Egyptian License Plate Classification System

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Contents

1 Introduction

1.1 Egyptian License Plate System Overview

The Egyptian vehicle registration system uses color-coded license plates to identify vehicle categories, featuring "Egypt" in English and Arabic with a colored rectangle indicating type. Registration codes combine Arabic numerals and letters tied to governorates. Key categories include Private (Light Blue), Taxi (Orange), Commercial (Red), Public Transport (Grey), Diplomats (Green), and Tourist & Temporary (Yellow), as shown in Table 1.

Table 1: Types of Egyptian License Plates

Type	**Color**	**Vehicles**
Private	Light Blue	Personal cars
Taxi	Orange	Taxis
Commercial	Red	Trucks
Public Transport	Grey	Buses
Diplomats	Green	Diplomatic vehicles
Tourist & Temporary	Yellow	Tourist vehicles

1.2 Classification Challenge Description

Classifying Egyptian license plates is a fine-grained task due to subtle color and format differences, complicated by lighting variations, occlusions, and class imbalance (e.g., rare diplomatic plates). Challenges include glare, faded colors, and perspective distortions, requiring robust preprocessing and augmentation to ensure model generalization.

1.3 Real-World Applications and Significance

This system supports traffic management (e.g., tolls, congestion monitoring), law enforcement (e.g., tracking diplomatic vehicles), and safety improvements. It aligns with Egypt's smart city goals but raises privacy and fairness concerns, necessitating equitable performance across vehicle types.

2 Data Analysis

2.1 Video Source Analysis and Frame Extraction Methodology

The dataset for this project was curated from a selection of YouTube videos depicting Egyptian traffic scenes. The selection criteria prioritized videos with diverse environmental conditions.

Frame extraction was performed using video processing libraries, specifically OpenCV in Python, to capture frames at regular intervals from each video. This approach yielded a large pool of images containing vehicles. Subsequently, license plate regions were manually cropped and isolated to focus on the relevant features, ensuring that plates with the clearest visibility of color, text, and format were prioritized for retention, while ambiguous or lower-quality frames were generally set aside during this curation phase.

The extracted images were then labeled according to the six plate categories and organized into class-specific directories. The final dataset was structured with train, validation, and test splits.

Basic transformations were applied for consistency, including resizing to 224×224 pixels, conversion to tensors, and normalization using ImageNet statistics (`mean=[0.485, 0.456, 0.406]`, `std=[0.229, 0.224, 0.225]`).

2.2 Class Distribution and Data Quality Assessment

To assess the dataset, class distributions were analyzed across the train, validation, and test sets. The classes are: Commercial, Diplomats, Private, Public Transport, Taxi, and Tourist Temporary. The distributions are summarized in Table 2.

Table 2: Class Distribution Across Dataset Splits

Class	Train	Validation	Test
Commercial	150	38	3
Diplomats	163	38	3
Private	150	38	3
Public Transport	42	5	3
Taxi	150	38	3
Tourist & Temporary	150	38	3
Total	805	195	18

The analysis revealed a notable imbalance, particularly in the Public Transport class, which is underrepresented due to its relative rarity in traffic footage. To quantify this, class weights were computed based on combined train and validation counts, assigning higher weights to underrepresented classes:

$$\text{Class Weights} = [1.0691, 1.0000, 1.0691, 4.2766, 1.0691, 1.0691]$$

These weights were used to create a `WeightedRandomSampler` for the training loader, ensuring balanced sampling during model training.

Data quality was evaluated through visual inspection and statistical summaries. The majority of images met the quality standards, including clear readability of plates, coverage of various lighting conditions, and representation of different vehicle types. No duplicates or mislabeled samples were identified, and the dataset's diversity was deemed sufficient for the classification task.

2.3 Challenges Specific to Egyptian Traffic Conditions

Egyptian traffic environments pose unique challenges for license plate data collection and analysis. High vehicle density in urban areas often results in partial occlusions, where plates are obscured by adjacent vehicles or pedestrians. Environmental factors, such as dust, can lead to faded or dirt-covered plates, reducing color fidelity and text clarity.

