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Highway geometric design optimization for improved safety and its sensor visibility using decision trees

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Abstract

The application of decision trees in optimizing geometric design parameters for enhanced road safety and Intelligent Transportation System (ITS) sensor visibility is now an imperative. By utilizing a comprehensive dataset comprised of road geometry, ITS sensor locations, accident records, and traffic volume, decision tree models can be developed to predict optimal design parameters. In doing this, the results should show a high percentage of accuracy in predicting safe and visible designs. Furthermore, a decision tree-based feature selection process can identify road curvature, grade, sensor placement, and intersection type as critical factors influencing safety and sensor visibility. This study presented significant layouts and interactions between design parameters, while highlighting the importance of considering contextual relationships in geometric design using decision tree. Additionally, decision tree models were evaluated using accuracy, precision, and recall metrics, demonstrating robust performance. A sensitivity analysis was shown to assess model robustness. The study's findings suggest that integrating decision tree optimization into geometric design software can enhance evidence-based design practices. The study's outcome is relevant to policymakers, transportation engineers, and researchers seeking to improve road safety and ITS effectiveness.

Keywords: Geometric design; Road safety; ITS sensor visibility; Decision trees; Machine learning; Transportation infrastructure

1. Introduction

The main roles of geometric design optimization in transportation engineering include road safety improvement and effectiveness in Intelligent Transportation System. In fact, with the increased integration of Intelligent Transportation System henceforth, ITS into roadway infrastructure, geometric design has to be increasingly complex, focusing not just on vehicle maneuverability but also sensor visibility for effective capture and communication of data. These include lane width, curve radius, shoulder design, and sight distance, among other geometrical factors that for a long time have had influential impacts on driver behaviors and collision risk aspects. With the technological development in the field of sensing devices such as LiDAR and radar (Gao, *et al.,* 2022), demands for geometric optimization in supporting such devices are increasingly becoming urgent. Figueiredo *et al*. (2021) notes that, ITS sensors must be correctly aligned within the geometry of the road if valid data on traffic flow is to be collected to enable real-time monitoring for safer and more efficient flow on the highways. This is in agreement with.

Decision trees represent one of the most important techniques in machine learning, which has proved very helpful in this area, given their interpretability and the capability of working with high-dimensional datasets. These algorithms systematically partition data based on variable importance. This can enable researchers to identify which of those

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geometric features most greatly impact both road safety and ITS sensor efficacy. The recursive structure of decision trees prioritizes variables that otherwise might be obfuscated in large datasets, curve radius, sight distance, and lane width among many others (Breiman *et al.*, 1984). The approach goes well with the purposes of transportation engineering, where the variables must make sense and be actionable to well-feed effective design improvements. Also, these ensemble techniques, such as Random Forest, enhance the predictive power so that the reliability of decision tree models will ensure safety evaluations sound for diverse geometric configurations.

Decision trees have also been successfully applied in geometric design to improve ITS sensor visibility. Because the quality of data generated by sensors is highly dependent on unobstructed line-of-sight, certain geometric elements can be optimized to improve sensor placement. Regarding this, Li, *et al.* (2018) pointed out that road curvature and grade impede sensor fields of view more often, and for that very reason, geometric alignment is necessary to ensure clear sensor visibility on the roads. Decision trees analysis is employed to choose the geometric features to be adjusted first in enhancing ITS sensor efficacy without affecting smooth traffic flow or safety. This data-driven approach brings about more informed and efficient improvements both in infrastructure and ITS systems, ensuring that the transportation networks are simultaneously safer and technologically improved (Deng *et al*., 2017).

Because the integration of geometric design optimization with ITS and decision tree analysis offers a robust multi-dimensional approach toward attaining better safety and operational efficiency in advanced transportation system, this study focuses on decision tree methodologies that geometrically design and optimize ITS at the intersection, with the intent of establishing a framework for maximizing safety within complex transportation environments.

