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**End-of-study Project**

**(Master)**

**Field** : Mathematics and Computer Science

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**THEME**

# Algerian License Plate Detection And Recognition System (ALCPDRS)

**Submitted by: Mohamed Ismail SAHLI**

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2023

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**PROJET DE FIN D'ETUDE**
**(Master)**

**Domaine :** Mathématiques et Informatique

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## Thème

# Système De Detection Et De Reconnaissance Automatique Des Plaques D'Immatriculation Algériennes (SDRAPMA)

**Par : Mohamed Ismail SAHLI**

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# DEDICATION

*I would like to dedicate this work to my loving parents who have given me unconditional love and support throughout my life. Their unwavering belief in me has been the driving force behind my success.*

*To my family, who have been my constant source of inspiration and encouragement. Their constant love and support have helped me to pursue my dreams and achieve my goals.*

*To my friends, who have always been there for me through thick and thin, I am truly grateful. Their unwavering support, encouragement, and friendship have helped me to navigate the challenges of life.*

*Thank you all for being a part of my journey and for helping me to reach this milestone in my academic career. This memoire is a testament to the love and support that I have received from each and every one of you.*

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*All my gratitude and thanks to Allah Almighty, who gave me strength, courage, and will in light of the current circumstances to develop this work.*

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*I would like to show our sincere appreciation to the committee members, Dr. Badra Kerrouche, pr. Nasreddine Lagraa, Dr. Chaker Abdelaziz Kerrache, I thank them for taking the time to consult our humble work, and we are looking forward to hear from them and consider their constructive critics and valuable advice to improve it.*

*I do not forget my gratitude to all the professors of the Computer Science Department, and thanks to everyone who contributed to the development of this work from near or far.*

**Mohamed Ismail SAHLI, May 2023**

# ARABIC ABSTRACT


## ملخص

مع التقدم المستمر في تقنيات الحساب والاتصالات في الماضي القريب ، يعد نظام اكتشاف لوحة الترخيص والتعرف عليها (LPDRS) باستخدام خوارزميات الذكاء الاصطناعي مجالًا مهمًا للبحث ويحتوي على مجموعة واسعة من التطبيقات في مختلف المجالات. LPDRS هي تقنية حيوية تستخدم لتحديد هوية المركبات وإدارة حركة المرور بمساعدة خوارزميات الذكاء الاصطناعي. في الواقع ، يمثل هذا النظام نوعًا من التفتيش الآلي لأنظمة النقل والمرور والأمن ، ويحظى باهتمام كبير نظراً لتطبيقاته المحتملة في مختلف المجالات ، بما في ذلك التحصيل التلقائي للرسوم ، وتطبيق قوانين المرور ، والمراقبة الأمنية في المناطق المحظورة . الهدف من هذا العمل هو تطوير نظام للكشف والتعرف على لوحات الترخيص الجزائرية (ALPDRS) الذي يتكون من مرحلتين رئيسيتين: (1) مرحلة إكتشاف لوحة الترخيص (LPD) و (2) مرحلة التعرف على لوحة الترخيص (LPR). تقدم مرحلة الكشف عن لوحة الترقيم طريقة فعالة وآنية لإكتشاف لوحة ترقيم السيارة وعزلها باستخدام خوارزمية اكتشاف الحواف والمورفولوجية الرياضية . تقدم مرحلة التعرف على لوحة الترخيص نموذجًا هجينًا SVM-CNN يعتمد على تقنيات التعلم العميق للآلة . تم تدريب هذا النوذج باستخدام مجموعة بيانات تتكون من أرقام مستخرجة من صور لوحات سيارات جزائرية ، والتي تم جمعها خصيصًا لهذا البحث. تم التحقق من صحة نظامنا باستخدام صور سيارة حقيقية في ظل ظروف بيئية مختلفة ووصل معدل اكتشاف لوحات الترقيم الى 90.51% ومعدل التعرف عليها الى 98.66% .لتحسين دقة التعرف ، من الضروري استخدام تقنيات معالجة الصور المختلفة. على سبيل المثال ، التحويل الضبابي، التحويل الرمادي للألوان ، وتصحيح التشويه البصري ، وخوارزمية اكتشاف الحواف.



**الكلمات المفتاحية :** LPDRS, التعلم العميق للآلة, الكشف, التعرف, الذكاء الإصطناعي, خوارزميات الذكاء الاصطناعي ,نموذج SVM-CNN , ALPDRS

# ABSTRACT

With the continuing advancements in computation and communication technologies in the recent past, License Plate Detection and Recognition System (LPDRS) using artificial intelligence algorithms is an important area of research that has a wide range of applications in various domains. LPDRS is a vital technology used for vehicle identification and traffic management with the help of artificial intelligence algorithms. In fact, this system represents a type of automated inspection for transportation, traffic, and security systems, and it garners significant interest due to its potential applications in various domains, including automatic toll collection, enforcement of traffic laws, and security monitoring in restricted areas. The objective of this work is to implement an Algerian License Plate Detection and Recognition System (ALPDRS) that uses two main phases: (1) License Plate Detection (LPD) and (2) License Plate Recognition (LPR). The detection phase presents a real-time and robust method of LPR using edge detection and mathematical morphology to isolate the license plate image. The recognition phase presents a hybrid SVM-CNN model based on deep learning techniques. This model has been trained using a dataset comprising digits extracted from Algerian car plate images, which were collected specifically for this work. Our system was validated using real car images under different environmental conditions and reached a detection rate of 90.51% and an overall recognition rate of 98.66%. To improve recognition accuracy, it is crucial to use various image preprocessing techniques. For instance, blurring,gray-scale transformation, distortion correction, and edge detection.

***Keywords:*** LPDRS, Deep Learning, Detection, Recognition, Artificial Intelligence Algorithm, SVM-CNN model, ALPDRS.

# RÉSUMÉ

Avec les avancées continues dans les technologies de calcul et de communication ces dernières années, le système de détection et de reconnaissance des plaques d'immatriculation (LPDRS) utilisant des algorithmes d'intelligence artificielle est un domaine de recherche important qui trouve de nombreuses applications dans divers domaines. Le LPDRS est une technologie essentielle utilisée pour l'identification des véhicules et la gestion du trafic grâce à des algorithmes d'intelligence artificielle. En réalité, ce système représente un type d'inspection automatisée des systèmes de transport, de circulation et de sécurité, et suscite un intérêt considérable en raison de ses applications potentielles dans divers domaines, notamment la collecte automatique de péage, l'application des lois sur la circulation et la surveillance de la sécurité dans les zones restreintes. L'objectif de ce travail est de mettre en oeuvre un système algérien de détection et de reconnaissance des plaques d'immatriculation (ALPDRS) qui utilise deux phases principales : (1) la détection des plaques d'immatriculation (LPD) et (2) la reconnaissance des plaques d'immatriculation (LPR). La phase de détection présente une méthode en temps réel et robuste de LPR utilisant la détection de contours et la morphologie mathématique pour isoler l'image de la plaque d'immatriculation. La phase de reconnaissance présente un modèle hybride SVM-CNN basé sur des techniques d'apprentissage approfondi. Ce modèle a été entraîné à l'aide d'un ensemble de données comprenant des chiffres extraits d'images de plaques d'immatriculation algériennes, qui ont été spécifiquement collectées pour ce travail. Notre système a été validé à l'aide d'images réelles de voitures dans différentes conditions environnementales et a atteint un taux de détection de 90,51% et un taux de reconnaissance global de 98,66%. Pour améliorer la précision de la reconnaissance, il est crucial d'utiliser différentes techniques de prétraitement d'image. Par exemple, le floutage, la conversion en niveaux de gris, la correction de la distorsion et la détection de contours.

***Mots-clés:*** LPDRS, Apprentissage profond, Détection, Reconnaissance, Algorithme d'intelligence artificielle, SVM-CNN, ALPDRS.

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**AI** Artificial Intelligence. 8, 9, 10, 17, 19, 39, 43, 47

**ALPDRS** Algerian License Plate Detection and Recognition System. iv

**ALPR** Automatic License Plate Recognition. 2, 3, 5, 6, 17, 19, 28, 29, 30, 43, 44, 45, 47, 48

**ANN** Artificial Neural Networks. 8, 39

**CNN** Convolutional neural network. 19, 39, 45

**DL** Deep Learning. 8, 9, 16

**ETC** Electronic Toll Collection. 4

**EU** European Union. 3

**ICT** Information and Communication Technologies. 3

**IoT** Internert Of Things. 1

**ITS** Intelligent Transport Systems. 2, 3, 6, 47

**LPD** License Plate Detection. 6, 19, 21, 30, 31

**LPDRS** License Plate Detection and Recognition System. iv, 7, 46

**LPR** License Plate Recognition. 6, 23, 24

**ML** Machine Learning. 9, 10

**PGIS** Parking Guidance and Information Systems. 5

**SPS** Smart Parking System. 5

**SVM** Support Vector Machine. 39, 45

**US** United States. 3

**VANET** Vehicular Ad-Hoc Network. 5

# CHAPTER 1

## INTRODUCTION

**Contents**



## 1.1 Context

The recent surge in urbanization presents a complex global challenge that demands a comprehensive solution. Urban populations have grown as a result of a consistent influx of individuals into megacities. Statistics are clear about the global urban population which is expected to reach 4.9 billion by 2023 according to United Nations. This surge raises diverse concerns, encompassing issues like environmental pollution, traffic congestion, and resource allocation. With the advent of the Internet of Things Internert Of Things (IoT), there have been a lot of IoT devices interconnected within networks. These devices continuously collect data and transmit it to computing nodes for subsequent analysis. Thanks to notable advancements in deep learning techniques, many applications now leverage deep learning for thorough examination of the collected data, enabling the attainment of "intelligence" and "automation." Consequently, rooted in the foundation of data analysis and IoT infrastructure, the concept of "Smart Cities" has gained widespread traction. These Smart Cities encompass a wide array of facets, including intelligent energy grids, streamlined transportation systems, sophisticated manufacturing processes, astute building management, and more. [1, 2, 3].

Intelligent Transport Systems (ITS) have arisen as a vital resource for assessing and controlling the flow of vehicles in both urban and road networks. ITS involves the application of information and communication technologies in the realm of road transport, covering infrastructure, vehicles, and users. It encompasses functions related to traffic management, mobility management, and interfaces with alternative modes of transportation. [4].

These are a type of advanced transportation technology that uses sensors, communication networks, and computer systems to improve transportation efficiency, safety, and sustainability, ITS can help reduce congestion, prevent accidents, and optimize transportation operations. Some examples of ITS applications includes systems of electronic toll collection, traffic management, and traveler information systems [5].

