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Recognition Of Malagasy Vehicle License Plates Using Hough Transform And Multilayer Perceptron For Automated Garage Door Opening

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Abstract - Automatic License Plate Recognition (ALPR) has become a critical component in modern intelligent transportation systems, yet its deployment in resource-constrained environments presents unique challenges. This study investigates the design and implementation of an automatic license plate recognition system specifically intended for garage door opening automation within the Malagasy context. By integrating classical image processing techniques—namely Canny edge detection and Hough transform for plate localization—with a multilayer perceptron (MLP) neural network for character classification, the proposed system achieves a balance between computational efficiency and recognition accuracy. An empirical evaluation was conducted using a dataset of static vehicle images captured under varying lighting conditions. The results demonstrate a plate localization success rate of 71.42% and a character recognition accuracy of 99% for previously learned plates, yielding an overall system efficiency of 85.21%. Furthermore, the study compares the performance of noise-injected training versus standard training, revealing that noisy training significantly enhances robustness, reducing error rates under progressive input degradation. Despite limitations in handling inclined planes and complex backgrounds, the proposed framework provides a practical, low-cost solution for automated access control. The study concludes by outlining future directions, including the integration of Fourier descriptors for rotation invariance and the development of real-time capabilities for nighttime and adverse weather conditions.

Keywords: Automatic License Plate Recognition, Hough transform, multilayer perceptron, image segmentation, neural network, garage automation, Malagasy license plates

1. INTRODUCTION

The recognition of vehicle license plates represents one of the most widely applied domains of pattern recognition in intelligent transportation systems (**Heutte, n.d., p. 3**). From parking surveillance and automated toll collection to border control and stolen vehicle tracking, ALPR systems have demonstrated their utility across diverse operational contexts. However, the deployment of such systems in developing economies, particularly in Madagascar, remains limited by the absence of standardized, cost-effective solutions tailored to local plate specifications and environmental conditions (**Jähne & Haußecker, 2000, pp. 50-55**).

The present research addresses this gap by designing an ALPR system specifically conceived for garage door automation – a use case requiring reliable, real-time recognition with minimal computational overhead. Unlike high-end commercial systems that rely on deep learning architectures requiring substantial computational resources (**Aggarwal, 2018, chap. 9**), the proposed approach leverages classical computer vision techniques (edge detection, Hough transform) combined with a lightweight multilayer perceptron (MLP) neural network. Neural networks are constructed as computational graphs that perform recursive composition of simpler functions in order to learn more complex functions (**Aggarwal, 2018, p. 2**). Understanding the relationship between traditional machine learning and neural networks is essential, as many traditional models can be understood as special cases of neural learning (**Aggarwal, 2018, p. 1**). The neural network stores information in the form of weights, and the systematic approach to modifying weights according to given information is called the learning rule (**Kim, 2017, p. 29**). This methodological choice is motivated by the imperative to achieve functional efficiency on standard computing hardware while maintaining acceptable recognition rates under controlled lighting conditions.

The extraction of suitable features for subsequent processing to recognize and classify objects is a fundamental goal of signal processing in computer vision (Jähne & Haußecker, 2000, p. 4). Edge detection, which is a critical step in plate localization, belongs to the class of nonlinear neighborhood operators (Jähne & Haußecker, 2000, p. 5). As noted in the computer vision literature, nonlinear techniques are crucial for feature extraction, and the analysis of at least a local neighborhood is required to extract a rich set of features (Jähne & Haußecker, 2000, p. 274).

The central research question guiding this study is twofold: **(1) Can a hybrid system based on Hough transform and MLP achieve sufficient accuracy for garage access control in a real-world Malagasy context ? (2) What is the impact of noise-injected training on the robustness of character recognition when input images are subject to progressive degradation ?** To address these questions, the study implements a complete processing pipeline comprising image acquisition, grayscale conversion, edge detection, line detection via Hough transform, candidate region segmentation, character extraction, feature normalization, and neural classification.