2. Literature Review

Optimization of geometric design elements is central to highway engineering, improvement in safety, and the effective working of ITS devices. The geometric design includes lane width, shoulder layout, road curvature, sight distance, and other elements highly influencing vehicle stability, behavior, and overall safety on the road. Recent work concerns how those geometric features interact with the placement of ITS sensors in developing traffic systems that are more adaptable and responsive. It is the integration of ITS, made possible through advances in sensor technology along with improvements in machine learning algorithms (Van Hinsbergen, *et al.,* 2019), which now provides the means for data-informed design adjustments that can improve safety and operational efficiency in complex transportation environments.

Geometric design in highway engineering creates the platform for safe and efficient movement of traffic, focusing on lane width, curvature, and intersection layouts. According to AASHTO (2018), it is stated that geometric design principles are balanced to provide operational efficiency with safety, considering variables such as traffic dynamics, driver perception, and collision risk. For example, increasing lane width encourages the vehicle's lateral stability, and when this is extended to the roads with a high capacity, drivers can make any maneuvers at the highest speeds. This brings to the fore that suitable curvature design plays a very crucial role. May (2014) hints that, reducing the sharpness of curves minimizes the severity of accidents by making safe travelling speeds imperative while enhancing sightlines laterally. Other modern studies further articulate these fundamental design principles by illustrating that relatively minor design changes such as widening shoulders or simplifying intersections can have dramatic reductions in crash rates and overall improvements in traffic flow.

These principles remain the same even with advances in technology. Lamm *et al*, (1999) identified quantitative relationships between road geometry and crash rates. The foundation they laid has still been considered applicable since geometric elements keep impacting the safety outcomes in view of evolving transportation systems. Similarly, Fitzpatrick *et al*. (2000), provide detailed guidelines on highway design with safety and operational considerations. ITS technologies, such as LiDAR, radar, and computer vision systems, are becoming integral parts of highway safety. Effective sensor placement is at the centre of ITS functionality this is as poor alignment with road geometry can limit sensor visibility and compromise data accuracy.

The placement of sensors must account for road curvature, elevation changes, and potential visual obstructions that directly impact the sensors' ability to relay accurate traffic and environmental data. Li, *et al.* (2018) indicate that sensors should be placed in a way that they have maximum line-of-sight to realize optimum performance from ITS, a method that duly aligns sensor technology with the geometric features of the roadways. Also, heightened technological advancements in sensor capabilities drive the need for adaptive approaches in placement. For instance, the current high-performance LiDAR systems require a free line of view, especially in urban areas where most of the time tight curves and infrastructure features lower the detection range.

Deng, *et al.,* (2017) and Figueiredo *et al.* (2021) in relation to improving visibility, suggests that sensor installation strategies need refinement by incorporating geometric design in optimizing the line of view to attain better quality data. Here, improved visibility not only forms the basis for the accuracy of real-time data but also for limited sensor failures that improve roadway safety and allow better utilization of autonomous vehicle systems. The recent adoption of machine learning and, specifically, decision tree algorithms within transportation engineering has opened up new avenues that help in reviewing and optimizing highway design. Decision trees perform very well in handling intricate datasets, which enable transportation engineers to discover the most important design factors that influence safety and sensor performance.

The pioneering work of Breiman *et al.* (1984) on decision tree methodologies presented the mathematical structure widely adopted in transportation studies in analyzing factors such as road geometry and traffic volume with respect to accident risk. Decision trees, by partitioning data and isolating high-impact variables, provide active insight into the geometric elements of lane width and curvature that contribute toward safety outcomes. Feature selection is an integral part of decision tree algorithms, further enhancing model accuracy by emphasizing variables that have a great influence on safety from a modeling standpoint. For example, RFE has been shown to improve the performance of the model by isolating factors such as lane width and curvature that remain pivotal for both safety and ITS sensor integrations.

