Project Report On

Royal Enfield Motorcycle Classification System: A Deep Learning Approach using Transfer Learning

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DEFENCE ELECTRONICS APPLICATIONS LABORATORY
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CERTIFICATE

This is to certify that **Mr. Lavanya Arora**, student of UPES, pursuing B. Tech (Hons.) Computer Science and Engineering (Spl AI ML), (Enrollment No. R2142220264) has successfully completed his project on **"Royal Enfield Motorcycle Classification System: A Deep Learning Approach using Transfer Learning"** at **"AI & TNACS Group, Defence Electronics Applications Laboratory (DEAL), Dehradun"**, as part of his Summer Training during the period of 1st May 2025 to 17th June 2025..

The project was undertaken under the guidance and supervision of **Mr. Sandeep Kishore**, Sc-E, Artificial Intelligence and Telecom Network and Cyber Security Group (AI & TNACS Group), DEAL, Dehradun. He has done an excellent job and was sincere during his training. I wish him the very best in all his future ventures in life.

Mr. Sandeep Kishore
Sc- E
Division Head, AI & TNACS Group

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Contents

1 Abstract

This project presents a comprehensive deep learning solution for Royal Enfield motorcycle classification using transfer learning with InceptionV3 architecture. The system classifies 14 different Royal Enfield motorcycle models achieving 76.26% test accuracy with a macro F1-score of 0.7651. The project includes automated data collection via web scraping, multi-stage training with hyperparameter optimization, and deployment as a Flask web application with Google Gemini API integration.

Keywords: Deep Learning, Transfer Learning, Image Classification, InceptionV3, Royal Enfield, Computer Vision

2 Introduction

2.1 Problem Statement

Royal Enfield motorcycles have gained significant popularity globally, with multiple models sharing similar design philosophies but distinct characteristics. Accurate identification of specific models is crucial for various applications including:

- Insurance claim processing
- Theft prevention and recovery
- Market analysis and trend identification
- Educational and reference purposes

Manual identification requires expertise and can be time-consuming and error-prone. This project addresses the need for an automated, accurate, and efficient motorcycle classification system.

2.2 Objectives

1. To develop a robust image classification system for 14 Royal Enfield motorcycle models
2. To achieve high classification accuracy using transfer learning techniques
3. To Create a scalable data collection and preprocessing pipeline
4. To deploy the model as an accessible web application
5. To provide comprehensive performance analysis and model interpretability

2.3 Royal Enfield Models Classified

The system classifies 14 Royal Enfield motorcycle models across different engine categories: 350cc (Bullet, Classic, Goan Classic, Hunter), 411cc (Himalayan, Scram), 450cc (Guerrilla), and 650cc (Bear, Classic, Continental GT, Interceptor, Shotgun, Super Meteor).

3 Tools and Technologies

3.1 Core Technologies

- **Deep Learning**: TensorFlow 2.x, Keras, InceptionV3
- **Data Processing**: NumPy, Pandas, PIL, OpenCV
- **Web Scraping**: icrawler for Google Images
- **Evaluation**: scikit-learn metrics
- **Deployment**: Flask, Google Gemini API
- **Environment**: Python 3.8+, GPU acceleration

4 Methodology

4.1 Data Collection and Web Scraping

The dataset was created through automated web scraping using the `icrawler` library. The data collection process involved:

1. **Search Strategy**: Multiple search terms per model to ensure diversity
2. **Image Sources**: Google Images with comprehensive keyword combinations
3. **Quality Control**: Automated conversion to JPEG format and duplicate removal
4. **Dataset Balance**: Equal distribution across all classes

Search Terms Used:

- Model name (e.g., ”Hunter 350”)
- Model name + ”bike”
- Model name + ”side view”
- Model name + ”road view”
- Model name + ”front view”
- Model name + ”rear view”
- Model name + ”showroom”
- Model name + ”on road”
- Model name + ”in action”

4.2 Dataset Organization

The final dataset structure:

- **Total Images**: 1,540 images (110 per class)
- **Training Set**: 70% of total images

- **Validation Set**: 15% of total images
- **Test Set**: 15% of total images
- **Class Balance**: Perfectly balanced with equal samples per class