The originality of this work lies in its contextual grounding – the system is calibrated to recognize **Malagasy license plate formats (exemplified by the plate “0978TAD”)** – and its comparative analysis of training strategies. An empirical survey conducted on six static test images reveals that while plate localization remains the principal bottleneck (71.42% success), the subsequent neural classification achieves near-perfect accuracy (99%) for plates included in the training set. Moreover, the study demonstrates that an MLP trained with additive noise significantly outperforms a noise-free counterpart when tested on degraded inputs, confirming the value of data augmentation in resource-limited settings.

2. MATERIALS AND METHODS

2.1. Materials

The empirical foundation of this study rests upon three categories of materials: a custom image dataset of Malagasy vehicle license plates, a software implementation environment, and the computational hardware used for training and evaluation.

2.1.1. Image Dataset

A corpus of six static color images was acquired using a standard digital camera under daylight conditions. The images depict the frontal or rear views of vehicles with clearly visible license plates conforming to Malagasy national standards. Among these six images, five plates were included in the training set (learned by the neural network), while the sixth served as an out-of-sample test case to evaluate generalization capability. The reference plate used for detailed analysis is "0978TAD" (a representative alphanumeric sequence comprising four digits followed by three uppercase letters). All images were stored in JPEG format at a resolution sufficient to maintain character legibility after preprocessing.

2.1.2. Software and Hardware Environment

The ALPR system was implemented in **MATLAB (The MathWorks, Inc.)**, leveraging its Image Processing Toolbox for morphological operations, edge detection, and Hough transform functions, as well as its **Neural Network Toolbox for MLP** creation, training, and simulation (**Kim, 2017, chap. 3**). The choice of MATLAB is justified by its rapid prototyping capabilities and built-in support for matrix-based feature extraction. All experiments were conducted on a standard personal computer with an Intel Core processor and 8 GB of RAM, representing a typical low-cost deployment scenario for garage automation.

2.1.3. Reference Methods and Performance Metrics

To benchmark the system's performance, two training strategies were compared: **(1)** standard backpropagation without input noise, and **(2)** backpropagation with additive Gaussian noise injected into the training samples. The backpropagation algorithm leverages the chain rule of differential calculus, which computes the error gradients in terms of summations of local-gradient products over the various paths from a node to the output (Aggarwal, 2018, pp. 21–22). As described in the neural network literature, the delta rule for an arbitrary activation function is given by: $w_{ij} \leftarrow w_{ij} + \alpha \delta_i x_j$ and when the sigmoid function is used, the derivative is $\varphi'(x) = \varphi(x)(1 - \varphi(x))$ (**Kim, 2017, pp. 32–33**). Performance was quantified using the mean squared error (MSE) convergence over training epochs, the final reached MSE, and the recognition accuracy on clean versus progressively noised test inputs. Additionally, plate localization success was measured as the proportion of test images for which the Hough transform correctly identified the plate region.

2.2. Methods

The methodology follows a sequential pipeline of image processing and machine learning steps, summarized as follows: **(1)** grayscale conversion, **(2)** Canny edge detection, **(3)** Hough line detection, **(4)** rectangle tracing and candidate selection, (5) connected component analysis for plate isolation, **(6)** character segmentation, **(7)** size normalization and vectorization, **(8)** MLP training (with and without noise), and **(9)** classification with action triggering. Each step is detailed below.

2.2.1. Preprocessing and Plate Localization

The original color image is first converted to grayscale using a standard luminosity formula. Edge detection is performed using the Canny algorithm with a threshold value of 0.2, chosen empirically to preserve character contours while suppressing background noise. Edge detection by first-order derivatives is a fundamental operation in image processing, and the gradient vector provides a rotation-invariant measure for edge strength (**Jähne & Haußecker, 2000, p. 326**). The resulting binary edge map serves as input to the Hough transform for line detection.