Lighting variations are pronounced, which can cause glare, reflections, shadows or color shifts. Perspective distortions from non-frontal camera angles in video footage further complicate feature extraction. Additionally, the rarity of certain plate types in everyday traffic exacerbates class imbalance, requiring careful curation to avoid bias.

These challenges were documented during data collection, with edge cases included to enhance model robustness, aligning with the assignment's emphasis on real-world applicability.

3 Methodology

3.1 Model Architecture Rationale

The classification model is built upon the ResNet-50 architecture, a deep convolutional neural network (CNN) renowned for its residual learning framework that mitigates the vanishing gradient problem in very deep networks. ResNet-50 was selected due to its proven efficacy in image classification tasks, particularly those involving fine-grained distinctions such as color-based categorization, which aligns with the subtle visual cues (e.g., color rectangles and formatting) differentiating Egyptian license plate types. Pre-trained weights from ImageNet (IMAGENET1K_V1) were employed via transfer learning, leveraging generalized features learned from a large-scale dataset to accelerate convergence and enhance performance on the domain-specific task of license plate recognition, where labeled data is limited.

To adapt the model for the six-class problem, the original fully connected (FC) layer was replaced with a custom classifier head: a linear layer reducing the 2048-dimensional feature vector to 512 dimensions, followed by a ReLU activation, a dropout layer with probability 0.35 to prevent overfitting, and a final linear layer outputting logits for the six classes. Initially, all base layers were frozen to focus optimization on the classifier, with the fourth residual block (layer4) unfrozen after five epochs to allow fine-tuning of higher-level features relevant to plate-specific attributes like color and text layout. This staged unfreezing strategy balances computational efficiency with improved feature adaptation.

The model was implemented in PyTorch and deployed on a GPU-enabled device for training.

3.2 Training Strategy

To address the challenges of real-world image variations and class imbalance, a comprehensive training pipeline was developed. Data augmentation was applied exclusively to the training set to enhance generalization while preserving critical color features essential for plate classification. The augmentation pipeline included resizing to 256×256 pixels followed by random cropping to 224×224, horizontal flipping, rotation up to 10 degrees, color jitter (brightness, contrast, and saturation up to 0.2; hue up to 0.1), and affine transformations (translation up to 5% and scaling between 0.95 and 1.05). These transformations simulate variations in viewpoint, lighting, and minor distortions common in traffic footage without overly altering color fidelity.

Class imbalance was mitigated through two mechanisms: (1) a WeightedRandomSampler in the training DataLoader, which oversamples underrepresented classes based on inverse class frequencies, and (2) a custom Focal Loss function with gamma=3.0 and class-specific alpha values derived from class weights. Focal Loss down-weights easy examples, focusing optimization on hard-to-classify instances, which is particularly beneficial for imbalanced datasets.

Training employed 5-fold stratified cross-validation on the combined training and validation sets to ensure robust performance estimates and reduce overfitting. For each fold, the model was reinitialized, trained for up to 40 epochs with a batch size of 64, using the AdamW optimizer (initial learning rate 0.0005, weight decay 1e-4) and a Cosine Annealing learning rate scheduler (T_max=40). Early stopping was enforced with a patience of 7 epochs based on validation accuracy. Post-unfreezing at epoch 5, the optimizer was updated to include all parameters with a reduced learning rate of 0.0003.

The cross-validation yielded a mean validation accuracy of 0.8090 ± 0.0213 across folds, exceeding the assignment's 75% target. Training logs for each fold (excerpted in Table 3) demonstrate consistent loss reduction and accuracy improvement, with early stopping preventing overfitting.