Automatic License Plate Recognition (ALPR) system plays a crucial role in integrating computer techniques into ITS. These systems are designed to tackle the task of vehicle identification using automated algorithms, reducing the necessity for manual involvement. ALPR systems have proven beneficial in numerous applications, including automatic toll collection, criminal pursuit, and enforcement of traffic laws. [6].

Number Plate Recognition (NPR) involves the utilization of a camera to capture images of license plates within a specified scene. These captured images, whether static or within a video, undergo a sequence of image processing algorithms to transform the visual information into an alphanumeric text entry. [7].

The last stage of ALPR system involves storing the recognized car plate characters in ASCII format into a database, enabling the system to identify and retain the license plate numbers for future uses, which may encompass but are not limited to law enforcement, toll collection, and parking management.

## 1.2 Intelligent Transportation Systems

ITS has arisen in reaction to the increasing call for advancements in transportation. It amalgamates information, communication, computing, and other technologies to establish an all-encompassing system that unifies individuals, roadways, and vehicles. This integration is accomplished by harnessing advanced data communication technologies within the transportation sector.

### 1.2.1 Overview

Advancements in technology, notably in the realms of computer science and communication networks, have opened doors to fresh approaches and applications in traffic management. ITS encompasses a collection of these innovative applications that are currently undergoing intensive examination and development by government bodies and scientific communities. The inception of the ITS concept traces back to the 20th century with its proposal by the United States United States (US). However, in contemporary times, it stands as a focal point of extensive research and development efforts globally, with significant attention from the US, Japan, and the European Union (EU). While ITS can encompass all modes of transportation, the EU has specifically delineated its application within the domain of road transport.

ITS incorporates Information and Communication Technologies (ICT) and employs them within the realm of transportation. These systems collect data from sensors and devices installed in both vehicles and infrastructure, offering services with the objective of enhancing the existing transportation system. The ultimate goal is to make it more efficient, sustainable, secure, and environmentally conscious. Various ITS technologies, like ALPR for vehicles, electronic toll collection systems, and traffic information networks, are currently operational and available in the market. [8, p. 4].

### 1.2.2 ITS Applications

ITS applications are diverse and can be classified into several categories, including traffic management, traveler information, and vehicle operations. As technology advances and becomes more integrated, ITS will persist in exerting a substantial influence on how we move and transport goods, leading to greater efficiency, sustainability, and safety in transportation.

### Electronic Toll Collection

Electronic Toll Collection (ETC) enables vehicles to pass through toll gates at regular traffic speeds, diminishing congestion at toll plazas and automating toll collection. Initially, ETC systems were introduced to streamline toll collection processes. However, more recent advancements have harnessed ETC for implementing congestion pricing within city centers through cordon zones and designated ETC lanes.

In recent times, there has been a shift towards the standardization of ETC protocols, with a focus on the Dedicated Short Range Communications (DSRC) protocol. This protocol has been advocated for vehicle safety by organizations such as the ITS of America, European Road Transport Telematics Implementation Coordination (ERTICO), and ITS of Japan [9, p. 530].

### Automatic Road Enforcement

A traffic enforcement camera system, comprising a camera and vehicle monitoring devices, is employed to identify and record vehicles that violate speed limits or other legal road requirements. It automatically issues tickets to offenders based on their license plate numbers, with the traffic tickets being delivered by mail. Some applications include:

- Speed cameras are deployed to identify vehicles exceeding the prescribed speed limit. Numerous devices of this kind employ radar technology to ascertain a vehicle's speed, while others utilize electromagnetic loops positioned in each lane of the road.
- Red light cameras are designed to identify vehicles that pass over a stop line or a designated stopping area when a red traffic light is illuminated.
- Level crossing cameras are utilized to recognize vehicles that unlawfully traverse railway crossings at ground level.
- Cameras for double white lines are employed to detect vehicles that cross these boundary lines.
- Cameras in high-occupancy vehicle lanes are used to spot vehicles that are not in compliance with the lane's occupancy requirements. [9, p. 531].

#### Smart Parking System (SPS)

Smart Parking System (SPS) assist motorists in locating unoccupied parking spaces through the utilization of sensors that detect the presence or absence of vehicles. Subsequently, they guide incoming drivers to accessible parking spots. SPS can be classified into various systems, including Parking Guidance and Information Systems (PGIS), transit-oriented information systems, intelligent payment systems, E-parking, and automated parking. [10, p. 205]

### 1.2.3 ITS Technologies

Intelligent Transportation System technologies are a collection of advanced technologies designed to improve transportation efficiency, safety, and sustainability, These technologies include various types of sensors, communication systems, data analysis, and smart cameras that can be used to monitor and manage traffic flow, reduce congestion, improve public transportation, and enhance the overall safety of transportation systems.

#### Vehicular Ad-Hoc Network (VANET)

Vehicular Ad-Hoc Network (VANET) primarily comprises vehicles, Road Side Units (RSUs), and the Infrastructure Domain. Communication within VANET relies predominantly on wireless standards. RSUs function as routers and have a broader range of coverage compared to individual vehicle ranges. Vehicles are equipped with an On-Board Unit (OBU) for communication purposes and are also fitted with a Global Positioning System (GPS) to determine their own location and track other vehicles. [11].

#### Roadside Camera With ALPR Recognition System

Cameras positioned along roadways serve a vital role in systems designed for monitoring congestion zones at entry and exit points. These cameras employ ALPR technology, a combined hardware and software module. ALPR identifies the content of license plates and produces the corresponding sequence of ASCII characters. Additionally, it can transmit this information digitally. [12, p. 60].

## 1.3 Problem statement and motivations

Once we've acquired a thorough comprehension of ITS and the ways ALPR systems contribute to further automating it, it becomes imperative for developing nations like Algeria to prioritize road enforcement automation. This initiative also addresses various everyday challenges, including:

- The incidence of traffic accidents.
- Automated toll collection system.
- Advanced traveler information systems to provide real-time traffic updates and route recommendations.
- Advanced parking management systems to reduce traffic and parking congestion in urban areas.
- Law enforcement.
- Implement automation for ensuring safety measures in restricted areas.
- Increase automation to improve the convenience of citizens' lives.

## 1.4 Objectives

The primary objective of this thesis is to create a rapid and precise ALPR system tailored for real-time usage in Algeria. To realize this aim, the thesis has established the following goals:

- To develop an innovative approach for License Plate Detection (LPD) and License Plate Recognition (LPR) system, meeting the criteria of real-time functionality and overall efficiency
- To craft and simulate the suggested LPD and LPR system, aiming for high-speed performance and a commendable accuracy rate.
- To assess the functionality and efficacy of the method in diverse scenarios, employing benchmark images of Algerian vehicles.

## 1.5 Organization of the Memoire

This memoire is organized as follows:

- In **Chapter 2**, we provide a comprehensive overview of artificial intelligence techniques, delving into their principles and types. This chapter serves as a valuable resource for understanding the significance of these techniques in our york.

- In **Chapter 3**, we present an in-depth exploration of previous implementations of LPDRS, highlighting their methodologies, strengths, and limitations. Through a detailed synthesis and comparison, this chapter provides valuable insights into the advancements and challenges in the field.

- In **Chapter 4**, we introduce our novel approach to implement the LPDRS. We begin by providing a comprehensive overview of the system components, followed by a detailed explanation of our image pre-processing algorithms, plate localization techniques, and character segmentation phase. Lastly, we delve into the implementation of the recognition model architecture, highlighting the methodology employed for achieving accurate license plate recognition. In addition, we present the experimental results of our LPDRS, providing a comprehensive analysis and discussion of the obtained outcomes, leading to insightful observations and conclusions regarding the system's performance.

- Finally, we summarize our work, highlighting potential avenues for future enhancements and advancements in the field of LPDRS.

# CHAPTER 2

## ARTIFICIAL INTELLIGENCE: BACKGROUND

**Contents**



## 2.1 Introduction

In this chapter, we will provide an overview of Artificial Intelligence (AI), its different branches, and how AI has changed the way we live our lives today. From advanced robots, and natural language processing to machine learning, AI is being a part of various industries to enhance productivity, efficiency, and decision-making. We will also discuss the latest developments in AI, including Deep Learning (DL) and Artificial Neural Networks (ANN). This chapter aims to provide a comprehensive understanding of AI and its different branches.

## 2.2 Artificial Intelligence

The concept of AI was first introduced in 1956. Since then, significant progress has been made in the field, leading to its recognition as the fourth industrial revolution in human history.

AI, Machine Learning (ML), and DL are sometimes used interchangeably, but it's crucial to understand their differences (Fig. 2.1). AI is the broader concept, involving computer systems simulating human intelligence for tasks like visual perception, decision-making, and voice recognition. ML, a subset of AI, emerged in the 1980s, enabling computers to improve task performance through experience or autonomous learning without explicit programming.

Finally, DL is a subset of ML that uses complex algorithms and intricate layered artificial neural networks to extract and manipulate features from data. The term "deep" signifies the presence of numerous hidden layers within these networks. The benefit of using multiple layers is the ability to analyze intricate inputs, including entire images. DL employs representation learning techniques with multiple levels of abstraction to automatically understand and process input data, generating outputs without the need for manual feature engineering. This approach facilitates the automatic recognition of complex structures in high-dimensional data [13].

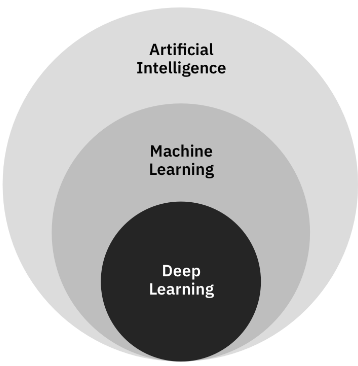


Figure 2.1: Relationship between AI, ML and DL

## 2.3 Machine Learning

Machine learning, as a facet of both AI and computer science, centers on leveraging data and algorithms to mimic the process of human learning, steadily enhancing its precision [14].

### 2.3.1 Machine Learning Methods

The learning process can encompass various approaches, with unsupervised and supervised learning being commonplace in many ML applications. Below, we enumerate a selection of learning methods.

#### Supervised Learning

Supervised learning, often referred to as supervised machine learning, is characterized by its utilization of labeled datasets to instruct algorithms in accurately classifying data or making predictions. When input data is provided to the model, it fine-tunes its weights until it aligns appropriately. This fine-tuning is an integral part of the cross-validation process, ensuring that the model steers clear of overfitting or underfitting [14].

#### Unsupervised Learning

Unsupervised learning, also known as unsupervised machine learning, involves using machine learning algorithms to analyze and group unlabeled datasets without human intervention. It discovers hidden patterns, making it valuable for tasks like exploratory data analysis, customer segmentation, and pattern recognition. It can also reduce the complexity of data through dimensionality reduction [14].

