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Deep Learning-Based Road and Lane Classification Using MobileNetV2 for Autonomous Driving Systems

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Abstract— Accurate road and lane classification is fundamental for autonomous vehicle navigation and safety. Traditional methods struggle with real-time processing, environmental variability, and computational constraints required for embedded deployment. This paper presents an intelligent deep learning system leveraging MobileNetV2 architecture with transfer learning for automated classification of four road types (Highway, Secondary, Urban, Rural) and two lane configurations (Straight, Curved). The system implements a comprehensive preprocessing pipeline incorporating data augmentation, normalization, and class balancing to ensure robustness across varying lighting conditions, weather scenarios, and road geometries. Implemented using Flask framework with MongoDB-style data management and deployed through an intuitive web interface, the system achieved 99.88% confidence for road classification and 98.75% for lane detection, with average processing time under 2 seconds per image. Comparative analysis demonstrates 4.2× parameter reduction compared to ResNet while maintaining comparable accuracy. The lightweight architecture enables edge deployment suitable for resource-constrained autonomous vehicle systems. User evaluation indicates 89% satisfaction with interface usability and significant improvements in classification speed compared to traditional computer vision approaches. This work contributes a scalable, efficient solution advancing intelligent transportation system capabilities.

Keywords— Road Classification, Lane Detection, MobileNetV2, Deep Learning, Autonomous Driving, Transfer Learning, Computer Vision, Real-Time Processing, Edge Computing, Intelligent Transportation Systems

I. INTRODUCTION

The proliferation of autonomous vehicle technologies has intensified demands for robust road perception systems capable of real-time environmental understanding. Accurate classification of road infrastructure and lane configurations forms the cornerstone of safe navigation, enabling vehicles to adapt driving behavior to environmental context and geometric constraints. Traditional approaches to road and lane detection rely heavily on handcrafted features, edge detection algorithms (Canny, Sobel), and geometric transforms (Hough), which exhibit significant limitations in generalization across diverse conditions.

Manual feature engineering cannot adequately capture the complexity and variability inherent in real-world driving environments. Factors including variable illumination (dawn, dusk, nighttime, shadows), adverse weather conditions (rain, fog, snow), diverse road surface materials, varying camera perspectives, partial occlusions, and worn or absent lane markings create scenarios where classical methods fail catastrophically. Furthermore, computational constraints in automotive embedded systems demand efficient algorithms capable of real-time processing while maintaining high accuracy—requirements difficult to satisfy with traditional approaches.

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized computer vision by enabling automatic feature learning from data. However, state-of-the-art architectures like ResNet, VGG, and Inception networks require substantial computational resources incompatible with embedded automotive platforms. MobileNetV2 addresses this challenge through depthwise separable convolutions and inverted residual blocks, dramatically reducing parameters and computational requirements while maintaining competitive accuracy.

This paper presents a comprehensive intelligent system for road and lane classification optimized for autonomous driving applications. Our key contributions include:

1. **Dual-Model Architecture:** Development of specialized MobileNetV2-based models for road type classification (4 classes) and lane configuration detection (2 classes) with custom classification heads optimized for each task.

2. **Robust Preprocessing Pipeline:** Implementation of comprehensive augmentation strategies including rotation, translation, shearing, zooming, and flipping to ensure environmental robustness and model generalization.

3. **Transfer Learning Strategy:** Selective layer freezing approach preserving low-level ImageNet features while fine-tuning high-level representations for domain-specific adaptation.

4. **Real-Time Web Deployment:** Flask-based application providing intuitive interfaces for single-image and batch processing with interactive visualization and result export capabilities.

5. **Comprehensive Evaluation:** Rigorous performance assessment demonstrating >98% classification confidence, significant computational efficiency gains, and superior user experience compared to existing solutions.

The remainder of this paper is organized as follows: Section II reviews related work in road perception and mobile architectures. Section III details system architecture and methodology. Section IV presents implementation specifics. Section V analyzes experimental results and performance metrics. Section VI discusses advantages, limitations, and comparisons. Section VII concludes with future research directions.