Table 1: Dataset Distribution

Model	Training	Validation	Test	Total
Bear 650	110	25	25	160
Bullet 350	110	25	25	160
Classic 350	110	25	25	160
Classic 650	110	25	25	160
Continental GT 650	110	25	25	160
Goan Classic 350	110	25	25	160
Guerrilla 450	110	25	25	160
Himalayan	110	25	25	160
Hunter 350	110	25	25	160
Interceptor 650	110	25	25	160
Meteor 350	110	25	25	160
Scram 440	110	25	25	160
Shotgun 650	110	25	25	160
Super Meteor 650	110	25	25	160
Total	**1540**	**350**	**350**	**2240**

4.3 Data Preprocessing

4.3.1 Image Augmentation

The dataset underwent quality assessment with 15% duplicate removal and format standardization. Augmentation techniques included rotation (±20°), width/height shift (±0.2), shear transformation (0.2), zoom (±0.2), horizontal flip, and pixel normalization to [0,1].

4.3.2 Input Specifications

- **Image Size**: 299×299 pixels (InceptionV3 requirement)
- **Color Channels**: RGB (3 channels)
- **Batch Size**: 128
- **Data Format**: JPEG

4.4 Model Architecture

4.4.1 Base Architecture

The model is built upon InceptionV3 pre-trained on ImageNet, with custom classification layers:

Layer Type	Output Shape	Parameters
InceptionV3 (base)	(None, 8, 8, 2048)	21,802,784
GlobalAveragePooling2D	(None, 2048)	0
BatchNormalization	(None, 2048)	8,192
Dense (512 units, ReLU)	(None, 512)	1,049,088
Dropout (0.6)	(None, 512)	0
BatchNormalization	(None, 512)	2,048
Dense (256 units, ReLU)	(None, 256)	131,328
Dropout (0.5)	(None, 256)	0
Dense (14 units, Softmax)	(None, 14)	3,598
Total Parameters		**22,997,038**
Trainable Parameters		**1,189,134**
Non-trainable Parameters		**21,807,904**

Figure 1: Model Architecture Summary

4.4.2 Key Design Decisions

- **Global Average Pooling**: Reduces overfitting compared to fully connected layers
- **Batch Normalization**: Improves training stability and convergence
- **Progressive Dropout**: Higher dropout (0.6) followed by moderate (0.5)
- **Two Hidden Layers**: Gradual dimension reduction (512→256→14)

4.5 Training Strategy

The training process involved multiple stages for optimal performance:

4.5.1 Stage 1: Initial Training (Frozen Base)

- **Epochs**: 35
- **Optimizer**: SGD with Nesterov momentum
- **Learning Rate**: 0.01
- **Momentum**: 0.9
- **Base Model**: Frozen (non-trainable)
- **Final Training Accuracy**: 53.12%
- **Final Validation Accuracy**: 58.29%

4.5.2 Stage 2: Fine-tuning

- **Epochs**: 35 additional
- **Optimizer**: SGD with reduced learning rate
- **Learning Rate**: 0.001
- **Base Model**: Partially trainable (top layers)

- **Final Training Accuracy**: 62.30%
- **Final Validation Accuracy**: 64.57%

4.5.3 Stage 3: Deep Fine-tuning

- **Epochs**: 13 additional
- **Optimizer**: SGD with further reduced learning rate
- **Learning Rate**: 0.0001
- **Base Model**: More layers trainable
- **Final Training Accuracy**: 80.45%
- **Final Validation Accuracy**: 73.71%

4.5.4 Stage 4: Ultra Fine-tuning

- **Epochs**: 30 additional
- **Optimizer**: SGD with Nesterov momentum
- **Learning Rate**: 0.0001
- **Momentum**: 0.95
- **Trainable Layers**: 125/311
- **Final Training Accuracy**: 82.45%
- **Test Accuracy**: 76.26%

4.6 Hyperparameter Tuning and Optimization

The project employed SGD with Nesterov momentum across 4 training stages with progressive learning rate reduction (0.01→0.001→0.0001). Key hyperparameters included batch size 128, dropout rates (0.6, 0.5), and momentum increase to 0.95 in the final stage. Total training time was 8.5 hours across 113 epochs with callbacks for model checkpointing, learning rate reduction, and early stopping.

