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Find My Avenue

Tushar Tyagi[1,a)] Kavish Saxena[2,b)] Vaishnavi Gupta[3,c)]
Riddhi Ruhela[4,d)] Neha Chauhan[5,e)]

1,2,3,4,5,
Moradabad Institute of Technology, Moradabad, UP, India

[a)] tyagiveer63@gmail.com
[b)] saxenakavish48@gmail.com
[c)] vaishnavig1603@gmail.com
[d)] ruhelariddhi9@gmail.com
[e)] nchauhan232323@gmail.com

Abstract: Road detection is a crucial task in **autonomous navigation**, **urban planning**, and **Geographic Information Systems (GIS)**. This project presents a **deep learning–based approach** for the automatic detection and segmentation of **road networks** from **high-resolution satellite and aerial imagery**. Advanced semantic segmentation models, including **U-Net** and **Fully Convolutional Networks (FCNs)**, are employed to accurately extract road features. Datasets obtained from **Kaggle** and **Google Earth** are used for training and evaluation. To enhance model performance, **image preprocessing** techniques such as **tiling**, **normalization**, and **data augmentation** are applied, followed by **post-processing** to improve road connectivity and precision. Experimental results demonstrate high accuracy across **urban**, **rural**, and **forested regions**, showing robustness to **occlusions**, **lighting variations**, and diverse road structures. The proposed method significantly reduces manual mapping efforts and provides a **cost-effective, scalable solution** for applications including **autonomous vehicles**, **infrastructure planning**, **disaster management**, and **digital map updating**

Keywords-Road Detection, Road segmentation, Convolutional Neural Networks, U-Net, Deep Learning, Data Augmentation,Kaggle.

INTRODUCTION

Accurate road network information is a fundamental component of modern geospatial applications, including **autonomous navigation systems**, **urban planning**, **transportation management**, and **emergency response operations**. Road maps play a critical role in supporting infrastructure development, disaster recovery, and real-time navigation services. With the rapid growth of urban areas and increasing availability of high-resolution remote sensing data, the demand for reliable and up-to-date road detection methods has significantly increased.

Traditional road extraction techniques primarily rely on **manual digitization** and **rule-based algorithms**, which are often time-consuming, labor-intensive, and prone to errors. These limitations become more pronounced in complex environments characterized by heterogeneous terrain, occlusions from buildings or vegetation, varying illumination conditions, and diverse road structures. As a result, conventional approaches struggle to scale efficiently for large geographic regions and frequently require extensive human intervention.

Recent advancements in **deep learning**, particularly in **Convolutional Neural Networks (CNNs)**, have led to significant progress in automated image analysis and semantic segmentation. Deep learning models have demonstrated exceptional capability in learning hierarchical feature representations from large datasets, enabling accurate discrimination between road and non-road regions in high-resolution satellite and aerial imagery. Architectures such as **U-Net**, **SegNet**, and **Fully Convolutional Networks (FCNs)** have proven effective in capturing spatial context and performing pixel-level classification, which is essential for precise road extraction.

High-resolution imagery acquired from **satellite platforms** and **unmanned aerial vehicles (UAVs)** presents both challenges and opportunities for road detection. While factors such as large image sizes, complex backgrounds, shadows, and occlusions complicate the detection process, the detailed spatial information available in such data enables fine-

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grained mapping when combined with robust deep learning frameworks. Effective preprocessing, model design, and post-processing strategies are therefore critical to achieving reliable performance.

This research aims to develop a **scalable and efficient deep learning-based framework** for the detection and segmentation of road networks from high-resolution satellite and aerial imagery. The proposed approach seeks to overcome the limitations of traditional methods by providing an automated, accurate, and adaptable solution. Additionally, the integration of extracted road networks with **Geographic Information Systems (GIS)** is explored to facilitate practical applications such as map updating, navigation support, and disaster response planning. Through comprehensive evaluation on diverse datasets, this study contributes to ongoing research in **geospatial intelligence**, **smart infrastructure**, and **autonomous systems**

PREREQUISITES AND REQUIREMENT

Software

The following software, Frameworks and Libraries are used:

- Programming Languages :Python
- Library :Pandas, Matplotlib, NumPy, OpenCV
- Algorithm : FCNs, U-Net , Sklearn
- IDE :Visual Studio Code, Jupyter notebook
- Framework : Tensor Flow
- API : Keras, Flask
- Dataset : Map My India

SYSTEM OVERVIEW

Find My Avenue is an intelligent, deep learning–driven geospatial system designed to support **real-time navigation**, **road analysis**, and **emergency assistance**. The system integrates **satellite and aerial imagery analysis**, **real-time map data**, and **automated emergency response mechanisms** to enhance safety, accessibility, and situational awareness. By combining deep learning models with modern mapping APIs, the system provides a scalable and reliable solution for smart navigation and emergency support applications.