II. RELATED WORK

A. Traditional Road Classification Methods

Early road classification systems employed classical computer vision techniques combining edge detection, morphological operations, and geometric constraints. These approaches utilized Canny edge detection with Hough transforms for lane boundary identification, achieving reasonable performance under controlled conditions. However, they suffered from poor generalization across environmental variations, high false positive rates in complex urban scenarios, and inability to adapt to novel road types without manual reconfiguration.

Kumar et al. developed rule-based systems incorporating domain knowledge for road type recognition, demonstrating improved reliability over purely data-driven classical methods. Nevertheless, manual feature engineering limited scalability and adaptation to diverse geographical regions with varying infrastructure characteristics.

B. Deep Learning in Road Perception

The introduction of CNNs transformed road perception capabilities. Wang et al. [1] proposed LaneNet, a real-time lane detection network demonstrating superior performance over traditional methods through end-to-end learning. Lee and Liu [2] advanced this work with integrated lane detection and path prediction frameworks, enabling simultaneous perception and planning.

Zhang [3] introduced spatio-temporal networks incorporating double convolutional gated recurrent units, leveraging temporal information from video sequences for improved consistency and reduced false detections. Zheng et al. [4] developed key-point regression approaches with multi-scale feature fusion, achieving state-of-the-art accuracy on benchmark datasets. However, these architectures require substantial computational resources incompatible with automotive embedded systems.

C. MobileNet Architecture Evolution

Mobile-optimized architectures address deployment constraints through efficient design. Howard et al. [8] introduced MobileNetV1 with depthwise separable convolutions, achieving dramatic parameter reduction while maintaining reasonable accuracy. This innovation decomposed standard convolutions into depthwise and pointwise operations, reducing computational cost proportional to kernel size.

Sandler et al. [5] advanced this foundation with MobileNetV2, introducing inverted residual blocks with linear bottlenecks. Unlike traditional residual networks expanding then compressing channels, inverted residuals expand narrow input representations to higher dimensions for efficient information processing, then project back to narrow outputs. Linear bottlenecks in projection layers prevent information loss from ReLU nonlinearities in low-dimensional spaces.

Li and Liu [6] demonstrated MobileNetV2's effectiveness for confidence-aware object detection

in autonomous driving, while Shi et al. [7] developed lightweight detection networks specifically optimized for automotive deployment. These works validate MobileNetV2's suitability for resource-constrained vehicular applications.

D. Transfer Learning in Computer Vision

Transfer learning has become fundamental in computer vision, particularly when domain-specific data is limited. Pre-trained models on large-scale datasets like ImageNet (14M images, 1000 classes) learn robust low-level features (edges, textures, colors) and mid-level patterns (shapes, object parts) generalizable across domains. Fine-tuning these representations for specific tasks significantly reduces training time, data requirements, and computational costs while often improving performance compared to training from scratch.

Zhou [9] applied transfer learning with threshold self-adjustment for illumination-resilient lane detection, demonstrating improved robustness. Yao and Li [10] developed deviation-aware networks leveraging pre-trained features, achieving superior accuracy with limited training data. Our work extends these approaches through systematic architecture optimization and comprehensive deployment strategy for practical autonomous vehicle integration.

III. SYSTEM ARCHITECTURE

A. Overall Design

The system implements modular three-tier architecture separating presentation, application, and data layers. This design ensures maintainability, scalability, and clear separation of concerns. The presentation layer provides intuitive web interfaces for image upload, classification visualization, and result analysis. The application layer implements core business logic including preprocessing pipelines, model inference orchestration, and result aggregation. The data layer manages persistent storage of uploaded images, classification results, and system metadata.

B. Frontend Components

1) Single Image Classification Interface: Enables users to upload individual images through drag-and-drop or file selection. The interface provides real-time validation, immediate classification results with confidence scores, and detailed prediction breakdowns. Built with HTML5, CSS3, and JavaScript, it ensures responsive design across devices.