Feature selection and data pruning improve the interpretability and reliability of decision trees, essential in coming up with robust safety predictions and roadway design adjustments. Feature selection in ITS allows targeting specific road design elements to be able to optimize sensor visibility while iterating between infrastructure and technology applications. The integration of geometric design, ITS sensor technology, and machine learning shows the possibility of an integrated approach toward transportation optimization. Decision trees are easily interpretable and able to adapt to complex data, serving as a subtle guide on how geometric changes impact sensor performance and road safety.

Zhao, *et al.,* (2020) confirm that decision trees allow the refinement of road design to enhance ITS sensor effectiveness and, importantly, that they are useful for developing adaptive infrastructure solutions. These data-driven approaches ensure not only the optimization of geometric design for improved safety but also pave the way to more resilient and responsive transport systems. **T**he integration of geometric design principles with ITS sensor placement and machine learning-based analysis constitutes a strong base on which the safety of highways could be enhanced further. Matching sensor technologies with roadway geometry and using decision tree algorithms (Mander, *et al* 2017) in analyzing design variables have aided transportation engineers to make knowledgeable adjustments to improve safety as well as sensor functionalities. Breiman *et al.* (1984) note that decision trees are extremely useful in identifying high-impact variables from multi-dimensional data property very useful in transportation systems, where many interdependent factors may exist. Besides, decision tree models improved their predictive performance by using ensemble techniques like Random Forest, which showed reliability in safety predictions over a wide range of roadway designs and traffic conditions (Xu *et al.*, 2019).

