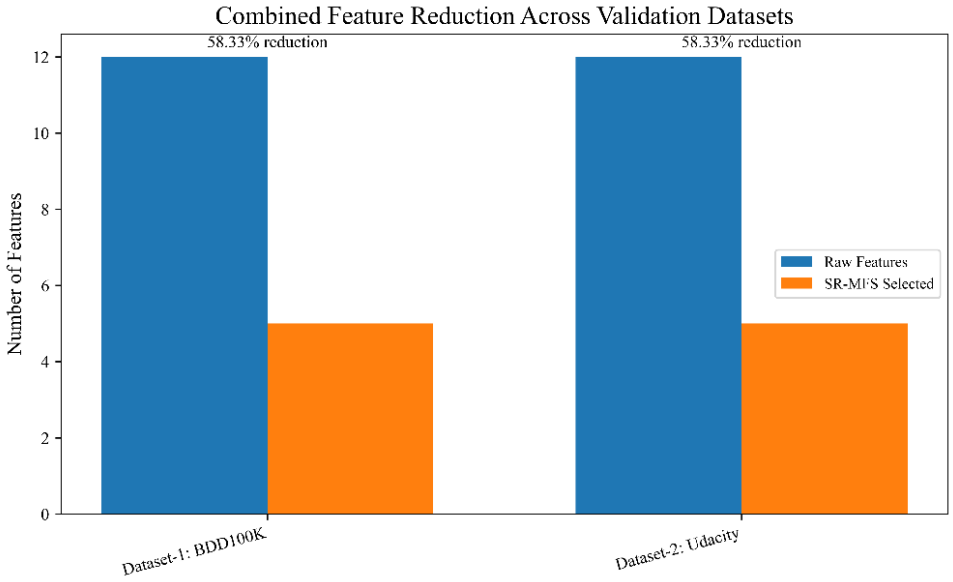


Figure 2. Combined feature reduction performance of the proposed SR-MFS framework across the BDD100K and Udacity datasets

3.3. Ranking consistency analysis

For determining whether or not the decision process is robust enough, a ranking analysis between the various MCDM methods is done by computing the Spearman and Kendall correlation values. This can be seen in Table 3.

Table 3. Hierarchical correlation comparison (baseline vs. proposed)

MCDM	Baseline Spearman/Kendall (M, E, S, P)	SR-MFS Spearman/Kendall (M, E, S, P)
SAW	.987/.843; .995/.867; .982/.821; .989/.835	.998/.952; .997/.948; .996/.941; .997/.946
TOPSIS	.521/.362; −.110/−.064; .476/.351; .439/.318	.912/.853; .894/.834; .931/.871; .921/.862
LINMAP	.598/.441; −.113/−.067; .612/.457; .569/.421	.964/.902; .943/.881; .952/.893; .961/.901
VIKOR	.492/.358; −.034/−.012; .587/.439; .593/.441	.951/.891; .932/.872; .958/.896; .949/.889
ELECTRE	.703/.512; .441/.307; .694/.503; .689/.497	.972/.921; .954/.903; .961/.912; .958/.907
NFM	.842/.653; .463/.331; .781/.602; .742/.561	.981/.936; .964/.919; .972/.928; .969/.924

In the baseline configuration, differences in the ranking stability depend strongly on the applied methods and weight generation schemes. In the case of entropy weighting, many combinations of approaches demonstrate poor correlation or even negative values for them. Such results mean that the decision-making scheme is rather unstable because changing the weight scheme causes drastic fluctuations in ranking. The cause of such instability lies in the presence of redundant information in the full feature space, which affects the consistency of MCDM methods.

Comparison of Spearman and Kendall ranking agreement scores for baseline and proposed SR-MFS feature spaces across the BDD100K and Udacity datasets. The proposed SR-MFS framework preserves

strong ranking consistency after reducing the feature space from 12 to 5 optimized features, demonstrating stable agreement across multiple MCDM methods and evaluation settings shown in Figure 3.