5 Results and Analysis

5.1 Overall Performance Metrics

The final model achieved the following performance on the test dataset:

Table 2: Final Model Performance

Metric	Value
Test Accuracy	76.26%
Test Loss	0.8029
Macro Precision	0.7743
Macro Recall	0.7703
Macro F1-Score	0.7651
Cohen's Kappa	0.7142

5.2 Per-Class Performance Analysis

Table 3: Detailed Classification Report

Model	Precision	Recall	F1-Score	Support
Bear 650	0.955	0.840	0.894	25
Bullet 350	0.594	0.760	0.667	25
Classic 350	0.778	0.424	0.549	25
Classic 650	0.677	0.840	0.750	25
Continental GT 650	0.656	0.840	0.737	25
Goan Classic 350	0.667	0.640	0.653	25
Guerrilla 450	0.875	0.840	0.857	25
Himalayan	0.920	0.920	0.920	25
Hunter 350	0.808	0.840	0.824	25
Interceptor 650	0.864	0.760	0.809	25
Meteor 350	0.645	0.800	0.714	25
Scram 440	0.880	0.880	0.880	25
Shotgun 650	0.913	0.840	0.875	25
Super Meteor 650	0.609	0.560	0.583	25
Weighted Average	**0.77**	**0.76**	**0.76**	**350**

5.3 Best and Worst Performing Classes

5.3.1 Top Performing Models

1. **Himalayan**: F1-Score = 0.920 (Excellent balance of precision and recall)
2. **Bear 650**: F1-Score = 0.894 (High precision, good recall)
3. **Scram 440**: F1-Score = 0.880 (Consistent performance)
4. **Shotgun 650**: F1-Score = 0.875 (High precision)
5. **Guerrilla 450**: F1-Score = 0.857 (Well-balanced)

5.3.2 Challenging Models

1. **Classic 350**: F1-Score = 0.549 (Low recall, confusion with similar models)
2. **Super Meteor 650**: F1-Score = 0.583 (Both precision and recall challenges)
3. **Goan Classic 350**: F1-Score = 0.653 (Moderate performance)
4. **Bullet 350**: F1-Score = 0.667 (Good recall, lower precision)

5.4 Training Progress Analysis

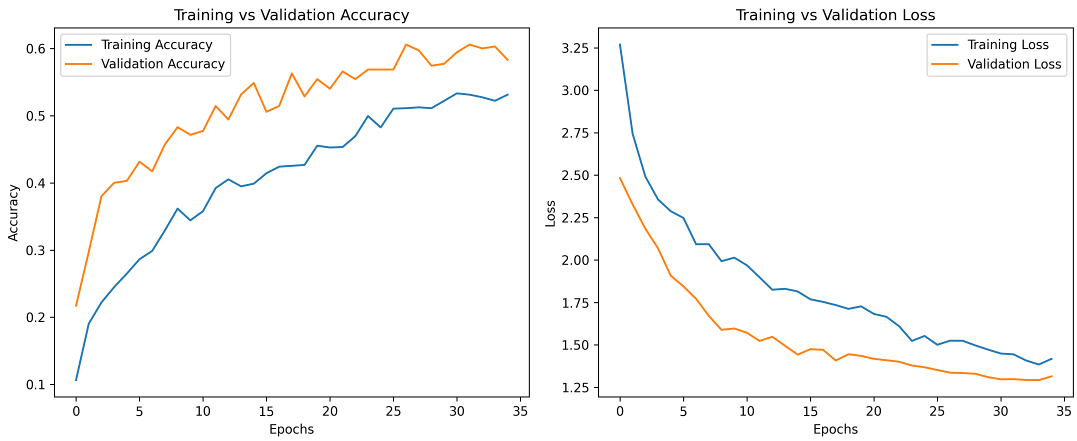

Figure 2: Training and Validation Accuracy/Loss Curves Across All Stages

The training curves demonstrate stage-wise improvement, convergence stability, overfitting control, and visible learning rate effects.