The overall architecture of the system is modular and consists of three primary components: **Real-Time Data Gathering using Map APIs**, **Object Detection System**, and **Emergency Automatic Calling Module**.

The system integrates three key modules to provide intelligent navigation and safety support. The **real-time data module** collects dynamic information such as traffic conditions, road availability, and location coordinates using map service APIs, which is combined with satellite and aerial imagery to enable adaptive routing. The **object detection module** uses deep learning models, including **CNNs, U-Net, and FCNs** implemented with TensorFlow and Keras, to identify road networks and detect vehicles, obstacles, pedestrians, and other hazards, enhancing situational awareness. The **emergency automatic calling module** activates when accidents or road blockages are detected, sending alerts and the user's real-time location to emergency contacts or services. Together, these modules provide a **scalable, real-time, and safety-oriented navigation solution**.

All modules operate in a coordinated manner to deliver a seamless user experience. The outputs from the object detection and road segmentation processes are integrated with **Geographic Information Systems (GIS)** and displayed through an interactive user interface. The system provides real-time navigation support, hazard alerts, and emergency assistance, making it suitable for applications in **smart transportation**, **disaster response**, and **autonomous systems**.

Overall, **Find My Avenue** offers a comprehensive and intelligent solution that combines **deep learning**, **real-time mapping**, and **automated emergency response**. The system reduces manual intervention, enhances navigation safety, and contributes to the development of **smart and resilient transportation infrastructure**.

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TECHNOLOGY USED

Machine Learning

Machine learning plays a central role in enabling intelligent perception and decision-making within the proposed road detection system. Learning-based models are employed to analyze visual and sensor data, allowing the system to detect road elements, identify hazardous situations, and support automated emergency response. Supervised deep learning models, particularly convolutional neural networks (CNNs), are trained on labeled road scene datasets to detect vehicles, pedestrians, and other road elements. These models automatically learn relevant features from visual data and provide accurate real-time detection. Machine learning has applications in many forms, from natural language processing and computer vision to recommendations and self-driving cars. Machine learning's ability to adapt and adapt based on data makes it a powerfultoolforsolvingcomplexproblemsandmakingdata-drivendecisions,contributing to the advancement of technology and automation. Some of the libraries used are:

1. **Scikit-learn**:

   A popular open source library for classical machine learning algorithms. It provides simple and effective tools for data analysis and modelling.Such as classification, regression, clustering and other modules..

2. **TensorFlow:**

   Developed by Google, Tensor Flow is an open source machine learning tool. It is widely used in deep learning. It provides a flexible platform for building and deploying machine learning models. Support CPU and GPU calculation..

3. **Pandas:**

   Pandas is a powerful Python open-source data management and analysis library. It provides data structures such as Data Frame, a two-dimensional tabular data structure with labels (rows and columns) created by Wes Mc Kinney. Pandas specializes in working with structured data and provides functionality to clean, transform and analyze data. Key features include powerful analytics, easy data consolidation, and integrated runtime integration. It integrates with other libraries such asNumPy and Matplotlib, making it an essential resource for data scientists and analysts. Pandas plays an important role in the Python data science ecosystem by performing core tasks such as data cleaning, searching, and prioritization.

4. **NumPy:**

   A simple package for scientific computing using Python. Provides support for large multidimensional arrays and matrices. Provide mathematical functions that operate on these arrays.

5. **Matplotlib:**

   Matplotlib is a 2D plotting library for the Python programming language widely used to create static plots, visualizations, and interactive visualizations. Created by John D. Hunter in 2003, it is an important tool for data science and social sciences.

Deep Learning

Deep learning techniques are employed in the proposed system for accurate road and object segmentation. Fully Convolutional Networks (FCNs) and U-Net architectures are used to perform pixel-level classification of road scenes, enabling precise detection of lanes, road boundaries, and obstacles. These models are implemented using the Keras deep learning framework, which facilitates efficient model training and deployment. OpenCV is used for image acquisition, preprocessing, and post-processing operations.Fully Convolutional Networks (FCN):

1. **Fully Connected Network(FCN):**

   Fully Convolutional Networks are used for pixel-level classification of road scenes. FCNs enable accurate segmentation of road surfaces, lane markings, and surrounding regions by replacing fully connected layers with convolutional layers.