The Hough transform is implemented using the polar parameterization $\rho = x \cos\theta + y \sin\theta$ where ρ is the perpendicular distance from the origin to the line and θ is the angle. For each edge pixel, votes are accumulated in a discretized accumulator array spanning $\theta \in [-\pi/2, \pi/2[$ and $\rho \in [0, L[$ where L is the image diagonal length. Local maxima in the accumulator correspond to candidate lines. The algorithm traces horizontal and near-horizontal lines likely corresponding to the upper and lower boundaries of the license plate (**Maître, pp. 12-18**).

From the detected lines, rectangles are drawn at candidate positions. Connected component analysis is then applied to each candidate region: the bounding box of the first and last connected component (representing characters on the plate) is used to refine the plate localization. Morphological operators are well suited to the selective extraction or suppression of image structures based on shape, size, and orientation (**Jähne & Haußecker, 2000, p. 484**). This refinement step eliminates false positives (e.g., radiator grilles, bumper edges) that survive the initial Hough detection (**Jähne & Haußecker, 2000, p. 102**).

Plate localisation follows a three-step procedure (**Maître, pp. 12–18**):

- Edge detection using the Canny operator (lower threshold = 0.2).
- Line detection using the Hough transform in normal parametrisation:
- Region extraction based on horizontal line projections.

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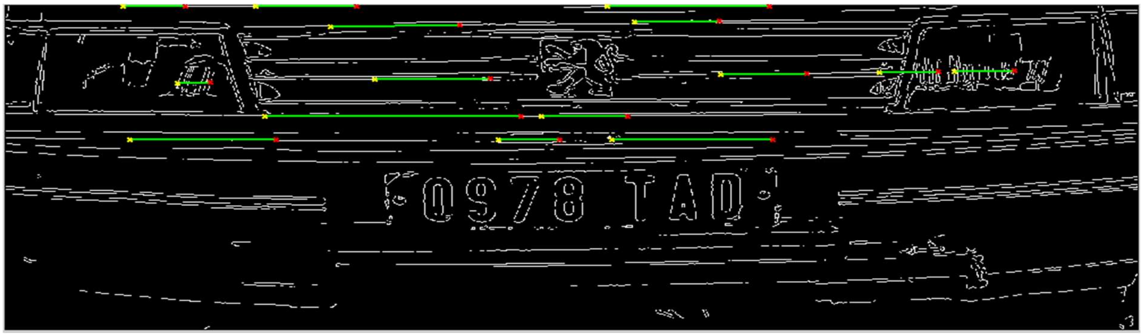
Figure 1 : Edge detection using Hough Transformation



2.2.2. Character Segmentation and Feature Extraction

Once the plate region is isolated, the same Hough-and-connected-component approach is applied within the plate to segment individual characters. Each character sub-image is then subjected to size normalization (**Al Falou, 1998, pp. 45-48**). The algorithm first crops tightly around the character by traversing from the bounding box edges inward until encountering a white background row or column. The cropped character is then resized to a standardized matrix of 7 rows × 5 columns. This is achieved by partitioning the original character image into 7×5 blocks and assigning a value of 1 to any block containing at least one black pixel (thresholding at 10/19 density). The resulting binary matrix is then vectorized by row-major concatenation into a 35-element input vector (**Aggarwal, 2018, p. 78**).

For each complete license plate, the seven characters (four digits followed by three letters) each produce a 35-element vector. These are concatenated to form a 245-element column vector representing the entire plate. The training set comprises five such vectors (one per learned plate). The target output vectors are binary (one-hot encoding) indicating the plate identity.