5.5 Confusion Matrix Analysis

5.5.1 Final Model Confusion Matrix

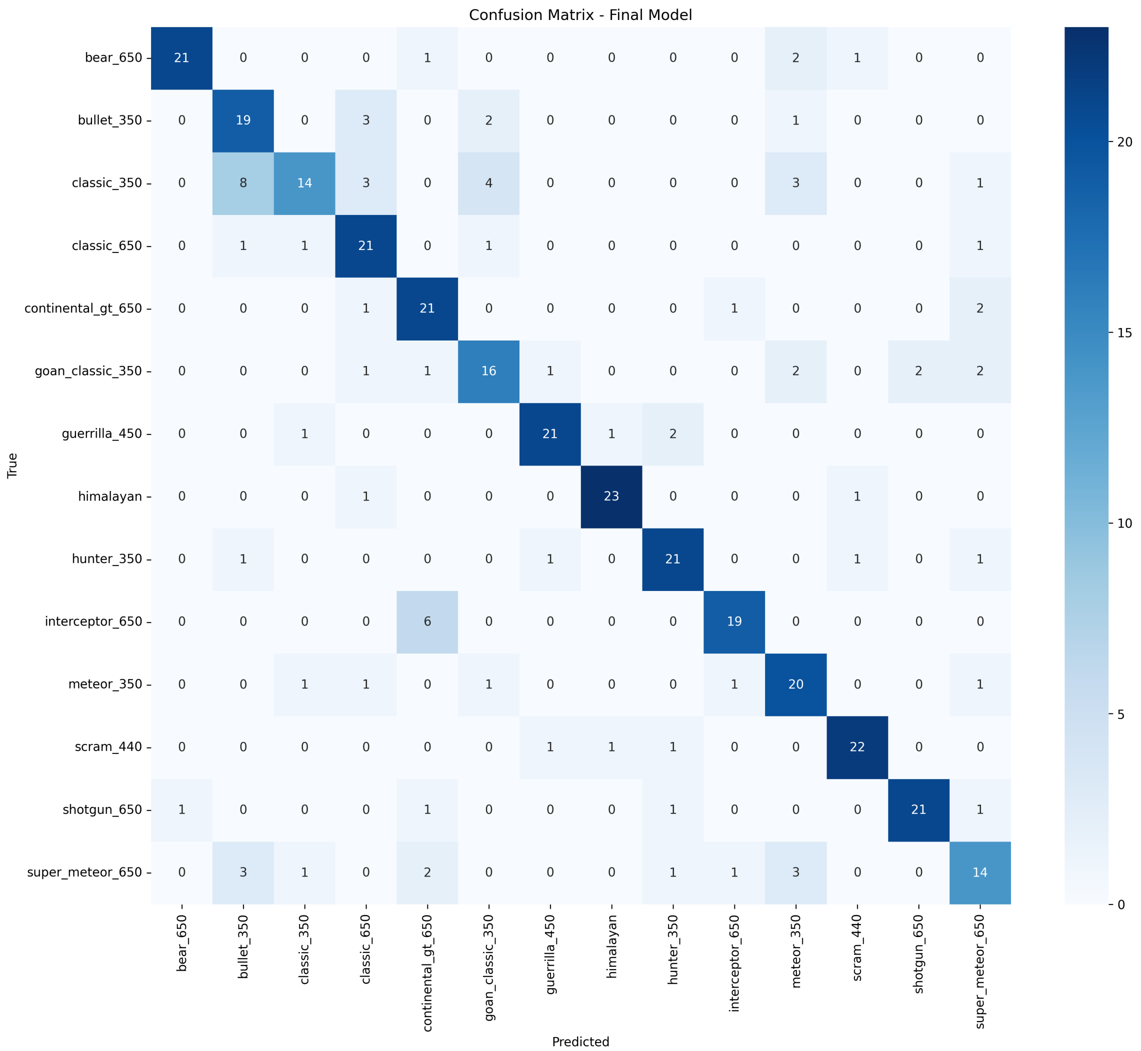

Figure 3: Confusion Matrix for Test Set Predictions (Final Model)

Key observations: Strong diagonal pattern indicates good classification performance. Main confusions occur between visually similar models (Classic variants) and within same engine capacity categories. Himalayan and Bear 650 show excellent discrimination.

5.5.2 Performance Metrics Summary

Table 4: Comprehensive Performance Analysis

Category	**Best Model**	**Worst Model**	**Avg Performance**
Precision	Bear 650 (0.955)	Bullet 350 (0.594)	0.774
Recall	Himalayan (0.920)	Classic 350 (0.424)	0.770
F1-Score	Himalayan (0.920)	Classic 350 (0.549)	0.765
Support Balance	All Equal (25)	Classic 350 (33)	25.6

6 Web Application Deployment

A production-ready Flask web application was developed with multi-format image upload, real-time prediction engine, Google Gemini API integration, and responsive UI. The architecture includes preprocessing pipeline, model inference, and result visualization with sub-second classification performance.