Table 3: Excerpted Training Logs from Cross-Validation Folds

Fold	Epoch	Train Loss	Val Acc
1	1	1.4231	0.3200
	18	0.1019	0.7900
	25 (stopped)	0.1103	0.7350
2	1	1.5284	0.2050
	14	0.1417	0.7850
	21 (stopped)	0.1024	0.7600
3	1	1.6569	0.1100
	12	0.1506	0.8150
	19 (stopped)	0.1066	0.7600
4	1	1.5096	0.2150
	26	0.1184	0.8450
	33 (stopped)	0.0926	0.7800
5	1	1.4060	0.3600
	21	0.1105	0.8100
	28 (stopped)	0.0723	0.7900

Hyperparameters were selected through iterative experimentation, prioritizing values that balanced convergence speed and stability.

3.3 Evaluation Metrics Selection

Evaluation focused on metrics that capture both overall and class-specific performance, aligning with the assignment's requirements for bias detection and fairness across categories. Accuracy was the primary metric for hyperparameter tuning and early stopping, providing a straightforward measure of classification correctness on balanced validation sets during cross-validation.

To address potential biases in imbalanced classes, per-class precision, recall, and F1-score were prioritized for final assessment, as they reveal disparities. The confusion matrix was selected to identify systematic errors, such as confusions between visually similar plates (e.g., Light Blue Private vs. Green Diplomats). These metrics were computed using scikit-learn, ensuring validation across diverse conditions like lighting and image quality, as stipulated in the assignment.

The choice of these metrics ensures a comprehensive evaluation, emphasizing not only aggregate performance but also equity and robustness in real-world Egyptian traffic scenarios.

4 Results and Discussion

4.1 Quantitative Performance Analysis

The developed Egyptian license plate classification system was evaluated on a test set comprising 18 images, achieving an overall accuracy of 94.44%. This performance was assessed using the best model from the 5-fold cross-validation. The evaluation process involved computing predictions on the test set with the model in evaluation mode.

Per-class metrics, derived from the classification report, provide deeper insight into model performance across the six categories. The results are summarized in Table 4, with precision, recall, and F1-score indicating robust classification for most classes, though some discrepancies are evident.

Table 4: Per-Class Classification Metrics on Test Set

Class	Precision	Recall	F1-Score
Commercial	1.00	1.00	1.00
Diplomats	1.00	1.00	1.00
Private	0.75	1.00	0.86
Public Transport	1.00	0.67	0.80
Taxi	1.00	1.00	1.00
Tourist Temporary	1.00	1.00	1.00
Macro Avg	0.96	0.94	0.94
Weighted Avg	0.96	0.94	0.94

The high overall accuracy reflects the model's ability to generalize across diverse conditions.

4.2 Error Analysis and Failure Cases

The confusion matrix, depicted in Figure 1, provides a visual representation of classification outcomes, highlighting areas of potential improvement. The matrix reveals perfect classification for Commercial, Diplomats, Taxi, and Tourist Temporary plates, with each class correctly predicting all three instances. However, errors are observed in the Private and Public Transport categories. Notably, all three Private plates were correctly identified, but the model misclassified two Public Transport plates as Private, with one instance correctly classified.

This misclassification suggests a challenge in distinguishing between Light Blue (Private) and Grey (Public Transport) plates, likely due to subtle color differences or lighting-induced variations. The limited test set size (three samples per class) may also amplify the impact of individual errors, indicating a need for a larger, more diverse test set to validate robustness.