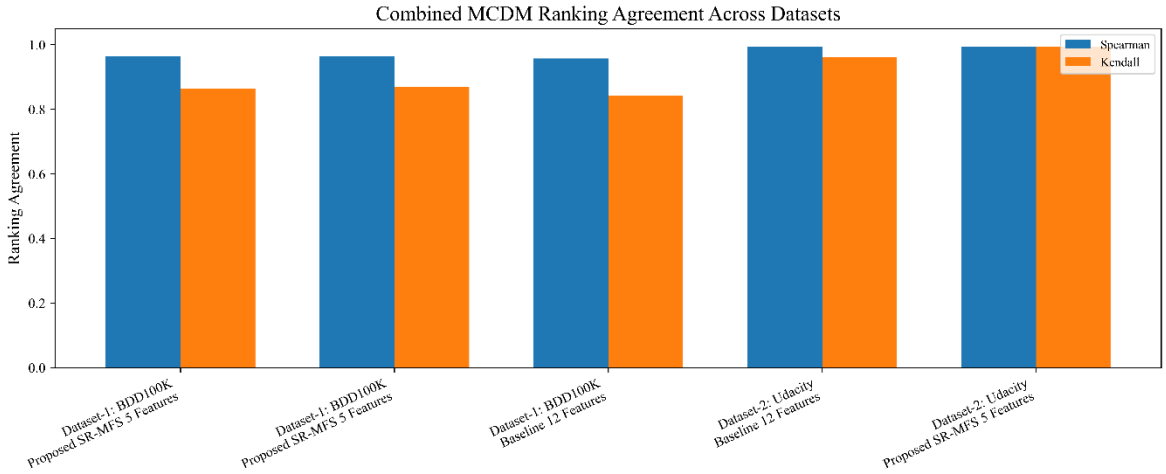


Figure 3. Combined MCDM ranking agreement across datasets

3.4. Ranking stability and Top-K analysis

Decision stability can also be assessed through the examination of the consistency of the top ranked choice options using various MCDM techniques. Table 4 reports the combined MCDM ranking agreement across the main and external validation datasets. In both datasets, SR-MFS reduces the feature space from 12 to 5 descriptors while preserving ranking agreement across 24 MCDM ranking sets. The Udacity external validation further confirms stable ranking behavior with Spearman = 0.9936 and Kendall = 0.9932. Clearly, the suggested model demonstrates a notable enhancement in terms of stability for all ranks considered, especially at the top rank. It can be seen that the optimization of the feature space leads to greater decision-making consistency irrespective of the applied MCDM approach.

Table 4. Combined MCDM ranking agreement across BDD100K and Udacity datasets

Dataset	Framework	Features	Spearman Agreement	Kendall Agreement	Ranking Sets
BDD100K	Baseline full features	12	0.599	0.468	24
BDD100K	Proposed SR-MFS	5	0.837	0.697	24
Udacity	Baseline full features	12	0.9934	0.9609	24
Udacity	Proposed SR-MFS	5	0.9936	0.9932	24

3.5. AI-based validation of selected feature space

To verify whether the SR-MFS-selected feature set is effective or not, supervised learning algorithms are employed by using the optimized feature set. The findings are shown in Table 5. Leakage-free AI validation confirms stable performance after excluding routing-priority scores, labels, and derived variables. SR-MFS reduces 12 features to 5, achieving 58.33% reduction while preserving decision relevance. The Spearman/Kendall correlation is now 0.837/0.697 for BDD100K and 0.9936/0.9932 for Udacity. Macro-F1 values vary between 0.752–0.774 and 0.919–0.976 respectively, while the two best

Table 5. Dataset 1: Leakage-free AI validation results using non-routing geometric scene features

Model	Accuracy	Macro-F1	Runtime (s)
Lightweight Tabular Transformer	0.7690	0.7715	192.3383
Neural Network	0.7698	0.7711	8.9744
HistGradientBoosting	0.7660	0.7678	8.6138
Random Forest	0.7630	0.7653	8.7736
XGBoost	0.7625	0.7649	3.4267
Extra Trees	0.7586	0.7604	2.8949
Graph kNN Scene-Similarity	0.7521	0.7536	0.3123
Decision Tree	0.7493	0.7516	0.4319

3.6. External validation on Udacity Self-Driving Car dataset

The findings from the external validation presented in Table 6 show that SR-MFS provides consistent predictive performance without leakage on the Udacity dataset, while still being compatible with traditional models and graph-based as well as transformer-based models. The method that showed the best results was graph kNN scene-similarity.

Statistical and XAI validation across BDD100K and Udacity identifies Neural Network and Graph kNN as the strongest models, respectively, with total_objects as the dominant explanatory feature. SR-MFS reduces 12 features to 5, lowers computational cost, prevents routing-derived leakage, and supports reliable deployment in resource-constrained robotic environments.

Table 6. Dataset 2: Udacity final leakage-free model results with confidence intervals

Model	Accuracy Mean	Accuracy CI Low	Accuracy CI High	Macro-F1 Mean	Macro-F1 CI Low	Macro-F1 CI High
Graph KNN Scene-Similarity	0.975943	0.972243	0.980138	0.975967	0.972188	0.980155
HistGradientBoosting	0.961368	0.956364	0.966260	0.961400	0.956222	0.966184
Random Forest	0.944743	0.939154	0.951250	0.944928	0.939328	0.951533
XGBoost	0.933868	0.927557	0.940304	0.934070	0.927790	0.940472
Extra Trees	0.931066	0.924335	0.937942	0.931521	0.924594	0.938115
Decision Tree	0.924983	0.918251	0.931849	0.925391	0.918630	0.932314
Lightweight Tabular Transformer	0.919918	0.913878	0.927666	0.919803	0.913826	0.927508
Neural Network	0.918685	0.911787	0.926236	0.919057	0.912170	0.926187

4. CONCLUSION

This study proposes a routing-aware explainable decision-support framework integrating SR-MFS, MCDM ranking, leakage-free AI validation, and XAI for autonomous-driving scene analysis. The framework reduces 12 scene features to 5 compact decision features while maintaining stable ranking agreement across the BDD100K and Udacity datasets. External validation, robustness testing, ablation analysis, statistical evaluation, runtime assessment, and leakage-free AI/XAI validation confirm its reliability. From a robotics and automation perspective, SR-MFS supports compact, explainable, and computationally efficient prioritization for autonomous mobile robots, AGVs, warehouse robotics, intelligent monitoring, and related industrial systems. However, large-scale environments with multiple interacting vehicles still require scalable decision-support mechanisms. Future work will focus on distributed validation under dense traffic, severe sensor noise, dynamic uncertainty, lightweight deployment in embedded and edge systems, and real-time testing using CARLA, ROS, and driving simulators. Further optimization of inference latency, memory usage, and real-time integration will also be investigated for practical resource-constrained automotive environments worldwide.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The datasets supporting the findings of this study are publicly available from the BDD100K [27] and Udacity autonomous-driving [28] repositories.

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