#### Semi-Supervised Learning

Semi-supervised learning provides a balanced approach between supervised and unsupervised learning. In its training process, it relies on a limited labeled dataset to steer the classification and feature extraction within a larger, unlabeled dataset. This approach effectively addresses the issue of inadequate labeled data, which can pose challenges in traditional supervised learning algorithms [14].

### Reinforcement Learning

Reinforcement machine learning shares similarities with supervised learning, but it differs in that it doesn't rely on predefined sample data for training. Instead, this model learns through a process of trial and error, continuously adapting based on the outcomes it experiences. It reinforces sequences of successful results to develop the optimal recommendation or policy for a specific problem [14].

## 2.4 Artificial Neural Network

Neural networks, alternatively referred to as artificial neural networks (ANNs) or simulated neural networks (SNNs), form a specialized branch within machine learning and serve as the foundation for deep learning algorithms. These networks draw inspiration from the human brain, replicating the communication patterns observed among biological neurons.

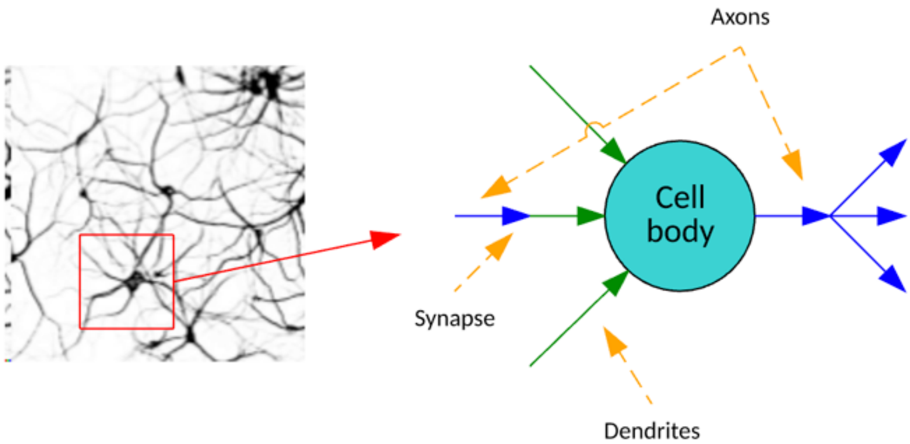


Figure 2.2: Natural neuron

In natural neurons, signals are received through synapses situated on the dendrites or cell membrane. When these incoming signals reach a sufficient strength, surpassing a specific threshold, the neuron becomes active and transmits a signal through its axon. This signal can subsequently travel to another synapse, potentially activating other neurons in the process.

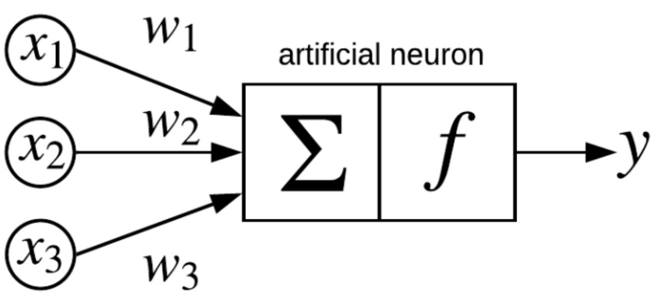


Figure 2.3: Artificial neuron

Artificial Neural Networks (ANNs) integrate these artificial neurons to process information. The magnitude of an artificial neuron's weight influences the impact of the input signal it multiplies. These weights can also be negative, indicating signal inhibition. Depending on the weights, the neuron's computation varies. Adjusting these weights allows us to obtain desired outputs for specific inputs. In ANNs with numerous neurons, manually finding the required weights can be exceedingly complex. Hence, algorithms are employed to fine-tune the weights, a process referred to as learning or training [15].

### 2.4.1 Types Of Artificial Neural Networks

Neural networks come in various forms, each tailored for specific tasks and data types. The choice of neural network architecture depends on the problem at hand.

- Feedforward Neural Network (FNN) used for basic pattern recognition.
- Convolutional Neural Network (CNN) specialized in image processing.
- Recurrent Neural Network (RNN) ideal for sequential data like text and speecht.
- Generative adversarial networks (GANs) for generating data.

Each type brings its unique strengths to the field of artificial intelligence and machine learning, allowing for diverse applications across various domains.

### 2.4.2 Loss Function

The loss function evaluates the performance of a specific algorithm in capturing the characteristics of the given data. There are two main categories of loss functions, which depend on the nature of the learning task:

- Regression Models, the aim is to forecast continuous values.
- Classification Models, the aim is to predict the outcome from a predefined set of categorical options.

### 2.4.3 Regression Loss Functions

**Mean Absolute Error (MAE)**

It signifies the average of the absolute differences between the actual values and the model's predictions for all data points in the dataset. These differences, known as "residuals," represent the variations between the model's predictions and the true values [16].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

**Mean Squared Error (MSE)**

It represents the average of the squared differences between the actual values and the model's predictions for all data points in the dataset. These differences are often referred to as "residuals," indicating how far off the model's predictions are from the actual values [16].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

**Huber Loss (Smooth Mean Absolute Error)**

It incorporates elements from both MSE and MAE, harnessing the advantages of both loss functions. By being less affected by outliers and remaining differentiable at minima, it strikes a balance between the two [16].

$$L_\delta(y, \hat{y}) = \begin{cases} \frac{1}{2}(y - \hat{y})^2 & \text{if } |y - \hat{y}| \leq \delta \\ \delta|y - \hat{y}| - \frac{1}{2}\delta^2 & \text{otherwise} \end{cases}$$

### 2.4.4 Classification Loss Functions

**Cross-Entropy Loss (Log Loss)**

Often referred to as "Negative Log Likelihood," this loss function is widely employed in classification tasks. Cross-entropy loss increases as the predicted probability moves further away from the true label [16].

$$CE(y, \hat{y}) = -\sum_{i=1}^{n} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$$

#### Hinge Loss

Also known as Multi-class SVM Loss. Hinge loss is applied for maximum-margin classification, prominently for support vector machines. It is a convex function used in the convex optimizer [16].

$$HL(y, \hat{y}) = \max(0, 1 - y \cdot \hat{y})$$

### 2.4.5 Activation function

Activation functions possess a non-linear character, enabling the approximation of intricate functions and introducing non-linear elements into the network. This mathematical representation takes the form of $Y = g(W_0 + X^t * W)$, where $Y$ represents the predicted value, $W_0$ represents the bias value, $X^t$ represents the transpose of the input matrix $X$, $W$ signifies the assigned weights, and g denotes the activation function (see Fig 2.3). Now, let's explore a couple of instances of activation functions [17].

### 2.4.6 Types Of Activation function

#### Sigmoid

This function is an S-shaped curve ranging from $[0, 1]$. This function is defined as the ratio of unit value to the sum of the inverse exponential of input value x and unit value. This is one kind of non-linear function and is mainly seen in logistic regression in machine learning concepts [17].

#### Hyperbolic Tangent

This function is also a type of s-shaped curve like a sigmoid with a left-shifted position. This function comes under nonlinear functionalities [17].

#### Rectified Linear unit (ReLu)

This is the widely used function in the real time implementations. It is defined according to interval basis, $Y = 0(whereX < 0)$ and $Y = X(whereX >= 0)$ [17].

### 2.4.7 Evaluation Metrics

Machine Learning Metrics are numerical measures used to gauge the performance of machine learning models. They are vital for evaluating a model's effectiveness in various tasks

#### Confusion Matrix

The matrix is applicable to any classification model and is generally structured as follows:

- Rows correspond to the actual class
- Columns correspond to the predicted class.

In the case of binary classification, where there are two classes Positive and Negative it results in a 2x2 matrix (Tab. 2.1) containing these fundamental values:

Table 2.1: Confusion Matrix

| | | Prediction Class | |
|---|---|---|---|
| | | **P** | **N** |
| **Actual Class** | **P** | **TP** | **FN** |
| | **N** | **FP** | **TN** |

- TP (True-Positive) represents the count of correctly classified positive cases.
- TN (True-Negative) indicates the number of accurately classified negative cases.
- FP (False-Positive) stands for instances where the model wrongly predicted a positive class, while the true class was negative. It's also referred to as Type 1 Error.
- FN (False-Negative) represents situations where the model incorrectly predicted a negative class, while the true class was positive. This is known as Type 2 Error.

#### Metrics Calculation

**Precision** Precision measures the accuracy of positive predictions, showing how many of the predicted positive cases were correct [18].

$$Precision = \frac{TP}{TP + FP} \tag{2.1}$$

**Recall** Recall gauges the model's ability to capture all actual positive cases, indicating what proportion of true positives was correctly identified [18].

$$Recall = \frac{TP}{TP + FN} \tag{2.2}$$

**Accuracy** Accuracy assesses the overall correctness of predictions by measuring the ratio of correctly predicted cases to the total cases [18].

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{2.3}$$

## 2.5 Deep learning

DL is simple as multiple classifiers working together, primarily built on linear regression followed by activation functions. Like traditional machine learning classifiers, deep learning models also require parameter optimization through mathematical tools such as gradient descent. When dealing with large datasets, smaller neural networks outperform classical classifiers. However, a larger neural network's performance improves when trained on extensive data. In comparison to classical models, as well as medium and smaller neural networks, the performance of larger neural networks scales positively with dataset size. [19]

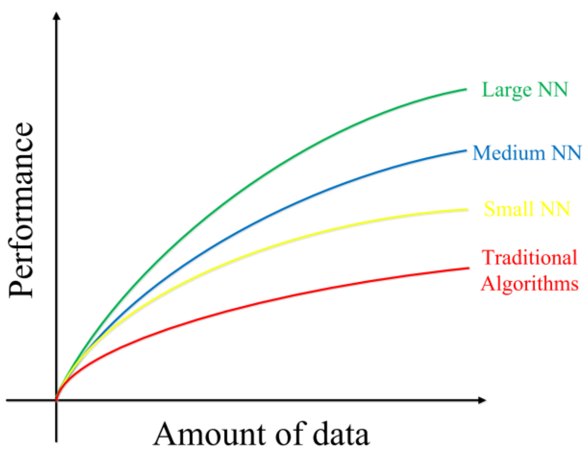


Figure 2.4: Performance of Deep Neural Network improves with data size

## 2.6 Conclusion

In conclusion, AI is one of the fastest-growing and most rapidly developing computer science fields in recent years. Every year, a large number of researchers publish their results in various AI fields. As AI technologies continue to advance, now we can expect to see significant advancements in a wide range of fields, After we provide to you comprehensive understanding about AI, Its branches ,Its famous algorithms and all the metrics to evaluate a AI model results, You are now ready to explore the current state of the art in ALPR systems and discover how researchers around the world have employed various techniques and AI algorithms to develop these systems.