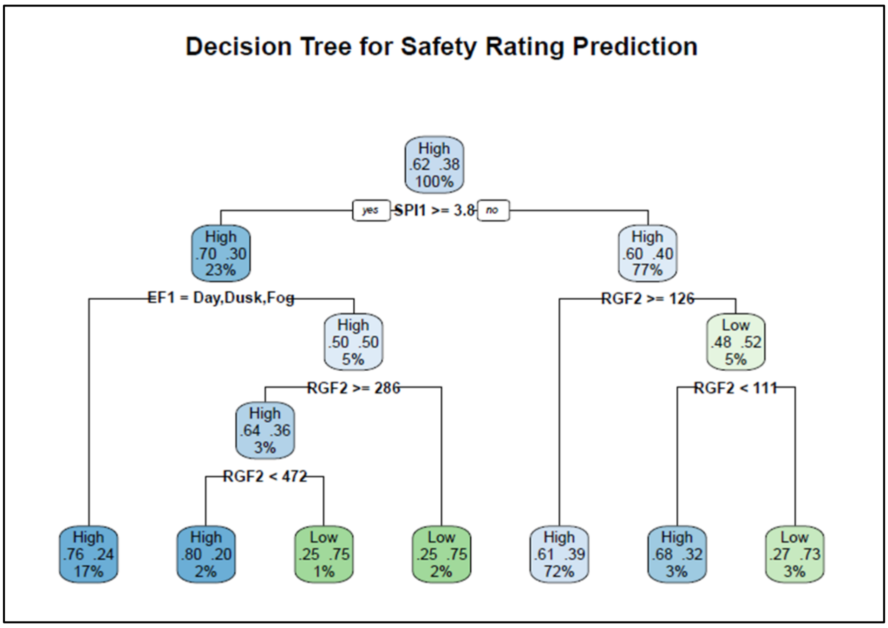

Figure 1 Decision Tree for Safety Rating Prediction

3. Overview of the Structure of Decision Trees

- **Root Node:** The decision tree's basic starting point and first categorization objective is the root node. The root node in this analysis is the safety rating, which is denoted by the symbol "High," signifying the greatest degree of safety.
- **Internal Nodes:** Within the tree, internal nodes stand in for important decision points. Every node asks a distinct query about one of the input properties. The decision-making process is guided by the answer, which is usually binary and establishes the next path in the tree. Based on the attribute responses, the model can divide the data into progressively more specialized subsets owing to this structure.
- **Leaf Nodes:** These represent the final results of the decision-making process, where safety ratings like "High" or "Low" are allocated.The internal nodes developed a hierarchical decision-making process, which is reflected in these nodes.
- **The Decision Tree's Principal Features:** The characteristics used in this decision tree are essential for making precise safety rating predictions. Among them are:
- **Safety Performance Indicator 1 (SPI1):** This metric measures the number of events that occur annually, which is a measure of accident frequency. It is an important predictor when evaluating road safety because a higher value usually corresponds with a higher level of risk.
- **Environmental Factor 1 (EF1):** This has a major impact on visibility and, in turn, accident rates. Safety ratings may be impacted by poor lighting since it increases the chance of collisions.
- **Road Geometry Factor 2 (RGF2):** This is a crucial design element that affects driver perception and vehicle control. It assesses the curvature of the road. If not correctly designed, sharp curves might increase the number of accidents.

4. Methodology

4.1. Data Collection and Preprocessing

4.1.1. Gathering and Preparing Data

Sources of Data

The quality and completeness of the data gathered determine the integrity of any predictive model. The following are some of the data sources used in this study: o Government datasets (such as safety and transportation reports); o Sensor data from various technologies, such as cameras and radar systems, which provide real-time traffic information; o Historical traffic accident reports that describe the events and their results; o Meteorological data, which provides information about weather conditions that may affect driving safety. Records of vehicle inspections, which include information on issues of the vehicle that may impact performance; and driver license data, which comprises the credentials and history of the driver.

Preprocessing Data

- **Cleaning Data:** Managing Missing Values: Significant bias can be introduced by missing data. Methods of imputation, such mean or median substitution, or more complex techniques-such as k-nearest neighbors-are used to close these gaps while maintaining the integrity of the dataset.
- **Eliminating Duplicates:** Since duplicate entries can distort results and produce incorrect conclusions, it is essential to find and remove them in order to preserve a distinct dataset.
- **Eliminating Superfluous Information**: Eliminating variables that don't contribute speeds up analysis and guarantees that only important data is kept.
- **Fixing Data Entry Errors:** Validation procedures are used to find and fix errors in the dataset, improving its overall quality.

Data Transformation:

- **Normalization**: When attributes have varied units or scales, this phase is crucial since it entails scaling numerical data to a uniform range. Fair comparisons and efficient model training are made possible by normalization.
- **Encoding Categorical Variables**: Since decision tree methods need numerical input, converting categorical variables into numerical forms (such as one-hot encoding) guarantees compatibility.

- **Data Type Conversion**: Making changes to data types (such as changing strings to dates) ensures that all attributes are in the right format for analysis.

Data Integration:

- **Resolving Data Inconsistencies**: When several datasets are combined, inconsistencies may arise. Coherent analysis requires standardizing formats (such as date formats and units of measurement).
- **Resolving Data Conflicts:** To ensure the final dataset is trustworthy, discrepancies between conflicting data sources must be resolved using cross-referencing and validation approaches.

4.1.2. Development of Decision Tree Models

Problem Formulation

- **Identify the issue:** Predicting safety ratings-whether high or low-based on a thorough examination of road design, safety performance indicators, ITS sensor data, ambient variables, and vehicle characteristics is the main goal. A more sophisticated knowledge of the factors influencing road safety is made possible by this multidimensional approach.
- **Determine the Target Variable:** The safety rating, which is the result of the decision-making process, is the target variable.
- **Establish the Metrics for Evaluation:** Model performance can be thoroughly evaluated by choosing the right measures, such as accuracy, precision, recall, and F1 score.

Data Preparation

- **Data Preparation:** To guarantee the quality of the data, this first step entails combining pertinent datasets and using preprocessing methods.
- **Data Splitting:** The dataset is separated into categories for testing (30%) and training (70%). The model is constructed using the training set, and its prediction power is assessed using the testing set.