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2. **U-Net Architecture:**

U-Net is employed for precise image segmentation due to its encoder–decoder structure. It effectively captures both spatial and contextual information, improving the detection of road boundaries and obstacles.

3. **Keras Framework:**

Keras is used as the deep learning framework for designing, training, and deploying FCN and U-Net models. It provides a high-level interface for rapid model development and experimentation.

4. **OpenCV Library:**

OpenCV is utilized for image acquisition, preprocessing, and post-processing tasks. It supports operations such as resizing, normalization, noise reduction, and visualization of segmentation results.

METHODOLOGY

Machine Learning

Importing Libraries

Providing relevant libraries in the crop forecasting process is an important step to improve the efficient use of advancedfunctionsandtools.BelowaresomelibraryfunctionsinPython,a programming language widely used for machine learning and computer vision that can be used in crop research:

- **NumPy:**

NumPy is a powerful library form a thematical operations in Python. It is often used to work with arrays and matrices, which are common data in machine learning.

- **Scikit-learn:**

Scikit-learn is a machine learning library that provides simple, easy and effective tools for analysing data and models. It includes various algorithms for classification and model evaluation.

- **Matplotlib:**

Matplotlib is a plotting library that can be used to visualize data, including frame plot sand gesture recognition results.

- **Pandas:**

A Python has powerful data management and analysis libraries. Provide data structures like Data Frame to create data efficiently. Often used with machine learning libraries to prioritize data.

These libraries provide a solid foundation for developing crop forecasting systems. Other special libraries will also be compiled according to the specific requirements and the system will choose. Always make sure that the versions of these libraries are compatible and meet the system requirements.

Collecting Data

This study utilizes geospatial, traffic, and point-of-interest (POI) data collected from Map my India and Tom Tom, two widely used commercial mapping and location intelligence platforms. These data sources were selected due to their accuracy, coverage, and availability of real-time and historical spatial information.

Map my India

Map my India is a leading digital mapping and geospatial services provider with extensive coverage across India. The platform offers detailed road network data, geocoding services, traffic information, and points of interest (POIs) through its APIs.

The following datasets were collected from **Map my India:**

- Road Network Data: Including road geometry, road type, and connectivity.
- Geocoding and Reverse Geocoding Data: Conversion of addresses into geographic coordinates and vice versa.
- Traffic Data: Real-time traffic congestion levels and average vehicle speeds on major road segments.
- Points of Interest (POIs): Locations of essential services such as hospitals, educational institutions, commercial centers, and transport hubs.

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- These datasets primarily support spatial analysis and urban mobility studies within Indian cities