# CHAPTER 3

## STATE OF THE ART

### Contents

## 3.1 Introduction

Our main objective in the preceding chapter was to provide a comprehensive understanding and a firm grasp of AI fundamentals. In this chapter, we will come to mention some studies have been conducted on various aspects of ALPR technology, including the development of efficient algorithms for LPD and recognition, some of the key research areas in ALPR include the use of machine learning techniques such as artificial neural networks and support vector machines, the integration of deep learning methods such as Convolutional neural network (CNN), research has been focused on improving the robustness of ALPR systems to handle challenging real-world scenarios such as varying lighting conditions, occlusions, and license plate distortions. This introduction sets the stage for understanding the current state-of-the-art in ALPR technology and the challenges that remain to be addressed.

## 3.2 License Plate Detection

### 3.2.1 Study 01: Detection By HOG Algorithm [20]

#### Proposed Approach

In this work, the researchers adopt a technique that relies on Histogram of Oriented Gradients (HOG) features for License Plate Detection (LPD) in the Brazilian context. This approach involves systematically scanning the entire image at multiple scales to precisely identify the license plate. The protocol for parameter calibration can be delineated into four distinct modules:

1. Examining the geometric attributes of license plates, such as their width, height, and aspect ratio, to determine the appropriate number of scales, sliding window size, and aspect ratio for use in the calibration test.

2. Assessing various HOG configurations by altering the number of blocks and cells to identify the optimal combination that balances precision and recall effectively.

3. Fine-tuning the sliding windows to determine the most suitable spacing (stride) between two consecutive windows.

4. Assessing the impact of incorporating background information within the sliding window.

**Results**

The dataset employed in this study comprises 377 images divided into two subsets: 300 for training and 77 for testing. Following the utilization of Support Vector Machines (SVM) as a classifier, the primary finding of this research indicates a 93% accuracy rate in correct detections, as compared to a hybrid-edges approach. hybrid-edges as shown in (Fig. 3.1)

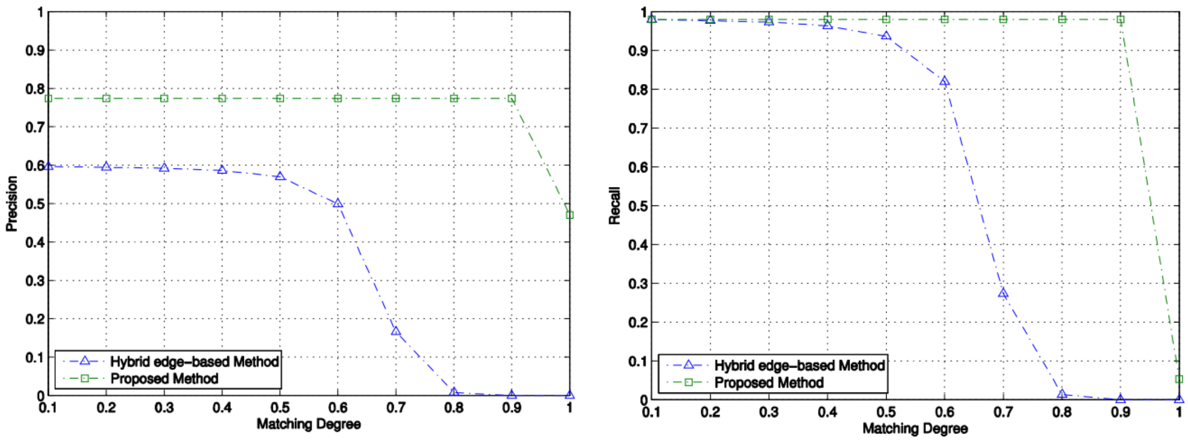


Figure 3.1: Experimental result of HOG algorithm[20, p. 50].

### 3.2.2 Study 02: Detection By Edge Detection [21]

**Proposed Approach**

In this study, Musoromy and Ramalinga conducted a performance evaluation of image enhancement filters when integrated with edge detection algorithms, coupled with connected component analysis to extract license plate regions. The experimental comparison encompasses Canny, Kirsch, Rothwell, Sobel, Laplace, and SUSAN edge detectors, as detailed in (Tab. 3.1). The detection process unfolds across four key stages:

1. Normalization

2. Enhancement of edges using filters

3. Edges Detection

4. Edges connection and identification of potential license plate candidates areas.

#### Results

When applied to grayscale images, Canny edge detection demonstrates strong license plate detection performance, achieving a rate of 98.2%. This assessment was conducted on a dataset consisting of 45,032 UK images, each with license plates at a resolution of 720x288 pixels, and these images were captured under diverse lighting conditions. The average processing time for analyzing a single image was recorded at 56.4 milliseconds.

Table 3.1: Experimental Result (Edge Detection)

| Edge Detector | Sample Size | Success% | Performance (ms) |
|---|---|---|---|
| Sobel | Not reported | Not reported | Not reported |
| Sobel vertical | 161,218 and 75 | 100,100 and 97.0 | 47.9 |
| Robert and Rank | Algorith | 96.3 and 81.2 | Not reported |
| Sobel vertical | 610 | 96.2 | Not reported |
| Smoothing Filter and Edge Mapping | 478 | 96.0 | 100 |
| Sobel | 102 | All | Not reported |
| Sobel | 710 | Not reported | Not reported |

### 3.2.3 Study 03: Detection By Mathematical Morphology [22]

#### Proposed Approach

This study concentrates on LPD using mathematical morphology image processing techniques, taking into account characteristics such as license plate width, height, ratio, and angle (Fig. 3.2). The key advantage of the proposed system lies in its versatility, as it is capable of functioning effectively with diverse types of license plates that vary in size and shape.

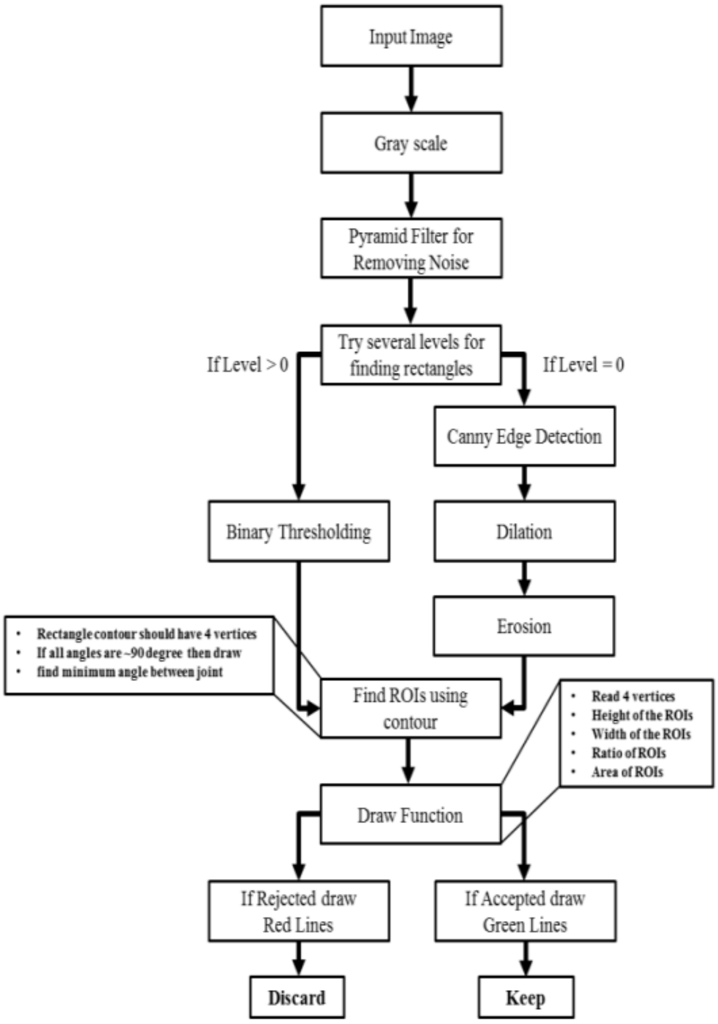


Figure 3.2: Detection By Mathematical Morphology method main steps[22, p. 2].

### Results

The Results indicate an average accuracy of 78% in detecting Korean vehicle license plates. The authors evaluated the system using a total of 1,580 dynamic images, successfully identifying the license plates in 1,233 of these images. However, in the remaining 347 images, the system either misidentified the plates or failed to detect them accurately.

## 3.3 License Plate Recognition

### 3.3.1 Study 04: Recognition by KNN [23]

#### Proposed Approach

In this research, an approach for LPR focuses on the utilization of the k-nearest neighbors (KNN) Algorithm. It involves the detection of character contours within a given plate image, isolating them from the parent image (Fig. 3.3). These outcomes are then employed to segment the characters. Subsequently, each character is identified using the KNN algorithm. The KNN algorithm was trained using various sets of training data, each comprising 36 characters. The effectiveness of the algorithm was assessed on the previously segmented characters.

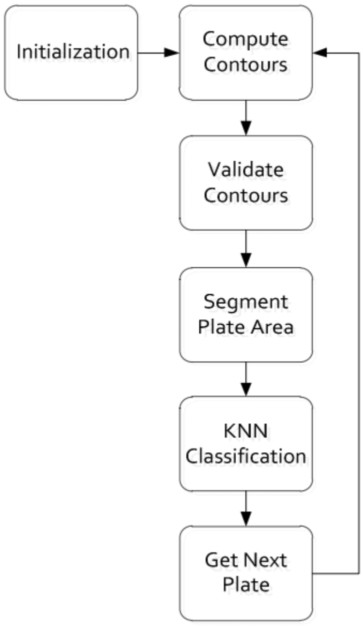


Figure 3.3: Recognition by k-nearest neighbors method main steps[23, p. 2].

#### Results

The character recognition results achieved their highest accuracy with the KNN algorithm at its most accurate setting, which is when k=1, also known as 1NN. The comprehensive character recognition method was tested on a set of 30 license plate images, yielding an accuracy rate of 87.43%.

### 3.3.2 Study 05: Recognition by KNN-SVM [24]

#### Proposed Approach

In this research, a hybrid model referred to as K-Nearest Neighbors and Multi class Support Vector Machines (KNN-SVM) is presented. In this strategy, K-NN is utilized as the primary classification model due to its simplicity, robustness against noisy datasets, and efficiency with large datasets. To tackle the difficulty of differentiating similar characters on license plates, a multi-class SVM classification model is incorporated. This SVM model enhances the performance of K-NN in the recognition of characters that bear close resemblance to each other.

#### Results

To assess the efficacy of the method introduced in this paper, a total of 257 car license plate images were subjected to testing in this study. These license plate images were randomly captured using a standard digital camera with a frame size of 1024*768 pixels. The camera was positioned at distances ranging from 5 to 10 meters from the cars. The captured images were categorized into two groups: T1-Plates containing at least one similar character (n=137) and T2-Plates without any similar characters (n=120). as shown in (Tab 3.2).