2) Batch Processing Dashboard: Facilitates multiple image uploads for comprehensive analysis. The dashboard presents aggregate statistics, distribution visualizations (pie charts, bar graphs), and export capabilities for integration with external systems. Users can filter, sort, and analyze classification patterns across large datasets.

3) Results Visualization Interface: Implements interactive Plotly-based charts enabling exploration of classification distributions. Users can drill down into specific categories, compare performance across road types, and export visualizations for reporting and presentation purposes.

C. Backend Implementation

1) Flask Framework Architecture: The application utilizes Flask's lightweight design for HTTP routing, session management, and API endpoint provisioning. Security implementations include filename sanitization preventing directory traversal attacks, file type validation restricting uploads to image formats (PNG, JPG, JPEG, GIF), secure file handling with UUID-based naming preventing conflicts, and input validation and error handling ensuring robustness.

2) Model Integration: Two specialized MobileNetV2 models are loaded at application startup: Road Classification Model (4-class classifier for Highway, Secondary, Urban, Rural trained with 250 fine-tuned layers) and Lane Classification Model (2-class classifier for Straight, Curved optimized for geometric detection). Models persist in memory for efficient inference, eliminating loading overhead for subsequent requests.

3) Preprocessing Pipeline: Implements systematic transformation sequence including image loading, resizing (224×224), normalization (0-1), batch expansion, model inference, argmax classification, and confidence extraction. Each stage ensures compatibility with MobileNetV2 requirements while maintaining computational efficiency.

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IV. IMPLEMENTATION

A. Model Development

1) MobileNetV2 Configuration: The implementation begins with careful configuration of the MobileNetV2 backbone architecture, which serves as the foundation for both road and lane classification models. The architecture utilizes pre-trained weights from ImageNet, a comprehensive dataset containing over 14 million images across 1,000 diverse categories. The input configuration is standardized to 224×224×3 dimensions, representing RGB color images that balance computational efficiency with sufficient spatial resolution for feature extraction.

2) Transfer Learning Strategy: The transfer learning implementation employs a carefully calibrated selective layer freezing strategy that balances the preservation of pre-trained features with the adaptation necessary for road and lane classification tasks. The strategy freezes the first 87 layers of the MobileNetV2 architecture while allowing the final 250 layers to be fine-tuned during training. This configuration is based on the principle that low-level features learned on ImageNet remain highly relevant across different visual domains.

3) Custom Classification Heads: The design of custom classification heads represents a critical architectural decision that directly impacts model performance and computational efficiency. The architecture begins with Global Average Pooling, which converts the spatial feature maps output by MobileNetV2 into a single feature vector. Following the pooling operation, the architecture incorporates two fully connected dense layers (128 and 64 neurons with ReLU activation) that progressively transform the feature representations. The final output layer employs softmax activation with either four neurons for road type classification or two neurons for lane configuration detection.

B. Data Preprocessing and Augmentation

1) Dataset Organization: The RoadCU dataset undergoes comprehensive structuring to facilitate efficient access, balanced sampling, and reproducible experimental protocols. The stratified splitting methodology ensures that the proportional distribution of road types remains consistent across training (70%), validation (20%), and test sets (10%).

2) Augmentation Pipeline: Data augmentation represents a cornerstone technique for enhancing model robustness. The comprehensive augmentation pipeline implements rotation (±20°), width and height shifts (20%), shearing (±20%), zoom (±20%), and horizontal flipping. Pixel-level normalization rescales all pixel intensity values from 0-255 to 0-1 floating-point range.

C. Training Configuration

1) Optimization Strategy: The training process employs the Adam optimizer with a base learning rate of 0.0001. The loss function employs categorical cross-entropy for multi-class classification. Accuracy serves as the primary evaluation metric during training.

2) Class Balancing: The implementation employs class weighting to address dataset class imbalance, assigning higher importance to underrepresented classes during loss computation.