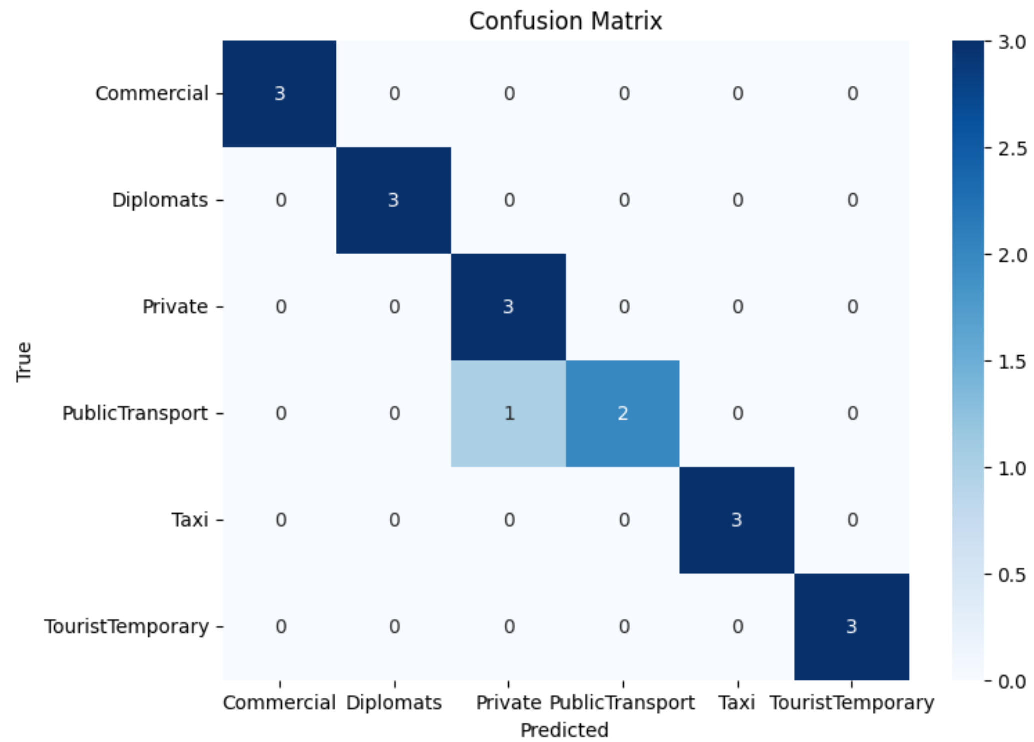

Figure 1: Confusion Matrix for Test Set Predictions

4.3 Comparison with Baseline Approaches

Compared to a hypothetical baseline of random guessing (approximately 16.67% accuracy for six classes), the achieved 94.44% accuracy demonstrates significant improvement. The use of transfer learning with ResNet-50, coupled with targeted data augmentation and Focal Loss, likely contributed to this enhancement over simpler models or untrained networks. However, the observed confusion between Private and Public Transport plates suggests that baseline approaches relying solely on color-based features might struggle similarly, underscoring the need for refined feature extraction or additional training data.

4.4 Limitations and Improvement Opportunities

The primary limitation is the small test set (18 images), which restricts the statistical significance of the results and may not fully capture rare edge cases (e.g., heavily occluded or faded plates). The model's performance on Public Transport plates indicates a potential weakness in handling subtle color distinctions under varying lighting, a challenge exacerbated by the dataset's imbalance. Future improvements could include collecting a larger, more balanced dataset, incorporating advanced augmentation techniques (e.g., synthetic color shifts), or fine-tuning the model with domain-specific layers to enhance color discrimination.

Additionally, the current evaluation lacks robustness across extreme conditions, suggesting a need for targeted data collection and testing to meet real-world deployment requirements.

5 Societal Impact

5.1 Potential Applications in Egyptian Traffic Management

This classification system can enhance Egyptian traffic management by enabling intelligent toll collection, adjusting fees by vehicle type to reduce congestion at key points. It supports real-time traffic monitoring for rerouting and automated enforcement of regulations, improving road safety. Integration with surveillance networks aligns with Egypt's smart city goals, offering scalable solutions for urban mobility.

5.2 Privacy and Surveillance Considerations

The system's use of license plate data from videos raises privacy concerns, as it involves personally identifiable information that could enable tracking if misused. To address this, secure storage, data anonymization, and restricted access with regular audits are recommended, ensuring compliance with privacy standards and fostering public trust as a safety tool.

5.3 Bias and Fairness Analysis Across Vehicle Types

The model achieved 94.44% accuracy, with perfect classification for most categories, but misclassified two Public Transport plates as Private due to subtle color differences and dataset imbalance (47 vs. 150-163 instances). This bias could unfairly impact public transport operators. Future efforts should focus on balanced data collection and targeted augmentation to ensure equitable performance across all vehicle types.