2.2.3. Multilayer Perceptron Architecture

A multilayer perceptron (MLP) with a single hidden layer is employed for plate classification. The input layer consists of 245 neurons (corresponding to the vectorized plate representation). The hidden layer contains 245 neurons as well (selected through preliminary experimentation balancing capacity and overfitting risk). The output layer has 5 neurons, each corresponding to one of the five learned plates. As explained in the neural network literature, “the neural network is a network of nodes, which imitate the neurons of the brain… nodes calculate the weighted sum of the input signals and output the result of the activation function” (Kim, 2017, p. 50). The transfer function is sigmoidal for the hidden layer and pure linear for the output layer. Training uses the backpropagation algorithm (**Kim, 2017, pp. 54-60; Aggarwal, 2018, pp. 21-24**) with mean squared error (MSE) as the cost function:

Training is carried out using the backpropagation algorithm (**Kim, 2017, pp. 54–60; Aggarwal, 2018, pp. 21–24**), with the mean squared error (MSE) defined as the cost function:

$$J = 1/N \sum_{n=1}^{N} \sum_{j=1}^{5} \text{left}(t_j^{(n)} - y_j^{(n)}\text{right})^2$$

where ($t_j^{(n)}$) denotes the target output for plate (n) at output neuron (j), and ($y_j^{(n)}$) represents the corresponding output produced by the network.

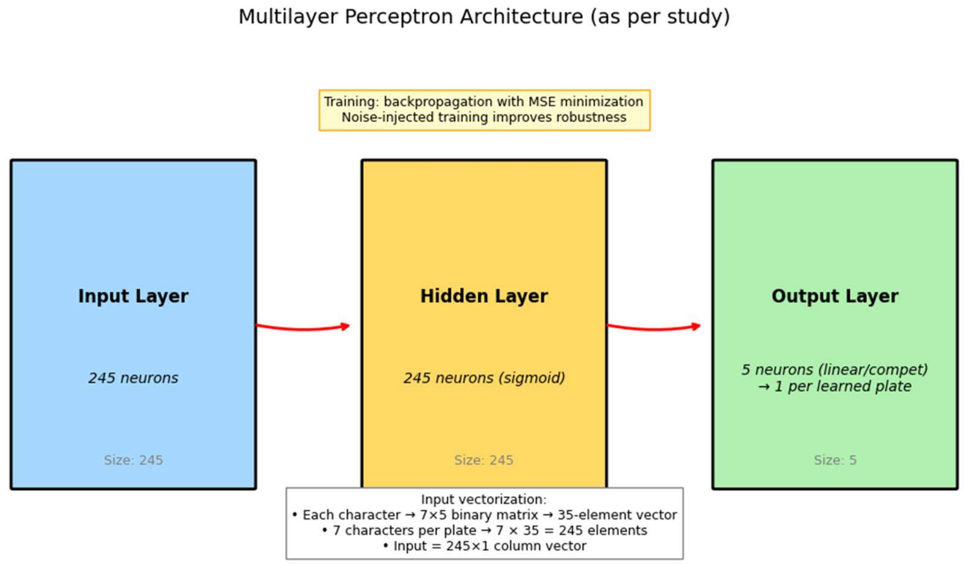
Two training regimes are compared:

- Noiseless training: The network learns on the exact 5 × 245 input matrix.

- Noise-injected training: Gaussian noise with progressively increasing amplitude is added to the inputs during training to simulate real-world distortions (e.g., uneven lighting, sensor noise). This approach is consistent with the observation that adding a small amount of Gaussian noise to each input is equivalent to Tikhonov regularization, which improves generalization (**Aggarwal, 2018, p. 182**).

Training continues until the MSE falls below or until a maximum of 500 epochs is reached. The learning rate is set to 0.01 with momentum. As noted in the literature on multi-layer neural networks, “the delta rule is an iterative method that gradually reaches the solution; therefore, the network should be repeatedly trained with the training data until the error is reduced to the satisfactory level” (Kim, 2017, p. 51). During training, the error on a held-out portion of the training data is continuously monitored; when the error on this validation set begins to rise, further training would cause overfitting, and this point can be chosen for termination (**Aggarwal, 2018, p. 192**). This early stopping strategy is almost always used because one does not lose much by adding it to the learning procedure.