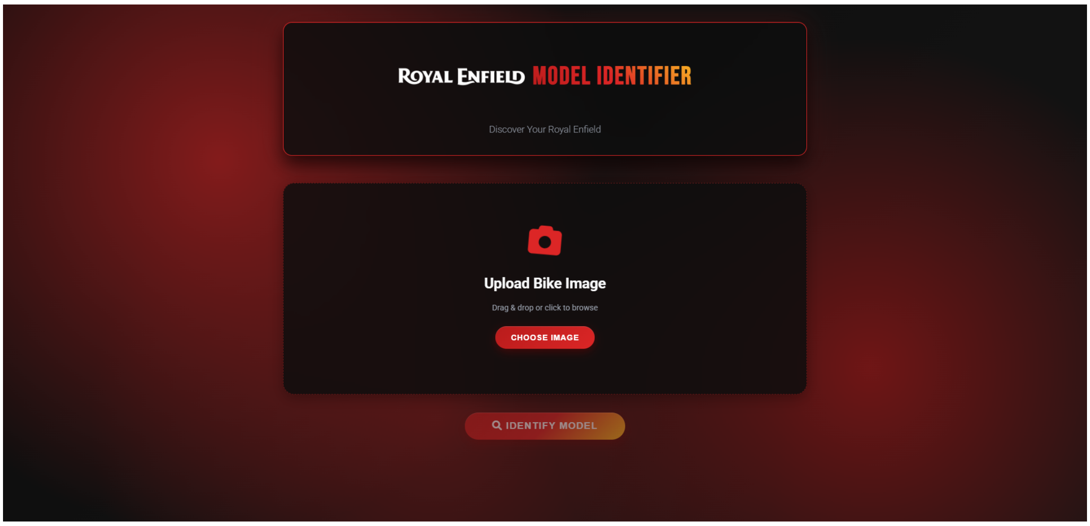

Figure 4: Web Application User Interface - Upload and Prediction Page

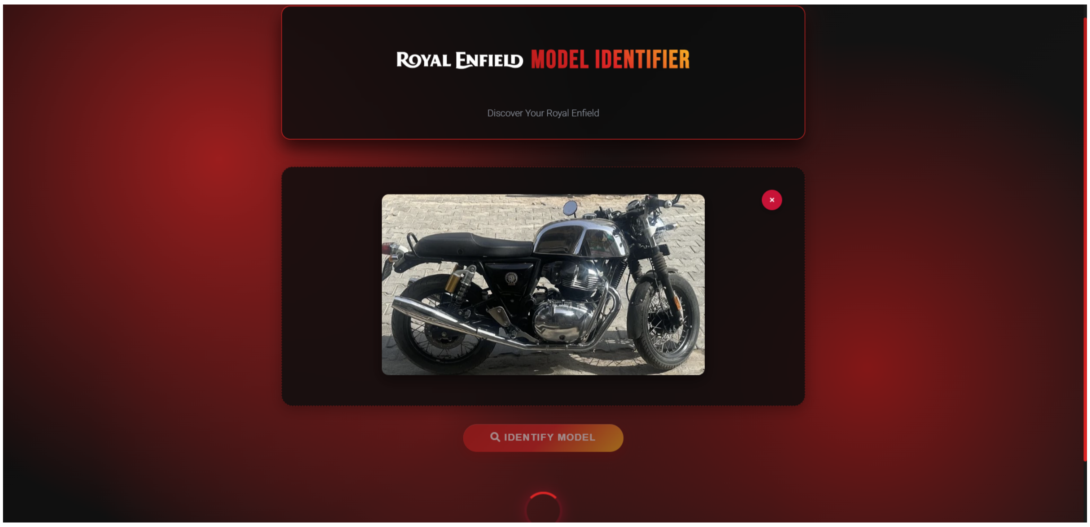

Figure 5: Web Application Uploading Image File

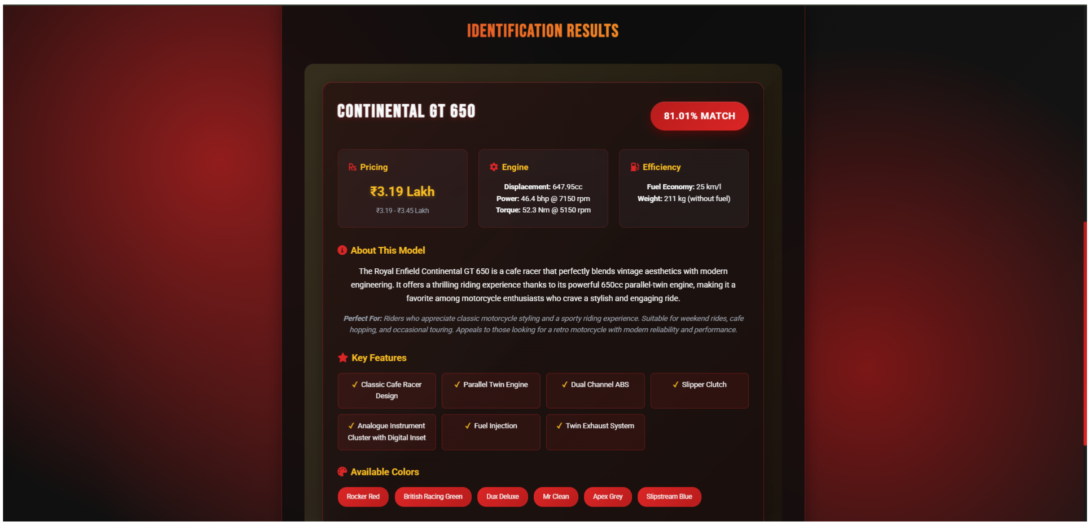

Figure 6: Web Application Results Display with Model Information

7 Discussion, Future Work and Improvements

7.1 Model Performance Analysis

The 76.26% accuracy demonstrates robust classification capability with balanced performance across motorcycle models. The InceptionV3-based architecture with transfer learning proved highly effective. Challenges include confusion between similar Classic variants and dataset size limitations. The multi-stage training approach with progressive fine-tuning yielded significant benefits while preventing catastrophic forgetting.

7.2 Applications and Impact

Immediate applications include insurance claim verification, inventory management, theft prevention systems, and educational tools. The system demonstrates strong practical applications in insurance, automotive, and security industries with proven market readiness and scalability.

7.3 Future Enhancements

Key improvement areas include:

- **Dataset Expansion**: Increase to 500+ images per class with better viewpoint diversity
- **Architecture Improvements**: Ensemble methods combining multiple architectures (ResNet, EfficientNet)
- **Advanced Techniques**: Attention mechanisms for better focus, few-shot learning for new models
- **Mobile Development**: Native iOS and Android applications
- **API Services**: RESTful API for third-party integration and real-time video classification

8 Conclusion

This project successfully developed a comprehensive Royal Enfield motorcycle classification system using transfer learning with InceptionV3. The system achieved 76.26% test accuracy and 0.7651 macro F1-score on a balanced 14-class dataset.