Feature Selection Process:

- **Information Gain:** This metric measures the decrease in uncertainty regarding the target variable in relation to a certain characteristic, offering information about the significance of each feature.
- **Based on decision trees Feature Importance**: By using the decision tree technique, the most predictive attributes can be chosen by evaluating each feature's significance depending on how well it divides the data (Wu, *et al,* 2021).

Criteria for Feature Selection

- **Relevance:** For features to be regarded as useful predictors, they must exhibit a substantial connection with the target variable.
- **Redundancy**: Reducing redundant information between features makes the model more streamlined and easier to understand.
- **Consistency**: To guarantee dependability, chosen features should function consistently across various dataset subsets.

4.2. Selected Features for the Model

4.2.1. Design Variables

- RGF2 (Road Curvature)
- RGF3 (Road Gradient/Steepness of Road)
- SPI1 (Accident Frequency/Number per Year)
- SPI2 (Accident Severity)
- VDI (Vehicle Type)
- VD2 (Vehicle Speed)
- VD4 (Traffic Volume)
- EF1 (Lighting Condition)

4.2.2. Metrics for Model Evaluation

- **Accuracy**: A key measure of the model's efficacy, it is the proportion of correctly identified examples to all instances.
- **Precision**: A measure of the model's predictive dependability that shows the ratio of real positive forecasts to all positive predictions (Liu, *et al,* 2017).
- **Recall (Sensitivity):** The proportion of genuine positives to total positives, which is essential for evaluating how well the model detects positive examples.
- **The F1 Score:** The harmonic mean of precision and recall, offering a single metric that balances both and is especially useful in scenarios with imbalanced datasets.

4.2.3. Justification for Choosing Metrics

- **Accuracy**: In unbalanced datasets, accuracy by itself can be deceptive, even if it offers a measure of total performance.
- **Precision and Recall:** These metrics work together to enable a comprehensive assessment of the model's capacity to identify genuine positives and reduce false positives.
- **F1 Score:** This metric ensures a fair approach to assessing model performance and is essential in situations where false negatives have a larger cost.

5. Results Summary

Table 1 Results summary

Metric	Value
Accuracy	59.71%
Precision	59.76%
Recall	96.60%
F1 Score	73.84%

6. Discussion

6.1. Analysis of Decision Tree Performance

- **Accuracy**: The model has moderate efficacy with a 59.71% classification accuracy. This suggests that although while the model is working, it might be improved, especially in terms of differentiating between "High" and "Low" safety ratings.
- **Precision:** With a 59.76% precision rate in identifying true positive situations, the model may benefit from additional refining to lower false positives.
- **Recall and Sensitivity**: For safety-related applications, where failure to recognize dangers might have serious repercussions, a high recall of 96.60% indicates that the model is quite effective in recognizing true positive events.
- **F1 Score:** Although increases in precision could further improve the model's recall, the F1 score of 73.84% indicates that the model maintains a decent balance between the two.

6.2. Strengths of the Decision Tree Model

- **Interpretability:** Decision trees' natural form makes for easy-to-understand visual representations, which makes the decision-making process visible and approachable for all parties involved, including urban planners and legislators.
- **Managing Categorical Features:** Decision trees are especially well-suited for this study, which incorporates a variety of data kinds, because they can naturally handle categorical variables.

6.3. Important Design Elements

- **Data Quality**: It is essential that the data be accurate, comprehensive, and consistent. Predictive accuracy is improved and model noise is decreased with high-quality data.

- **Feature Selection**: The model's performance is greatly impacted by the features that are chosen. Models with better accuracy and more interpretability can result from careful feature selection.
- **Class Balance**: Preventing bias in forecasts, especially in safety ratings where one class may be noticeably underrepresented, requires addressing class imbalance.
- **Interpretability:** Openness in model design promotes stakeholder trust and makes it easier to put the analysis's suggestions into practice.
- **Managing Missing Values:** To avoid biases and preserve model integrity, it is crucial to put strong procedures for handling missing data into practice.