Table 3.2: Experimental result (KNN-SVM)

| **Unit of LPR system** | **Number accuracy** | **Percentage of accuracy** |
|---|---|---|
| **Extraction Plate** | 35/40 | 87.5% |
| **Recognaition** | 30/35 | 85.7% |

### 3.3.3 Study 06: Recognition by ANN [25]

#### Proposed Approach

In this research by Turkyılmaz and Kaçan, they introduced an LPR system comprising three main components: plate region determination, character segmentation, and character recognition. However, our focus will be on the latter two components, specifically segmentation and recognition, which are central to this study.

In the segmentation phase, the characters are isolated from one another within the plate region using vertical projections. These segmented characters are then prepared for the character recognition stage through a thinning process. In the character recognition phase, a three-layer feed-forward artificial neural network is employed, utilizing the backpropagation learning algorithm with sigmoid activation functions.

#### Results

The performance of the Artificial Neural Network (ANN) was evaluated using a dataset consisting of 357 images, as summarized in the table below:

Table 3.3: Experimental results (Detection By ANN)

| LPRS stage | Number of images/ success | Performance (%) |
|---|---|---|
| **LP region determination** | 357/357 | 100 |
| **Character segmentation** | 357/357 | 100 |
| **Character recognition** | 357/346 | 96.92 |

### 3.3.4 Study 07: Recognition by CNN [26]

#### Proposed Approach

The ALPR model presented by the researchers in this study exhibits a central graphical user interface (GUI) housing numerous functionalities. These encompass image acquisition, pre-processing, application of thresholding techniques, masking, model training, and classification tasks. The incorporation of these functionalities is simplified with user-friendly push buttons. This intuitive design allows users to navigate and utilize the various elements of the ALPR model seamlessly, optimizing the overall workflow and improving efficiency.

The proposed system adheres to a structured workflow that encompasses several pivotal stages aimed at achieving precise license plate detection and recognition. (see Fig 3.4).

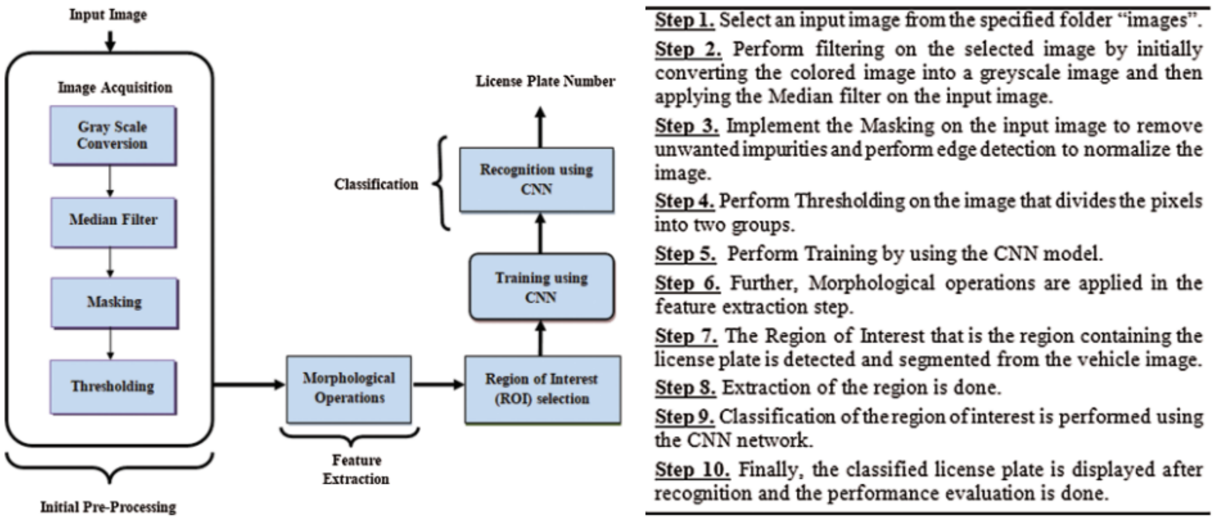


Figure 3.4: Workflow and steps of the proposed system [26, p. 38]

#### Results

The Convolutional Neural Network (CNN) achieved its performance evaluation using a dataset comprising 160 images, as summarized in the table presented below:

Table 3.4: Average recognition accuracy based on different features

| **Feature(s) of the system** | **Average recognition accuracy (%)** |
|---|---|
| Multi-line license plate | 97.84 |
| Multi-font license plate | 97.17 |
| Tilted license plate images | 96.91 |
| Different vehicle types | Bike: 98.47, Auto–rickshaw: 98.52, Cars: 97.41 |
| Night mode | 97.52 |
| **Overall system accuracy** | **98.13** |

## 3.4 Comparison and Summary

### 3.4.1 Detection Algorithms

In the field of image processing and computer vision, hog, edge detection, and mathematical morphology are all important algorithms used usually to detect objects in object detection systems in the image preprocessing stage. While they have high accuracy and efficiency, each algorithm has its own strengths and limitations. First, the hog algorithm has limitations in terms of sensitivity to changes in illumination and contrast, dependence on the size and position of the object, and increased computational complexity. second, in the edge detection algorithm has main challenges in the trade-off between edge localization and noise suppression, which can result in either missing important edges or detecting false edges. Lastly, the mathematical morphology algorithm always has a dependence on the choice of structuring element, which can affect the accuracy of the morphological operation. The best algorithm may be a combination of two or three of these algorithms to enhance the accuracy and robustness of the overall system.

### 3.4.2 Recognition Algorithms

In the last few years, artificial neural networks have dominated the field of artificial intelligence over non-neural network classification algorithms like KNN, SVM, K-means, etc. Also by adding Convolutional layers to a simple ANN makes what's called Convolutional Neural Networks (CNNs), in which these special ANNs can learn hierarchical features from the raw input data. However, All ANNs are computationally expensive and require large amounts of labeled data to train effectively, but by combining CNNs and SVMs, the CNN can learn hierarchical features from the raw input data, and the SVM can use these features to perform accurate classification and improve classification accuracy. Additionally, the combination of CNNs and SVMs can improve the interpretability of the model. CNNs are often criticized for their lack of interpretability, as it can be difficult to understand how they arrive at their decisions. Finally, combining CNNs with SVMs can help reduce overfitting, as the SVM can provide regularization to the model, preventing it from learning noise in the data.

## 3.5 Conclusion

In conclusion, there are several algorithms that can be used to implement an Automatic Number Plate Detection and Recognition (ALPDR) system, each with unique advantages and drawbacks. Furthermore, the choice of algorithms will depend on the specific requirements and constraints of the ANPDR system, including factors such as accuracy, speed, and robustness. Finlay, developing an ALPR system is a complex task that requires expertise in computer vision, machine learning, and software engineering. All these technologies will be cover in our detection and recognition system in the next chapter.

# CHAPTER 4

## ALGERIAN LICENSE PLATE DETECTION AND RECOGNITION: OUR SYSTEM

### Contents



## 4.1 Introduction

In simple terms an ALPR system combines both hardware and software components to recognize license plate content and produce the associated ASCII character sequence [12, p. 60]. In essence, an ALPR system is a technological solution that combines computer vision, image processing, and machine learning algorithms to independently identify, read, and interpret license plates on vehicles. Moreover, ALPR systems have various practical uses, such as traffic surveillance, toll collection, management of parking lot access, and law enforcement.

Every ALPR system can be divided into three main stages: (1) License Plate Detection (LPD), (2) character segmentation (CS), and (3) character recognition (CR) (see Fig. 4.1). Additionally, the initial two stages require additional image processing algorithms, which include activities like reducing noise, correcting image distortions, and adjusting colors. Upcoming sections will thoroughly explore these phases to offer a complete insight into the ALPR system and how it operates.

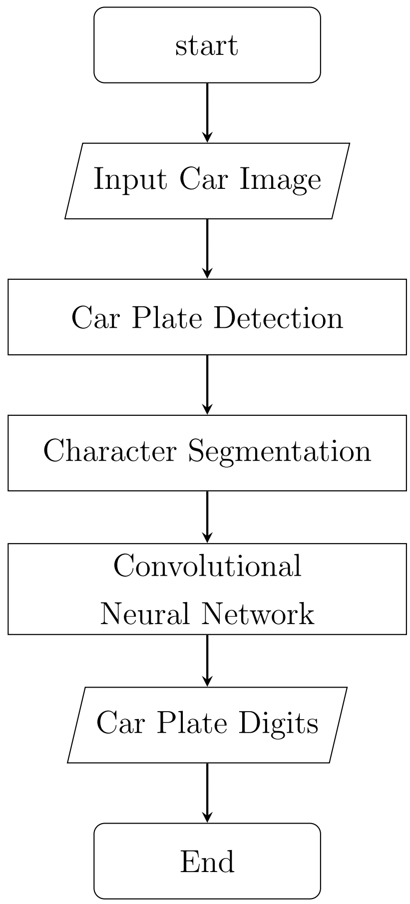


Figure 4.1: Licence Plate Detection flowchart

## 4.2 Licence Plate Detection

License Plate Detection (LPD) involves the process of identifying and isolating sections within an image that are highly likely to contain a license plate (LP). Essentially, LPD focuses on pinpointing potential regions within an image where a license plate could be located. These regions can then undergo further processing for character recognition and extraction. Typically, LPD is achieved using computer vision methods such as edge detection, template matching, or machine learning algorithms that have been trained to recognize license plates.

### 4.2.1 Basic Concepts

License plates for vehicles are subject to legislation and regulations in most countries worldwide. These regulations encompass a variety of key aspects: (size and dimensions, character requirements, material and durability, mounting and display, special plates, registration stickers and validation, reflectivity and visibility) [27]. A license plates are typically forming a rectangular shape within specific parameters. This rectangle consists of lines and adheres to a defined size range. For digital license plates, the standard size is typically 52 cm in width and 11 cm in height, allowing for up to 11 characters. As an example, in Algerian legislation, the height of the characters is specified at 7.5 cm, with spaces counting as 0.5 characters. Consequently, Algerian license plates typically consist of either 10 or 11 characters [28]. Additionally, the dimensions of the license plate can vary based on the shooting angle, further impacting their observed width and height.

## 4.3 Image Pre-processing

### 4.3.1 Gaussian Blur

The process of Gaussian Blur filtering aims to reduce noise in the image significantly, while preserving essential information. This is essential because noise can adversely affect the accuracy of image analysis, particularly edge detection algorithms. Noise in the image can create false edges or distort genuine ones, making it crucial to minimize noise interference. [29].