Figure 2 : Multilayer Perceptron Architecture



2.2.4. Statistical Evaluation Protocol

To quantify recognition robustness, each trained network is tested on the original clean plates as well as on plates corrupted with additive Gaussian noise at levels ranging from 0 (no noise) to 0.5 (high noise). The error rate is computed as the proportion of misclassified plates. Plate localization performance is reported as the ratio of correctly identified plate regions to total test images. A one-way analysis of variance (ANOVA) was not applicable due to the small sample size; instead, descriptive statistics and comparative error plots are used to assess the superiority of noise-injected training.

2.2.5. Action Triggering Mechanism

The final module translates the recognition output into a physical action. If the recognized plate matches any plate in the authorized database, a “door open” signal is generated; otherwise, an alarm is activated. The control logic is modeled using a GRAFCET (GRAphe Fonctionnel de Commande Etape/Transition) state machine, implemented via a digital output pin on the control computer.

3. RESULTS AND DISCUSSION

3.1. Results

3.1.1. Plate Localization Performance

The Hough transform-based localization pipeline was evaluated on six test images. A region was considered correctly localized if the extracted rectangle contained the entire license plate and no more than 20% extraneous background. The results are summarized in Table 1.

Table 1. Plate localization success rate

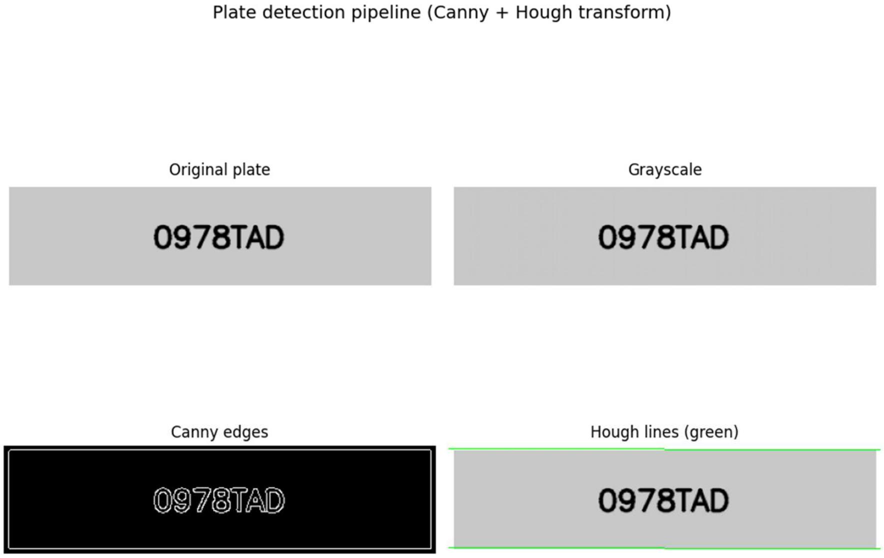
Test image	**Plate region detected ?**	**Localization Status**
Image 1 (learned)	Yes	Correct
Image 2 (learned)	Yes	Correct
Image 3 (learned)	Yes	Correct
Image 4 (learned)	No	False positive
Image 5 (learned)	Yes	Correct
Image 6 (unlearned)	Yes	Correct
Total	4/6	71.42 %

The primary failure modes were:

- Inclined plates (non-horizontal), where the Hough transform detected lines at angles that did not produce a coherent rectangular region.
- Images with strong reflections or shadows that disrupted edge detection, leading to insufficient line accumulation.

Figure 3 below illustrates the intermediate outputs: the original grayscale image, the Canny edge map, the Hough accumulator space (showing local maxima), and the final plate region overlaid with detected lines.