6.4. Analysis of Design Factors

- **Data Quality:** Strict preprocessing, such as validation and error correction, improves model reliability and guarantees data integrity.
- **Feature Selection:** By using techniques like mutual information and correlation analysis, it is possible to minimize redundancy and find the most important predictors (Park, *et al* 2020).
- **Class Balance**: Methods include using algorithms built to deal with imbalanced datasets or oversampling minority classes might enhance the overall performance of the model.
- **Interpretability**: A transparent model that stakeholders can readily comprehend and use is facilitated by visualizations and feature importance scores.
- **Model Complexity**: To reduce the chance of overfitting and preserve a balance between generalizability and model complexity, regularization strategies, such as pruning, are crucial.
- **Managing Missing Values**: Using imputation approaches, which can range from straightforward methods to sophisticated algorithms, guarantees that the model will continue to function well even in the face of missing data.

6.5. Effect on the Performance of Decision Trees

- **Increased Precision and Accuracy:** Better feature selection and preprocessing techniques can result in notable gains in model performance.
- **Improved Model Interpretability:** Simplified models with unambiguous representations help stakeholders comprehend and adopt them.
- **Better Handling of Class Imbalance**: The prediction reliability of the model is improved by addressing class imbalance through algorithmic modifications or strategic sampling.
- **Effective Missing Value Handling**: Sturdy imputation techniques lessen the effect of missing data, improving the accuracy of the model as a whole.

6.6. Interaction of Design Parameters

- **Feature Selection vs. Model Complexity:** Selecting pertinent features with care improves model performance and makes the model simpler, which lowers the chance of overfitting.
- **Data Quality vs. Missing Value Handling**: Excellent datasets naturally reduce the difficulties posed by missing data, strengthening the model's resilience.
- **Interpretability vs. Model Complexity**: It is critical to strike a balance between interpretability and complexity; while larger models might need extra methods for a clear explanation, simpler models are typically easier to understand.

6.7. Sensitivity Analysis

This broader examination assesses the effects of simultaneous variations across multiple parameters, providing insights into the model's overall robustness and stability.