### 4.3.2 Gray-scale Transformation

Detecting edges in color images presents a more complex challenge compared to grayscale images due to the consideration of color space as a vector space. However, it's important to note that approximately 90% of the edge information present in a color image can also be located within the corresponding grayscale version. Utilizing grayscale transformation can significantly reduce the complexity of the edge detection algorithm while retaining a substantial portion of the critical edge details. [30]. (as Fig. 4.2)


Figure 4.2: Gray-Scale Transformation

### 4.3.3 Black-hat Transform

In the field of morphology and digital image processing, the black-hat transform serves as a technique employed for isolating minute elements and intricate details within images.It's defined as the difference between the closing of the input image and the input image itself. This transform finds applications in various image processing tasks, including feature extraction, background equalization, image enhancement, and more. [31]


Figure 4.3: Black-hat Transformation

### 4.3.4 Edge Detection

In the realm of image processing, ”edge detection” refers to the set of algorithms designed to locate edges within an image. This concept is pivotal in the fields of feature selection and feature extraction within Computer Vision. An edge detector takes a digital image as input and generates an output called an ”edge map.” Some edge detectors provide detailed data concerning the edges' precise locations, their intensity, and even their orientations. [32]

#### Soble Operator

Among the classical methods, the Sobel operator stands out as one of the most renowned. This edge-detection technique employs a 2D spatial gradient convolution operation on an image. It utilizes convolution masks to calculate gradients along two directions, specifically along rows and columns. The Sobel edge detector offers a straightforward and efficient approach; however, it can be susceptible to noise. Additionally, the edges it detects tend to be relatively thick, which might not be ideal for applications that demand precise detection of the outermost contours of objects.[32]


Figure 4.4: Sobel Transformation

### 4.3.5 Binarization

Binary images are highly valuable in numerous image-processing tasks due to their straightforwardness and efficiency. These images result from the process of quantizing the gray levels in an image into typically two values, commonly 0 and 1. In the realm of digital image processing, the past two decades have seen a significant surge in research and development focused on binarization techniques. [33].

#### Otsu's Thresholding

Otsu's thresholding method aligns with the concept of linear discriminant criteria. It operates under the assumption that the image primarily comprises an object (foreground) and a background, with the intricacies and variations within the background being disregarded. Otsu determines the threshold in a way that aims to reduce the overlap between the class distributions. [33].

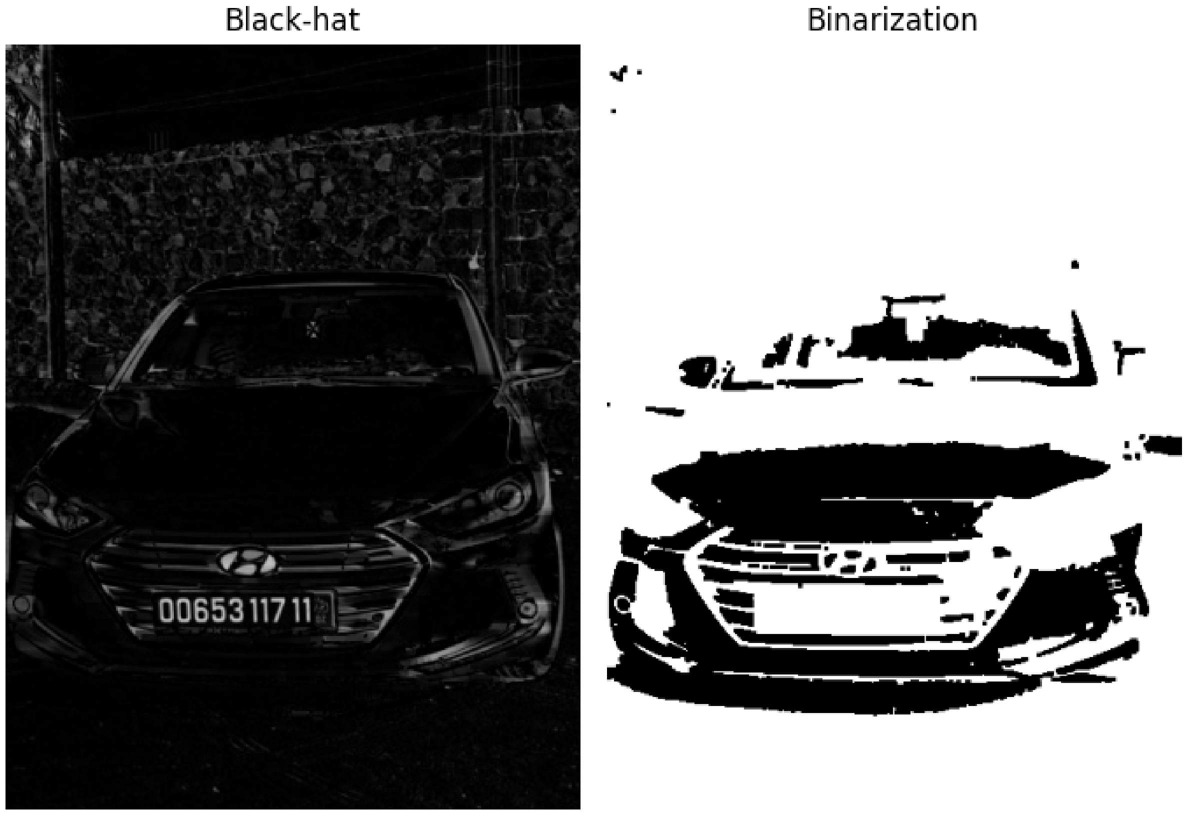


Figure 4.5: Binarization Transformation

## 4.4 Localization Algorithm

The license plate detection algorithm follows a systematic sequence of image processing steps to precisely identify license plates within images. It begins by transform the image to grayscale, simplifying subsequent analysis. The algorithm then applies the blackhat transform, emphasizing small, dark details on a brighter background. Following this, a close operation is performed to fill in gaps and refine the image.

Subsequently, thresholding is used to create a binary image, distinguishing between foreground and background. Edge detection, specifically using the Sobel operator, enhances regions of rapid intensity change, highlighting potential plate edges. Gaussian blur is then applied for noise reduction. Another close operation is performed to further refine the binary image. Thresholding is repeated to obtain a cleaner binary representation.

The algorithm proceeds with a series of erosion and dilation operations to fine-tune the detected regions. Canny contour detection is employed to identify precise contours, aiding in license plate delineation. Finally, various tests such as width, height, aspect ratio, and shape are conducted to verify and validate potential license plate candidates, ultimately ensuring accurate and robust license plate detection.

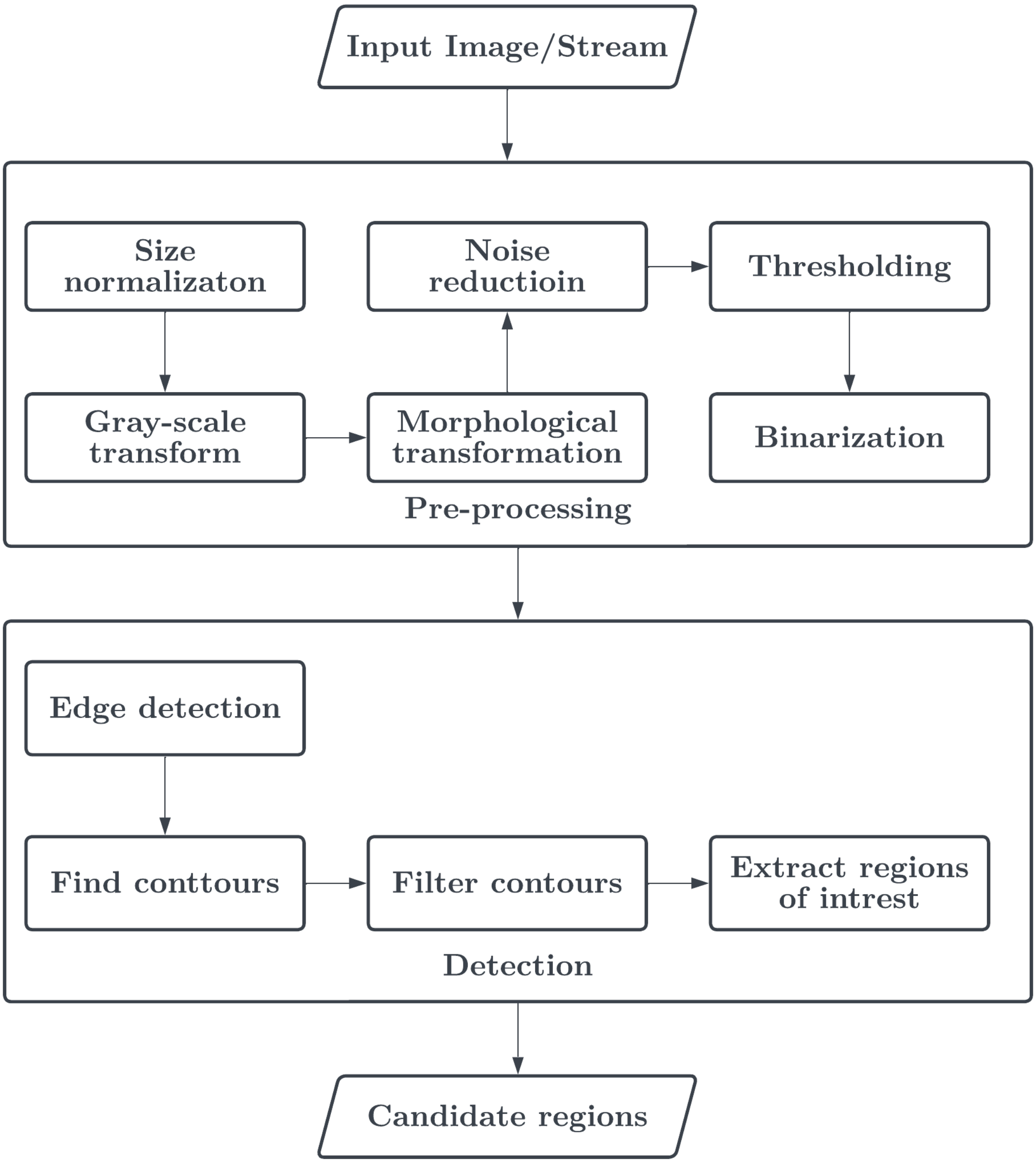


Figure 4.6: Algorithm Steps

## 4.5 Character Segmentation

Once the license plates have been successfully localized, the extracted plates are forwarded to the segmentation module for the purpose of isolating the characters on the license plate from any extraneous elements (see 4.7). It's crucial to note that any errors occurring during the segmentation process can directly impact the accuracy of character recognition.