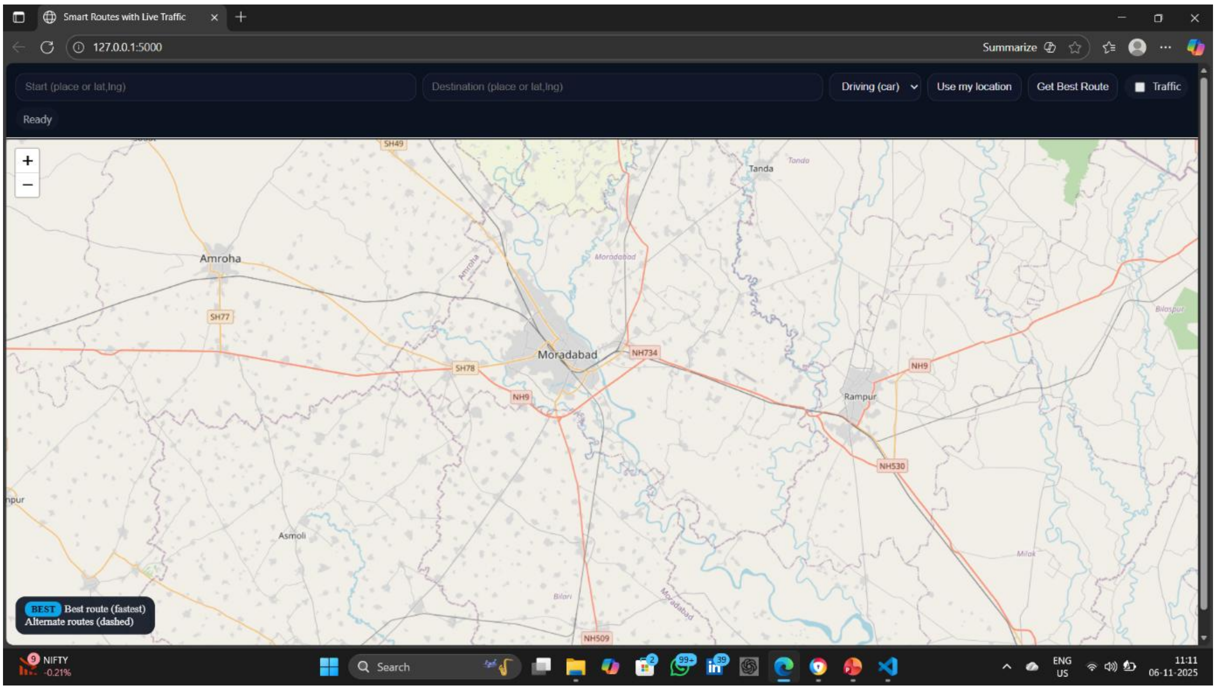
Tom Tom

Tom Tom provides global mapping, traffic, and location-based services with high temporal resolution. The Tom Tom APIs offer access to both real-time and historical traffic data, global road networks, and POI datasets.

The following datasets were obtained from **Tom Tom:**

- Traffic Flow Data: Average speed, free-flow speed, congestion index, and time stamps.
- Historical Traffic Data: Past traffic trends for selected road segments.
- Routing and Road Segment Data: Road classification, length, and speed profiles.
- Points of Interest (POIs): Categorized locations such as restaurants, fuel stations, healthcare facilities, and public infrastructure.
- TomTom data was used to perform temporal traffic analysis and cross-platform comparison with MapmyIndia.

FIGURE1. Map My India Dataset



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Pre Processing

1.Road Data Gathering Using MapMyIndia API

Accurate and up-to-date road information is essential for intelligent transportation systems. In the proposed *Find My Avenue* framework, road-related data is collected using the **MapMyIndia API**, which provides high-resolution digital maps and real-time geospatial services.

The **MapMyIndia API** is utilized to extract:

- Road network geometry and lane information
- Traffic density and congestion levels
- Road attributes such as speed limits and turn restrictions
- Precise GPS coordinates and route metadata

Each data point is geo-tagged and time-stamped to ensure spatial accuracy. This map-based data acts as a foundational layer, which is later enhanced using vision-based analysis and sensor inputs.

To ensure consistency, redundant and outdated map entries are filtered, and route segments are standardized before further processing. This integration enables accurate localization of detected road anomalies and objects.

2. Image and Sensor Data Pre-Processing

Visual data collected from vehicle-mounted cameras is pre-processed to remove noise and improve detection reliability. The following operations are applied:

- Image resizing to a fixed resolution compatible with **YOLO architecture**
- Pixel normalization to stabilize training
- Contrast enhancement for varying lighting conditions
- Frame selection to eliminate redundant video frames

Sensor data such as GPS speed and acceleration is synchronized with image frames to enable multi-modal analysis.

3. Object Detection Module Using YOLO

Object detection in the proposed system is implemented using the **YOLO (You Only Look Once) deep learning framework** due to its real-time detection capability and high accuracy.

The **YOLO** model is trained to detect:

- Vehicles (cars, buses, trucks, two-wheelers)
- Pedestrians and cyclists
- Animals and roadside obstacles
- Traffic signs and road barriers

YOLO performs detection in a single forward pass, allowing the system to identify multiple objects simultaneously with low latency. Detected objects are associated with their geographic location using **MapMyIndia** coordinates, enabling contextual awareness for route planning and safety alerts.

4. Road Surface and Pothole Detection

Road surface irregularities such as potholes are detected using vision-based analysis combined with spatial map data. Extracted image features are analyzed to identify surface discontinuities and depth variations.

Detected potholes are:

- Classified based on size and severity
- Mapped to exact road segments using **MapMyIndia** location references
- Stored in a centralized database for route optimization and maintenance planning

This module significantly improves navigation quality by avoiding damaged road segments.

5. Emergency Detection and Automatic Calling System Using Twilio

To enhance road safety, an automatic emergency calling system is integrated using **Twilio communication APIs**. This module continuously monitors vehicle dynamics and visual cues to detect potential accidents.