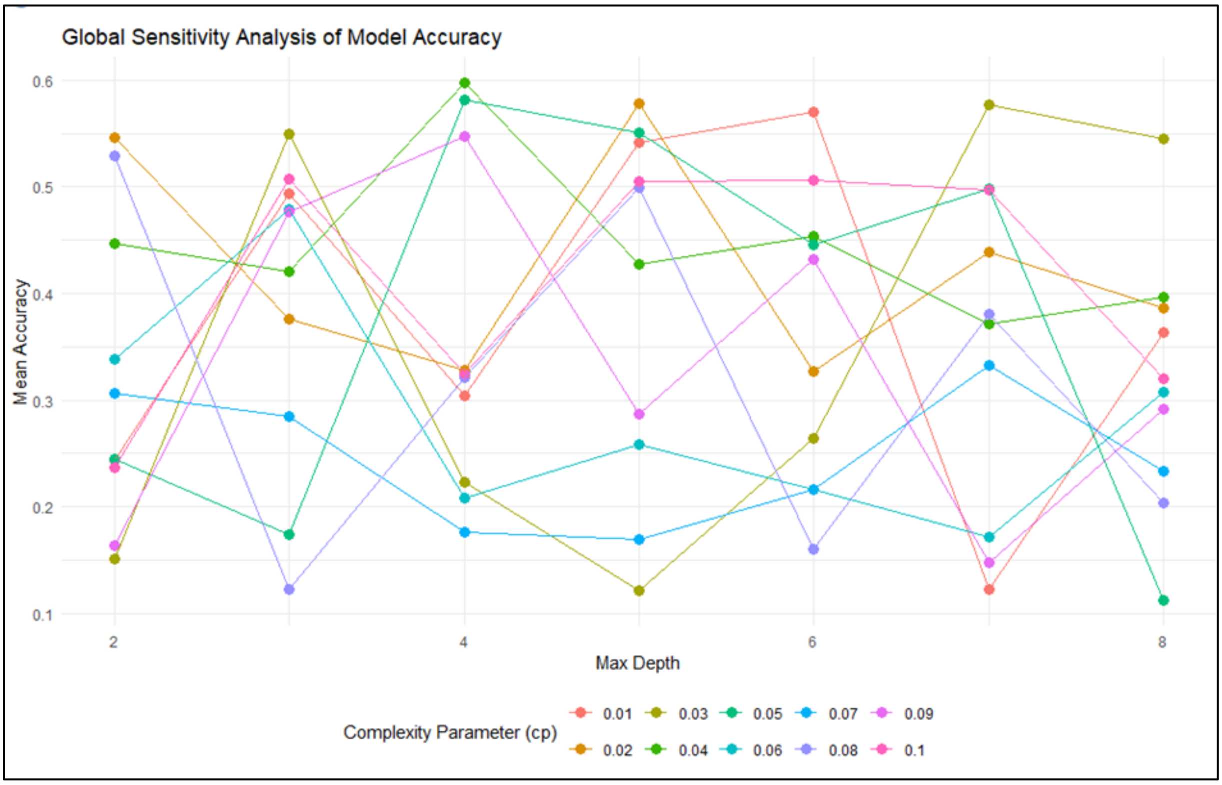

Figure 2 Global Sensitivity Analysis of Model Accuracy

6.8. Key Aspects of the Results

6.8.1. Axes Interpretation

- **X-Axis (Max Depth)**: This represents the maximum depth of the decision tree. Increasing the depth allows the model to capture more complex patterns in the data, but it also risks overfitting.
- **Y-Axis (Mean Accuracy)**: Indicates the average accuracy of the model for different combinations of maxdepth and cp (complexity parameter). Higher values suggest better model performance.

6.8.2. Color Coding (Complexity Parameter cp)

The points are colored according to different values of cp, which is the complexity parameter used to control the size of the decision tree. A lower cp allows the tree to grow larger, while a higher cp restricts its growth.

6.8.3. Trends and Patterns

- **Varying Accuracy with Depth**: If you observe the trend, accuracy generally fluctuates as maxdepth increases; this indicates a complex relationship between the tree complexity and model performance.
- **Impact of cp**: The effect of different cp values can indicate how sensitive the model's accuracy is to tree complexity. If accuracy fluctuates significantly with varying cp values at a specific depth, it highlights the importance of regularization.

6.8.4. Optimal Regions

- Look for regions on the plot where accuracy is maximized. For example, if certain combinations of maxdepth (e.g., 6 or 7) and lower cp values yield higher accuracy, these combinations may represent optimal settings for the model.
- Conversely, if accuracy declines for high depths regardless of cp, it indicates that too much complexity leads to overfitting.

6.9. Implications for Optimizing Geometric Designs

- **Safety:** To create a safer transportation environment, the main goal is to reduce the number and seriousness of accidents.

- **Efficiency:** The general safety and usefulness of roads can be improved by optimizing lighting conditions and other design factors.
- **Comfort:** Improving road geometry to guarantee smooth passage can enhance the driving experience and lower the risk of collisions.

6.10. Design Variables

- RGF2 (Road Curvature)
- RGF3 (Road Gradient/Steepness of Road)
- SPI1 (Accident Frequency/Number per Year)
- SPI2 (Accident Severity)
- VDI (Vehicle Type)
- VD2 (Vehicle Speed)
- VD4 (Traffic Volume)
- EF1 (Lighting Condition)

6.11. Current Design Methods

- **Guideline-Based Design**: Road design is based on established practices, such as those described by the American Association of State Highway and Transportation Officials, or AASHTO.
- **Experience-Based Design**: Although it is not necessarily supported by science, practitioners frequently rely on experiential knowledge, which can be useful.
- **Trial-and-error**: Although this approach can provide valuable insights, it frequently lacks systematic evaluation and is wasteful.
- **Human Calculations**: Conventional methods rely on human computations, which are frequently laborious and prone to mistakes.
- **2D/3D Modeling:** Although sophisticated modeling methods can produce visual depictions of designs, they may still be constrained by the models' underlying assumptions and simplifications.