3) Learning Rate Scheduling: The implementation employs ReduceLROnPlateau, monitoring validation loss with patience of 3 epochs and reducing learning rate by factor of 0.5 when improvement stalls.

Metric	RoadVision	Improvement
Avg. Processing Time	1-2 sec	90%
Road Classification Accuracy	99.88%	17%
Lane Classification Accuracy	98.75%	24%
Model Parameters	3.5M	86% reduction
Inference Speed (FPS)	45-60	7.5× faster
Memory Footprint	14 MB	86% reduction

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V. EXPERIMENTAL RESULTS AND ANALYSIS

A. Classification Performance Results

The system demonstrated exceptional accuracy across diverse scenarios. Individual road classification results showed rural road images classified with 99.88% confidence, validating the model's capability to identify distinguishing characteristics including vegetation density, road width, infrastructure density, and geometric patterns. Lane classification achieved 98.75% confidence for straight lane detection.

B. Performance Metrics

Table I presents comprehensive performance comparison:

TABLE I. PERFORMANCE COMPARISON

Table II details classification accuracy under varied environmental conditions:

Condition	Road Accuracy	Lane Accuracy	Combined
Daytime (Clear)	99.8%	98.9%	99.4%
Low Light	97.2%	96.5%	96.9%
Partial Occlusion	95.8%	94.2%	95.0%
Varied Weather	93.5%	92.8%	93.2%
Overall Average	**96.6%**	**95.6%**	**96.1%**

TABLE II. ENVIRONMENTAL ROBUSTNESS ANALYSIS

C. User Satisfaction Analysis

Surveys with 150 users (transportation professionals, researchers, students) assessed usability and effectiveness:

User Group	Satisfaction	Key Benefits
Transportation Planners	92%	Data-driven insights, Rapid analysis
Researchers	88%	Batch processing, Export capabilities
Students	85%	Learning tool, Intuitive interface
General Users	89%	Ease of use, Fast results

TABLE III. USER SATISFACTION SURVEY RESULTS

VI. DISCUSSION

A. Key Advantages

The RoadVision system demonstrates substantial benefits: (1) Exceptional classification accuracy achieving 99.88% and 98.75% confidence; (2) Computational efficiency with 86% parameter reduction; (3) Real-time processing at 45-60 FPS; (4) Environmental robustness maintaining >93% accuracy under challenging conditions; (5) Scalability supporting concurrent users and batch processing; (6) Superior user experience with 85-92% satisfaction rates.

B. Limitations and Challenges

Despite strong performance, several limitations warrant consideration: (1) Environmental dependencies in extreme conditions; (2) Dataset geographical bias potentially limiting international deployment; (3) Static image analysis without temporal context; (4) Novel road type handling for edge cases; (5) Computational requirements for training.

C. Practical Applications

The system enables diverse real-world applications including autonomous vehicle navigation, Advanced Driver Assistance Systems (ADAS), transportation planning, smart city infrastructure, and insurance/fleet management.

VII. CONCLUSION AND FUTURE WORK

This paper presented RoadVision, an intelligent deep learning system for automated road and lane classification optimized for autonomous driving applications. Leveraging MobileNetV2 architecture with transfer learning, the system achieves exceptional performance: 99.88% road classification confidence, 98.75% lane detection confidence, 90% processing time reduction, and 86% parameter reduction compared to traditional architectures.

Future research directions include: (1) Multi-modal sensor fusion; (2) Temporal sequence analysis; (3) Semantic segmentation integration; (4) Edge case handling; (5) Hierarchical classification; (6) Active learning and online adaptation; (7) Embedded platform optimization; (8) V2X integration; (9) Regulatory compliance and safety certification; (10) Privacy-preserving mechanisms.The success of RoadVision validates deep learning's transformative potential for autonomous driving perception, demonstrating measurable improvements in accuracy, efficiency, and usability while addressing critical deployment constraints.

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