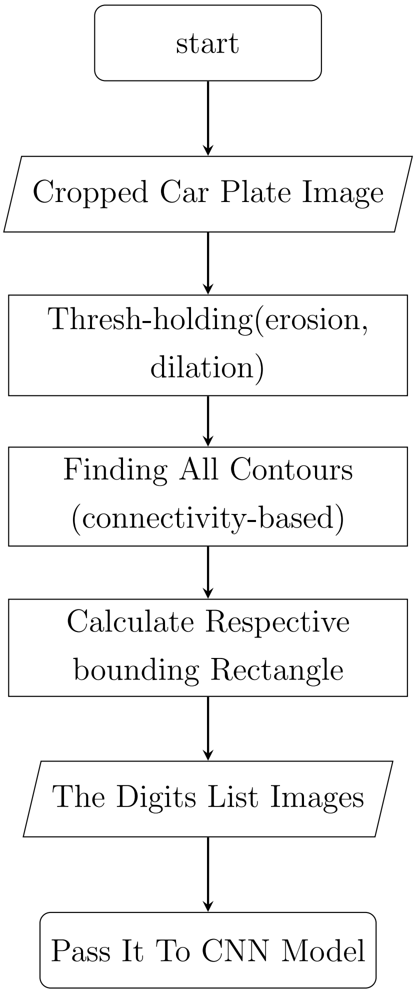


Figure 4.7: Character Segmentation Algorithm flowchart

### 4.5.1 Pixel connectivity-based approach [34]

Connected component analysis, alternatively referred to as connected component labeling, blob extraction, or region labeling, is an application rooted in graph theory that serves to determine the connectivity of "blobs" within an image. This segmentation technique entails labeling all connected pixels within a binary image. While the approach of connected component analysis is straightforward to implement, it encounters challenges when it comes to segmenting characters that fully connected like handwriting.


Figure 4.8: Plate digits bonding-box detection

Figure 4.9: Plate digits segmentation

## 4.6 Character Recognition

### 4.6.1 Dataset

The dataset utilized in this work was curated through an extensive process of data collection. Over 4000 images of Algerian car license plates were gathered from various online sources. Subsequently, the collected images underwent meticulous processing, where in each plate was carefully analyzed and the individual digits present in those plates were extracted.

Then the digits collection of images is divided into three main folders: train (3000), validation (750), and test (175). Each folder serves a specific purpose in training, evaluating, and testing the performance of the models. Within each folder, there are ten sub-folders representing the 10 different classes or categories of digits $[0-9]$. These sub-folders ensure that the dataset is well-structured and labeled, facilitating efficient training and evaluation processes. Each of these sub-folders contains an extensive collection of more than 250 digit images, providing a diverse and comprehensive range of examples for the models to learn from. This rich and varied dataset allows for robust training, accurate validation, and reliable testing of the digit recognition models being developed and evaluated (you can download my dataset from [35]).

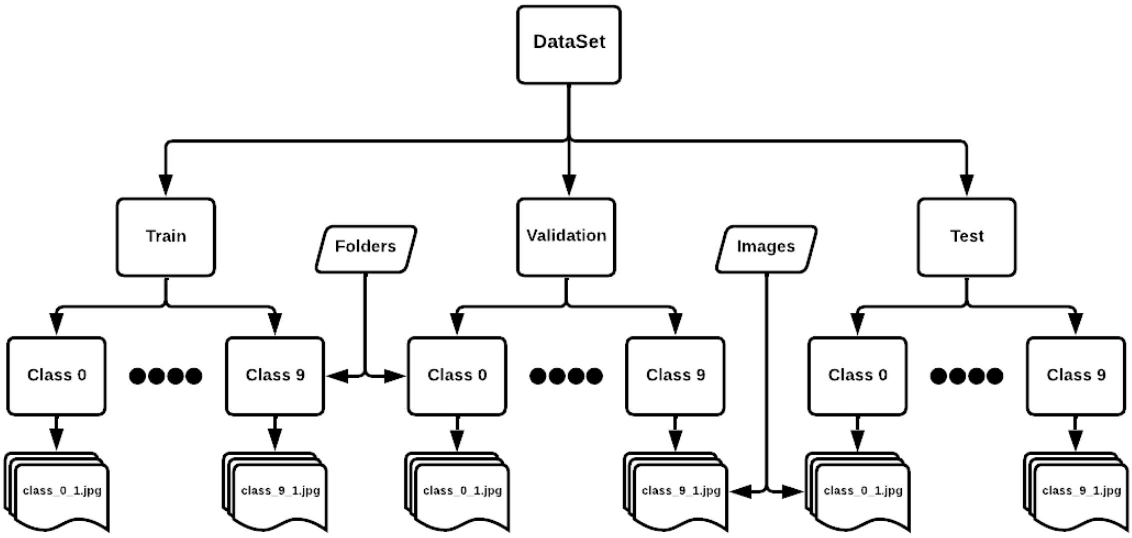


Figure 4.10: Dataset flowchart representation

### 4.6.2 Model Architecture

The data, consisting of digit images, is completely prepared and devoid of any imperfections. Now, it's time to construct an ANN capable of learning and identifying the characters through training. We will be use CNN (as choice) to develop AI model (see architecture Fig. 4.11). Also we use Support Vector Machine (SVM) as classifier to make even more accurate result (see Section 4.8).

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_1 (Conv2D)           (None, 28, 28, 32)        55328

 conv2d_2 (Conv2D)           (None, 28, 28, 32)        409632

 conv2d_3 (Conv2D)           (None, 28, 28, 32)        409632

 max_pooling2d_1 (MaxPooling  (None, 14, 14, 32)       0
 2D)