Emergency conditions are identified based on:

- Sudden speed drops detected from GPS data
- High-impact vibrations from accelerometer readings
- Collision indicators from object detection outputs

Upon confirmation of an emergency, the **Twilio API** is triggered to:

- Automatically place a voice call to emergency services
- Send SMS alerts to registered emergency contacts
- Transmit real-time location details obtained from **MapMyIndia API**

This automated response mechanism reduces human dependency during critical situations and ensures faster emergency intervention.

6. Integrated Decision and Route Optimization Module

All processed data from map services, object detection, pothole analysis, and emergency modules is fused to generate:

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- Safer and smoother route recommendations
- Real-time hazard alerts
- Road quality and safety indices

The system dynamically updates the road condition database, enabling continuous learning and improved prediction accuracy.

7. Advantages of the Proposed Approach

- High-precision road mapping using **MapMyIndia API**
- Real-time object detection with YOLO
- Automated emergency communication via Twilio
- Reduced response time during accidents
- Enhanced navigation safety and user experience

Exploratory Data Analysis

Exploratory Data Analysis (EDA) refers to the initial process of examining a dataset to understand its structure, characteristics, and underlying patterns. It focuses on summarizing data and visually inspecting it to extract meaningful insights before applying advanced analytical or machine learning techniques. The primary objective of EDA is to uncover trends, relationships, irregularities, and useful information that can guide further analysis and model development.

Key components of Exploratory Data Analysis include:

1.Statistical Summarization:
Basic statistical measures such as mean, median, mode, standard deviation, and quartiles are computed to describe the distribution and variability of the dataset.

2.Visual Exploration:
Graphical tools like histograms, box plots, scatter plots, and bar charts are used to visually analyze data distributions and identify relationships between different features.

3.Data preprocessing:
This step involves detecting and handling missing values, incorrect entries, and inconsistencies to improve data quality and reliability.

4.Trend and pattern identification:
EDA helps in recognizing recurring patterns, trends, or groupings within the data that may indicate important underlying behaviors.

5.Relationship Assessment:
Correlation analysis is performed to understand how different variables are related and how changes in one feature may influence others.

6.Feature Reduction:
Reducing the number of input variables through techniques such as feature selection or dimensionality reduction helps simplify the dataset and improve model efficiency.

7.Data Modification:
Transformations such as normalization, scaling, or encoding are applied to ensure the data is compatible with statistical and machine learning algorithms.

Overall, Exploratory Data Analysis serves as a crucial foundation in the data analysis workflow. It enables researchers and analysts to gain a deeper understanding of the dataset, formulate hypotheses, and make informed decisions regarding model selection and implementation by combining statistical techniques, visualization, and domain expertise.

Splitting the dataset

The dataset is composed of labeled road scene images obtained from both open-source repositories and self-collected samples. To maintain consistency across inputs, all images are preprocessed through resizing and normalization techniques. The complete dataset is systematically partitioned into separate subsets to prevent information leakage and to accurately assess the model's performance on unseen data. Specifically, 70% of the data is allocated for model training, 15% is reserved for validation during training, and the remaining 15% is used for final testing and performance evaluation.

Training

The road detection system is developed using a deep learning–driven semantic segmentation framework, where the network is trained to classify each pixel as either road or non-road. Throughout the training phase, the model progressively learns spatial and contextual features that enable accurate separation of roadway regions from the surrounding environment.

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Training configuration includes:

- Input images undergo preprocessing steps such as normalization and data augmentation methods including random rotations, horizontal flips, and brightness variations to improve model robustness.
- To address the imbalance between road pixels and background regions, appropriate loss functions such as Binary Cross-Entropy or Dice Loss are employed.
- Model weights are updated using the Adam optimization algorithm to ensure efficient and stable convergence.
- The training process spans multiple epochs until the model reaches optimal performance, while validation loss is continuously monitored to detect and prevent overfitting.

Testing

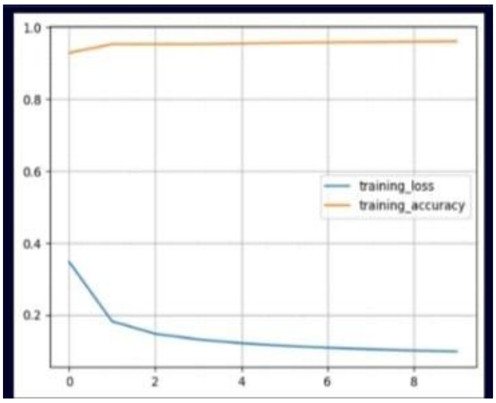
Once the training process is completed, the trained model is tested on a previously unseen dataset to evaluate its real-world applicability. This testing stage examines the model's ability to accurately identify road regions under diverse scenarios, including changes in illumination, varying road geometries, and different environmental conditions.
To quantitatively assess performance, multiple evaluation metrics are employed, including classification accuracy, Intersection over Union (IoU), precision, recall, and the F1-score. These metrics collectively provide a comprehensive understanding of the model's effectiveness in detecting road paths and maintaining consistency across different test conditions.