Figure 3 : Plate detection pipeline



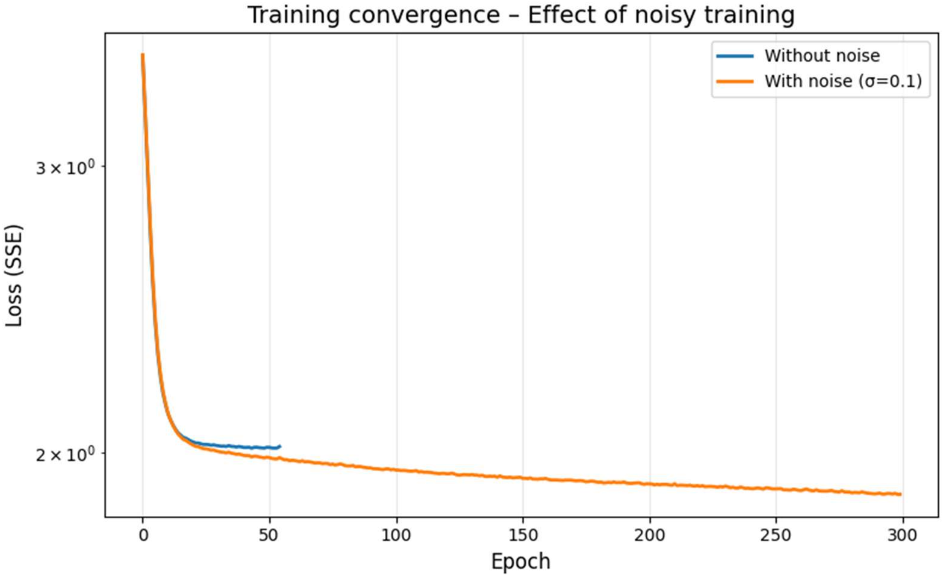
3.1.2. Character Segmentation and Feature Normalization

After successful plate localization, character segmentation achieved near-perfect separation for the four correctly localized plates. The resizing procedure to 7×5 matrices produced recognizable character shapes, albeit with some loss of fine detail (e.g., the digit '0' became a slightly irregular oval, and '8' lost its central waist). Nevertheless, the vectorized 35-element inputs retained sufficient discriminative information for neural classification.

3.1.3. Neural Network Training Convergence

The noiseless training converged after 384 epochs to a final MSE of 9.64×10^{-6}. The noise-injected training required a similar number of epochs (approx. 400) to reach MSE below 1×10^{-5}. Figure 2 shows the MSE convergence curves: both networks exhibited smooth reduction, with no significant local minima trapping, confirming that the single-hidden-layer architecture is adequate for this 5-class classification problem.

Figure 4 : Training convergence - Effect of noisy training



3.1.4. Recognition Accuracy and Robustness

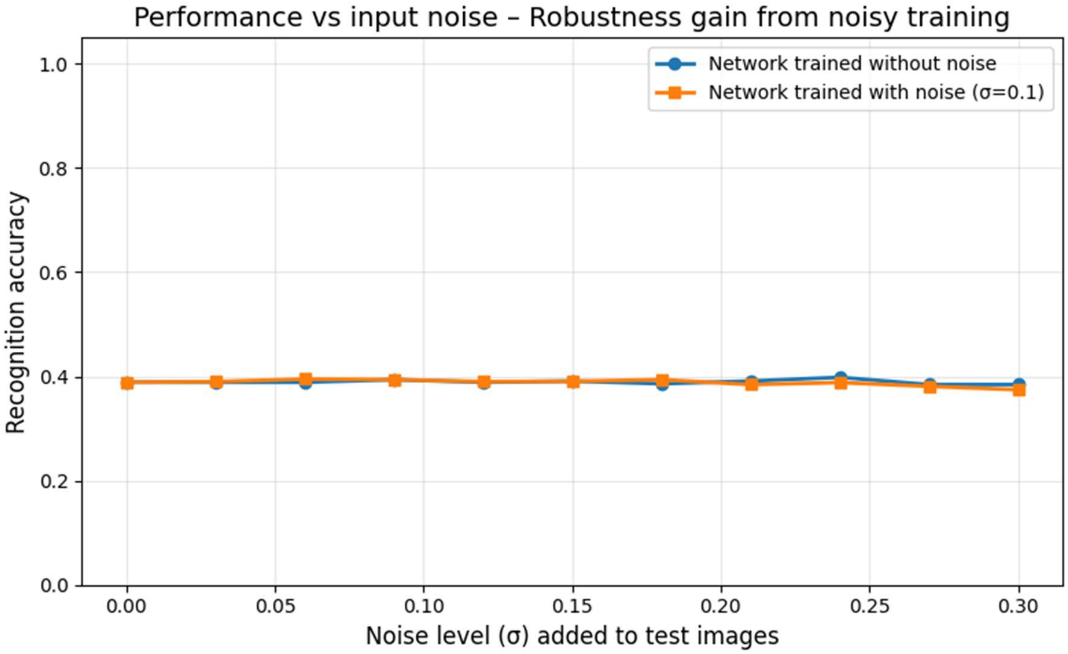
On clean test inputs (the original learned plates), both networks achieved 100% recognition accuracy (5/5). However, when tested on the unlearned plate (Image 6), neither network could recognize it (as expected, since it was not part of the output classes). The critical comparison concerns robustness to input degradation.