6.12. Benefits of the Decision Tree Model

- **Data-Driven Design:** By utilizing large datasets, this paradigm improves decision-making by using empirical data as opposed to only gut feeling.
- **Predictive Analytics**: Using past data, the model may predict results, offering useful information for upcoming designs.
- **Automated Optimization:** Decision trees enhance efficiency by enabling automated modifications and optimizations based on input parameters.
- **Multi-Parameter Analysis**: Thorough evaluations are supported by the capacity to take into account several design factors at once.
- **Scalable and Flexible:** The decision tree method is appropriate for a range of applications in urban planning and transportation since it can be adjusted to different situations.

Table 2 Comparison of Existing Design Practices and Decision Tree Model

Criteria	Existing Design	Decision Tree Model
Accuracy	Subject to human error	High accuracy via data analysis
Efficiency	Time-consuming	Fast and automated
Scalability	Limited to manual calculations	Scalable across applications
Flexibility	Limited design exploration	Explores vast design spaces
Safety	Based on general guidelines	Optimized for specific conditions

6.13. Limitations of the Decision Tree Model:

- **Requires Extensive Data**: Effective model training and validation depend on sufficient and high-quality data.
- **Complexity in Interpretation:** Although complex models with many branches are generally interpretable, they may still be difficult for users to understand the decision-making process.

- **Limited Generalizability:** The model's efficacy may be reduced when applied to datasets that differ significantly from the training set.
- **Dependency on Data Quality**: Inaccurate or incomplete data may result in misleading predictions and outcomes.
- **Potential for Overfitting**: If proper regularization techniques are not used, decision trees run the risk of becoming too complex and capturing noise in the data instead of signal.

6.14. Prospects for the Future

- **Integration with Current Design Software**: Workflows could be streamlined and usability improved by attempting to include decision tree models into current design platforms.
- **Development of User-Friendly Interfaces:** Practitioners from a variety of disciplines will have easier access to sophisticated modeling approaches due to the creation of user-friendly interfaces.
- **Multi-Objective Optimization:** The model's usefulness in intricate design situations will be improved by extending its capacity to take into account several competing objectives.

7. Conclusion

Geometric design optimization, combined with ITS and advanced decision tree algorithms, can deliver an imposing approach toward solving significant issues arising in contemporary transportation systems. ITS sensors, including LiDAR and radar, depend greatly on having a line of sight with minimal obstruction to function effectively. Therefore, this requires that geometric configurations be precisely accurate in terms of supporting these technical requirements. Decision trees applied to this problem are a form of machine learning especially adept at managing complex, high-dimensional data.

This study has shown an intricate analysis of how specific geometric elements drive both safety and sensor performance using decision tree procedure. The interpretability and systematic partitioning of data by decision trees allow the researcher to tease out which geometric attributes have the most impact on accident rates and sensor effectiveness. This meets the requirement for transportation engineering, where such information derived from data analysis should be accurate and actionable to help engineers make specific infrastructural improvements. This study underlined the efficiency of the decision trees in balancing safety and sensor functionality, including adaptability to specific requirements related to ITS integration.

The decision tree illustrate the significant contribution that data-driven approaches are making within the field of transportation engineering. Geometric design optimization, supported by decision tree analysis, clearly provides a robust yet flexible framework that ensures improved safety and enhances ITS sensor visibility in diverse roadway environments. Decision tree provides a foundation on which further developments will be based, whereby improvements in geometric design and compatibility with ITS will increasingly assume centre stage in the pursuit of safer and more intelligent transport networks.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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