 dropout_1 (Dropout)         (None, 14, 14, 32)        0

 flatten_1 (Flatten)         (None, 6272)              0

 dense_2 (Dense)             (None, 128)               802944

 dense_3 (Dense)             (None, 10)                1290

=================================================================
Total params: 1,678,826
Trainable params: 1,678,826
Non-trainable params: 0
_________________________________________________________________
```

Figure 4.11: Model Architecture Summary

### Convolutional Layers

To maintain model simplicity, we initiate by crafting a sequential object, utilizing the Keras library (keas library see. [36]). The initial three layers comprise convolutional layers with 32 output filters, a convolution window measuring (5,5), and the activation function 'Relu' see (Fig. 4.12).

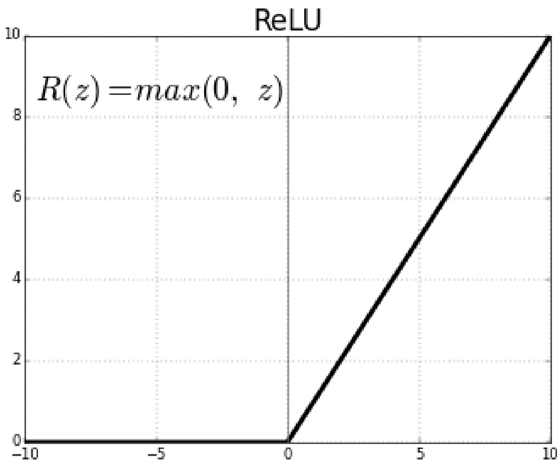


Figure 4.12: The Relu function activation graph

$$RELU(x) = \begin{cases} 0 \text{ if } x < 0 \\ x \text{ if } x >= 0 \end{cases} \tag{4.1}$$

### Max Pooling Layer

Following the convolutional layers, a max-pooling layer is introduced with a window size of (2,2). This layer identifies the maximum element within the specified filter coverage region within the feature map (Fig. 4.13). Consequently, the output subsequent to the max-pooling layer comprises a feature map that encapsulates the most salient characteristics of the preceding feature map.

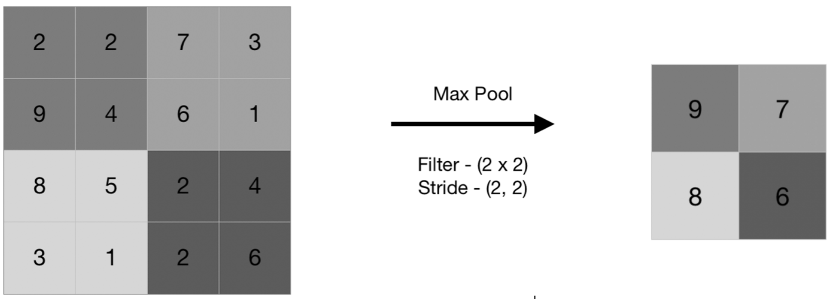


Figure 4.13: Max pooling functionality

### Dropout layer

Next, we incorporate a dropout rate to address the concern of overfitting. Dropout serves as a regularization hyperparameter that is introduced to prevent Neural Networks from overfitting. It involves randomly disregarding selected neurons during the training process, essentially 'dropping them out' in a random manner. In this instance, a dropout rate of 0.4 has been selected, signifying that 60% of the nodes will be retained, see (Fig.4.14).

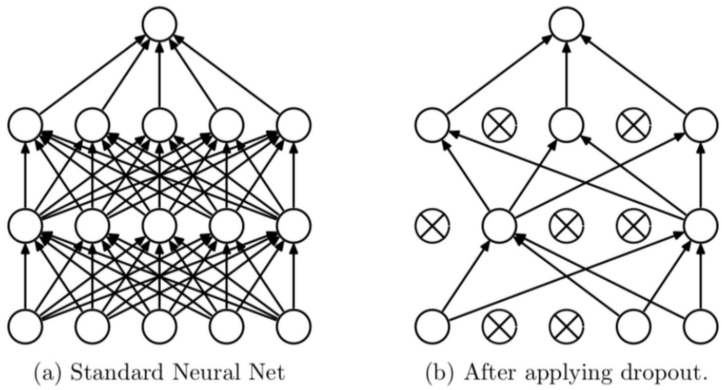


Figure 4.14: Max pooling functionality representation

### Flatten layer

Now, it's the moment to transform the node data into a flattened format, and for this purpose, we introduce a flatten layer. The flatten layer receives data from the preceding layer and condenses it into a single dimension see (Fig. 4.16).

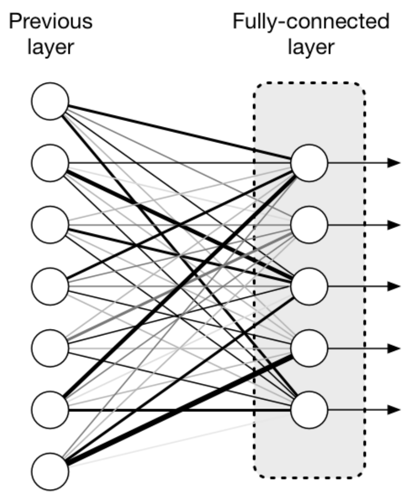


Figure 4.15: Flatten (fully-connected) layer representation

### Output Layer

In the concluding steps, we incorporate two dense layers. The first has an output space dimensionality of 128, employing the 'ReLU' activation function. The final layer comprises 10 outputs, aligning with the categorization of the 10-digit plates $[0-9]$, and employs the 'softmax' activation function.

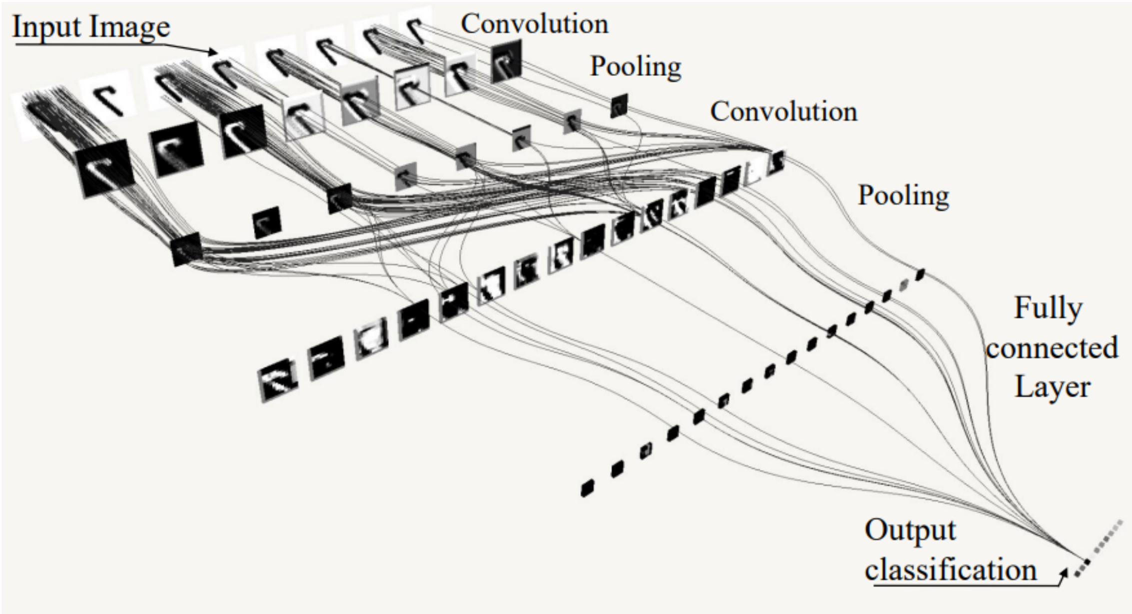


Figure 4.16: CNN architecture generated from the topological CNN 3D visualisation tool see [37]

## 4.7 Summary

In conclusion, our ALPR system encompasses a synergistic blend of computer vision techniques, image preprocessing methods, and an AI model constructed using Convolutional Neural Networks (CNN) in conjunction with a Support Vector Machine (SVM) classifier. This combination of cutting-edge technologies enables our system to achieve remarkable accuracy and significantly enhance its performance. Additionally, a meticulous analysis of the influence exerted by various parameters on the final outcomes will be examined in the next section of this study.

## 4.8 Results and Discussion

### 4.8.1 Experimental Results

To assess the effectiveness of the proposed system, a total of 104 Algerian vehicle images were utilized, obtained from various online sources. Furthermore, each ALPR module underwent individual testing, isolated from the other components, to thoroughly assess its performance and capabilities. Subsequently, a comprehensive evaluation was conducted by testing all the ALPR modules in conjunction with one another and assessing their combined performance.
The success rates for the three modules and the ALPR as single unit are given in (Tab. 4.1), Our system successfully recognized 80 out of 104 license plates in the vehicle images, resulting in an overall recognition rate of 76.92%.

Table 4.1: The performance rates of the suggested automatic license plate recognition system

| **Stage** | **Number of samples** | **Number of correct result** | **Success Rate** |
|---|---|---|---|
| Pate localization | 104 | 87 | 83.65% |
| Character segmentation | 87 | 82 | 94.25% |
| Character recognition | 82 | 79 | 96.34% |
| ALPR | 104 | 80 | 76.92% |

### 4.8.2 Result Discussion

To facilitate a more comprehensive understanding of the experimental results, this discussion will be divided into three main parts, with each part focusing on a specific module of the ALPR system. This approach allows for a detailed examination of the performance and outcomes of each module individually, providing valuable insights into their strengths, weaknesses, and overall contribution to the ALPR system as a whole.

#### Plate Localization Module Result

Unlike the character segmentation and character recognition modules, the plate localization module did not yield significant success in my endeavors. Despite various attempts and iterations, the results obtained from this specific component fell short of the desired

outcome.
The module dedicated to plate localization demonstrated a success rate, successfully localizing approximately 87 license plates out of a total of 104 car images, Translated to 83.65% accuracy rate.

The primary factor contributing to the relatively low success rate in this module can be attributed to the nature of the tested car images. It is worth noting that all the images used for testing were sourced from the Internet, lacking the specific characteristics and conditions required by our system, such as side road clip car images. This disparity between the testing images and the expected localization algorithm input, including distortion, angled images, low resolution, and variations in luminosity. These aspects contribute to the complexity of accurately identifying and localizing license plates.

#### Character Segmentation Module Result

Upon thorough testing, the character segmentation module demonstrated a satisfactory success rate. However, it is important to note that there are certain cases where the license plate undergoes severe distortion, posing challenges in accurately recovering the original character (digit) structure. Furthermore, the presence of additional marks, such as "·" or other symbols like flags, situated between license plate characters, can significantly impact the accuracy of character segmentation. These factors contribute to the complexity of accurately segmenting individual characters within the license plate. Addressing these challenges by enhancing the distortion recovery techniques and developing robust algorithms to handle additional marks will be instrumental in improving the accuracy and reliability of the character segmentation module in future iterations.

#### Character Recognition Module Result

The true accomplishment of this work lies in the character recognition module, where a notable success rate of 98.86% has been achieved (see Fig. 4.17 and Fig 4.18). This remarkable feat can be attributed to the synergistic fusion of CNN and SVM. The integration of these two powerful machine-learning techniques has led to exceptional results in accurately identifying and classifying characters within the ALPR system.

This breakthrough achievement holds significant implications for advancing the field of Automatic Number Plate Recognition, paving the way for enhanced accuracy and

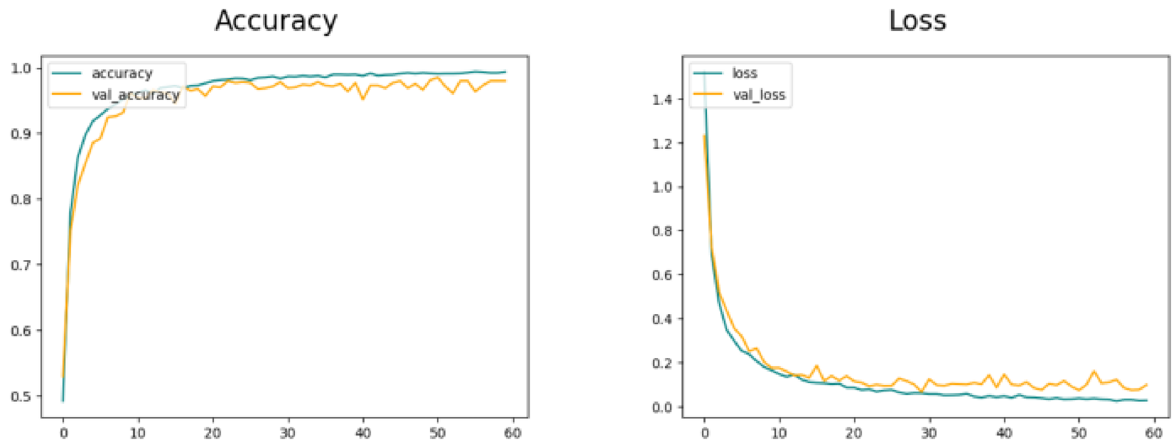


Figure 4.17: (Accuracy , Loss) graphs

```python
loss,acc =model.evaluate(test_generator)
print(f"loss = {loss*100:0.2f}% \naccuracy = {acc*100:0.2f}%")
```

[16] Python

```
22/22 [==============================] - 0s 12ms/step - loss: 0.0476 - accuracy: 0.9886
loss = 4.76%
accuracy = 98.86%
```

Figure 4.18: (Accuracy , Loss) percentage

reliability in character recognition tasks.

## 4.9 Conclusion

In this chapter, we presented our novel approach to implement the LPDRS. We started by providing a comprehensive overview of the system components, followed by a detailed explanation of our image pre-processing algorithms. Finally, we presented the experimental results of our LPDRS, providing a comprehensive analysis and discussion of the obtained outcomes, leading to insightful observations and conclusions regarding the system's performance.

# CHAPTER 5

## CONCLUSION AND FUTURE PERSPECTIVES

**Contents**



## 5.1 Summary of our Work

In conclusion, the escalating challenges in traffic management, law enforcement, traffic accidents and vehicle identification have underscored the urgent necessity for the implementation of ITS in Algeria. The significance of ITS has become an obligation and a high-priority research field, as it offers effective solutions to address these challenges. By leveraging advanced technologies and techniques, ITS can revolutionize traffic management, enhance law enforcement capabilities, mitigate traffic accidents, and improve vehicle identification processes. The integration of cutting-edge technologies, such as ALPR systems, within the framework of ITS, hold immense potential to transform the transportation landscape in Algeria. Further research and development in this domain are essential to harness the full potential of ITS and ensure the seamless and efficient operation of transportation systems in the country. Improving the image preprocessing stage of ALPR systems can help address challenges such as image distortion, noise, and variations in lighting conditions. Advanced techniques like image enhancement, noise reduction, and illumination normalization can enhance the quality and clarity of license plate images. Additionally, training AI models on large-scale datasets and optimizing network architectures can enhance the recognition capabilities for various font styles and character variations. Moreover, ALPR systems can benefit from increased scalability, flexibility, and computational resources provided by the cloud-computing field. The cloud enables ALPR systems to offload intensive tasks, such as image processing and data analysis, to remote servers, reducing the burden on local hardware. Finally, achieving a recognition rate of 91.3% is a promising result and serves as an encouraging milestone in the field of ALPR systems.

## 5.2 Future Perspectives

To build on the work accomplishments, some future perspectives should be considered to design new approaches. One of the future work directions is to implement advanced deep learning architectures, such as recurrent neural networks (RNNs) or transformer-based models, to further enhance the precision and robustness of the ALPR systems. Additionally, exploring the integration of multi-modal information, such as using text recognition algorithms in conjunction with image-based methods, could lead to improved performance in challenging scenarios. Furthermore, investigating real-time deployment options and optimizing the system for resource-constrained environments, such as edge computing platforms, would be beneficial. Finally, conducting extensive field tests and evaluations in varying environmental circumstances would validate the system's effectiveness and provide insights for further refinements.

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