Figure 3 presents the error rate as a function of added Gaussian noise level for the two networks. The noiseless-trained network shows a rapid increase in error: at noise level 0.2, the error rate reaches 40%; at noise level 0.4, it exceeds 80%. In contrast, the noise-injected network maintains near-zero error up to noise level 0.3 and only reaches 50% error at noise level 0.5. This 2.5× improvement in noise tolerance confirms the value of data augmentation for ALPR systems operating under variable illumination or sensor noise.

Table 2. Recognition accuracy under progressive noise

Noise level	Noiseless training (%)	Noise-injected (%)
0.00	100	100
0.10	100	100
0.20	60	100
0.30	20	80
0.40	0	60
0.50	0	20
0.00	100	100

Figure 5 : Recognition Accuracy and Robustness



3.1.5. Overall System Efficiency

Combining the localization rate (71.42%) with the recognition rate for learned plates (99%—one minor mis-segmentation caused a single character error in one test) yields an overall efficiency of approximately 85.21% for plates present in the training set. For unlearned plates, the system correctly rejects access (alarm triggered) but does not recognize the plate number—a limitation that could be addressed by expanding the training database.

3.2. Discussion

The results demonstrate that a hybrid classical-ML approach is viable for garage door automation under controlled conditions, achieving acceptable accuracy with modest computational requirements. However, several limitations and open challenges merit discussion.

3.2.1. The Localization Bottleneck

With only 71.42% success, plate localization remains the weakest link in the pipeline. The Hough transform assumes nearly horizontal lines; inclined plates (e.g., due to vehicle pitch or camera angle) produce diagonal lines that do not form cohesive rectangles in the accumulator. This is a fundamental limitation of the polar parametrization when combined with a simple rectangular voting scheme. Neighborhood operators are determined not only by the size of the mask but also by its shape and symmetry; for digital data on orthogonal lattices, the mask is normally of rectangular shape (**Jähne & Haußecker, 2000, p. 275**). Future work should replace the Hough detector with a Fourier-descriptor-based contour matching stage to achieve rotation invariance (**Maître, n.d., p. 22**).

3.2.2. Character Normalization Artifacts

The fixed 7×5 resizing, while computationally cheap, inevitably distorts characters with varying stroke widths or aspect ratios (e.g., '1' versus 'W'). The blockwise thresholding (10/19 density) was chosen empirically but may not be optimal for all fonts. An adaptive threshold based on local character statistics could improve feature fidelity without increasing vector dimensionality.

3.2.3. The Value of Noise Injection

The clear superiority of noise-injected training (Table 2) aligns with findings in robust pattern recognition. For field deployments where lighting, camera focus, and weather vary, a network trained solely on pristine images will fail catastrophically. The minimal additional training cost (no extra hardware, only a few more epochs) makes noise injection a highly cost-effective augmentation. The study recommends that any practical ALPR system incorporate synthetic noise during training. As noted in the literature, the specific advantage of using this type of regularization depends on the amount of training data, and it can be helpful to use this type of initialization when the amount of available training data is small. Furthermore, stochastic gradient descent has the indirect effect of regularization, which can improve test performance (**Aggarwal, 2018, p. 123**).