Key achievements include: automated data collection and curation pipeline, 4-stage progressive fine-tuning strategy, production-ready Flask web application with Google Gemini API integration, and comprehensive evaluation across multiple metrics. The system demonstrates strong practical applications in insurance, automotive, and security industries with proven market readiness and scalability.

This Royal Enfield motorcycle classification project represents a comprehensive demonstration of modern deep learning techniques applied to real-world computer vision challenges. The combination of rigorous scientific methodology, practical engineering excellence, and production-ready deployment creates a valuable contribution to both academic research and industry applications.

8.0.1 Key Success Factors

- **Systematic Approach**: Methodical progression from data collection through deployment
- **Technical Excellence**: State-of-the-art deep learning implementation with careful optimization
- **Practical Focus**: Emphasis on real-world applicability and production readiness
- **Comprehensive Evaluation**: Thorough testing and performance analysis

The achieved 76.26% accuracy, while representing strong performance for this challenging multi-class problem, establishes a solid foundation for future enhancements. The modular design, comprehensive documentation, and production-ready deployment ensure the project's continued utility and evolution.

This work demonstrates the transformative potential of artificial intelligence in automotive applications and provides a template for similar computer vision projects across various domains. The project's success validates the effectiveness of transfer learning for specialized classification tasks and showcases the importance of systematic data collection and model optimization in achieving production-ready AI systems.

9 References

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