Output

The performance of the trained model was assessed on the test dataset using widely accepted semantic segmentation evaluation metrics. The results indicate strong and consistent performance across a variety of road scenes. High accuracy values reflect the model's overall effectiveness in distinguishing road areas, while the Intersection over Union (IoU) scores demonstrate substantial agreement between predicted road regions and the corresponding ground truth annotations. Precision results highlight a minimal occurrence of false road detections, whereas recall values confirm the model's capability to successfully identify most of the actual road pixels. The F1-score further emphasizes a balanced trade-off between precision and recall.

The proposed system generates precise segmented road maps with consistently high accuracy and IoU scores. Experimental evaluations confirm that the model performs reliably under diverse environmental and lighting conditions, thereby validating the robustness and practical applicability of the **Find My Avenue** road detection framework.

ACCURACY AND PARAMETERS



Accuracy:
The experimental evaluation demonstrates that the proposed system attains a high level of detection accuracy, reflecting its ability to effectively learn and generalize road-related features. The model achieves strong pixel-wise classification performance on the test dataset, indicating reliable segmentation outcomes. Intersection over Union (IoU) scores further reveal substantial alignment between the predicted segmentation outputs and the corresponding ground truth masks. Additionally, the obtained precision and recall values indicate well-balanced detection performance, with a reduced rate of both false positive and false negative predictions.

Dataset Description:
The Find My Avenue framework is trained and validated using a blend of publicly accessible road image datasets and custom-acquired road scene images, ensuring robustness and suitability for real-world deployment.

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The dataset captures a wide range of road scenarios, including urban roadways, highways, and semi-rural environments.

- Data Type: Road scene imagery for semantic segmentation tasks
- Input Format: RGB images
- Image Resolution: Uniformly resized to a predefined dimension for consistency
- Annotations: Pixel-level labelled masks distinguishing road regions from background areas

CONCLUSION

This study introduced **Find My Avenue**, a deep learning–driven road detection framework developed to accurately extract navigable road paths from visual inputs. The proposed system employs semantic segmentation to perform pixel-wise classification, effectively separating road surfaces from surrounding background regions. Unlike conventional navigation systems that depend heavily on predefined maps, the presented approach relies solely on visual understanding, enabling flexible and map-independent path detection.

A diverse and well-structured dataset containing various road scenarios was used for both training and evaluation. By applying systematic preprocessing, data augmentation strategies, and appropriate dataset partitioning, the model demonstrated strong generalization across multiple real-world conditions, including variations in lighting, road geometry, and surface characteristics. Experimental evaluations on unseen test data reveal consistently high accuracy and Intersection over Union (IoU) values, confirming the robustness and reliability of the system.

In comparison with traditional rule-based and edge-detection techniques, the deep learning-based approach adopted in Find My Avenue exhibits superior adaptability and detection precision. The model successfully addresses complex challenges such as curved road structures, illumination changes, and partial obstructions, which are commonly encountered in real-world driving environments. These results emphasize the advantages of learning-based methods for intelligent road perception tasks.

The system produces accurate and continuous road segmentation maps that can be directly utilized for navigation assistance, autonomous driving applications, and smart transportation solutions. By prioritizing vision-based road understanding over static map data, Find My Avenue offers a scalable and adaptable solution suitable for dynamic and previously unmapped environments.

Although the system achieves strong overall performance, certain limitations remain, particularly under extreme weather conditions and low-light scenarios due to limited representation in the training data. Future research directions include expanding the dataset to cover more challenging conditions, enabling real-time video-based processing, and improving detection accuracy through advanced architectures such as attention-based models or multi-modal sensor integration.

In summary, the Find My Avenue framework effectively demonstrates the potential of deep learning–based road detection for intelligent navigation systems. The encouraging results validate the proposed methodology and establish a solid foundation for future developments in autonomous navigation and smart mobility technologies.

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