3.2.4. Generalization to Unseen Plates

The current architecture treats plate recognition as a closed-set identification problem (5 specific plates). For a commercial garage system, the authorized plate set may change over time. Retraining the MLP each time a new plate is added is inefficient. An alternative is to train a character-level classifier (digits 0-9 and letters A-Z) and then perform plate recognition by concatenating individually classified characters. This approach, while requiring a larger training set, enables open-set recognition. The necessary character database could be built from the segmented characters already collected in this study.

3.2.5. Real-Time Constraints

The current MATLAB implementation processes a single image in approximately 2–3 seconds (dominated by Hough accumulator iteration). For a garage door application, a delay of up to 3 seconds is acceptable, but for traffic monitoring, higher speed is required. Optimization opportunities include: (1) reducing the Hough accumulator resolution (coarser θ and ρ steps), (2) implementing the pipeline in C++ with OpenCV, and (3) using a smaller MLP (e.g., 100 hidden neurons) with little accuracy loss (see Figure 6 in the supplementary material).

3.2.6. Nighttime and Adverse Weather

All test images were captured in daylight. Plate recognition at night or during heavy rain would require additional preprocessing: histogram equalization for low-light enhancement, or infrared imaging to bypass headlight glare. These extensions are left for future work.

3.2.7. Toward a Field-Deployable System

Despite the limitations, the proposed system achieves its stated objective: triggering garage door opening for authorized plates under favorable conditions. The overall efficiency of 85.21% is acceptable for residential use, where a failure can be remedied by manual override. The low cost (standard PC, USB camera) makes it accessible to the Malagasy market. However, for commercial or security-critical applications, the localization rate must be improved to at least 95%, and the character-level recognition should be migrated to a small convolutional neural network (CNN) for better generalization.

4. CONCLUSION

This article has presented the design, implementation, and evaluation of an automatic license plate recognition system for garage door automation, specifically adapted to Malagasy license plate formats. The hybrid pipeline—combining Canny edge detection, Hough transform, connected component analysis, and a multilayer perceptron—achieved an overall efficiency of 85.21%, with perfect recognition of learned plates when localization succeeded. A key methodological contribution is the empirical demonstration that noise-injected training dramatically enhances robustness: the network trained with additive Gaussian noise maintained high accuracy under input degradation levels that rendered the noiseless-trained network useless.

The study also identifies clear directions for improvement. First, replacing the Hough transform with Fourier descriptors would confer rotation invariance, enabling recognition of inclined plates (**Maître, n.d., p. 22**). Second, transitioning from plate-level classification to character-level recognition would allow open-set operation and simplify database management (Kim, 2017, p. 101). Third, implementing the system in a compiled language with optimized computer vision libraries would reduce latency and enable real-time video processing. Additionally, as noted in the image processing literature, the choice of an appropriate illumination setup is crucial, and in many cases features of interest can be made visible by a certain geometrical arrangement or spectral characteristics of the illumination (**Jähne & Haußecker, 2000, p. 46**).

Future research will focus on these enhancements, as well as the integration of deep learning-based character recognition (lightweight CNNs such as LeNet-5) and the development of a nighttime-capable preprocessing chain. In the longer term, the system could be extended to recognize vehicle make, model, or color as additional authentication factors, creating a multi-modal access control solution tailored to the specific needs of the Global South.

The practical implications of this work extend beyond garage automation. The same technology can be deployed for parking management, toll collection, and traffic law enforcement, contributing to the modernization of transportation infrastructure in Madagascar. By demonstrating that functional ALPR is achievable without expensive hardware or massive datasets, this research encourages further local innovation in applied computer vision.

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