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Theme

Detection of Road and Airfield Runway Pathologies Using Artificial Intelligence

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Or far from developing this humble work, you can find it here

As an expression of our deep gratitude and

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Dedication

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I dedicated this modest work to those who are dearest to me, I remember:

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Dedication

I would like to dedicate this work to those to whom I owe the greatest respect and appreciation to the parents, Abdul Rahim and congratulations to all my brothers to the best friends, both YassinFouad, Zaki who supported me during my path Colleagues of the Mathematics Department of Pak 2019 to all classmates, the electronic master class of 2024 is dedicated to all members of our large family, my brothers and uncles, especially Mohammed al-Hafid

Abstract

Road layer quality is critical for transportation efficiency and infrastructure safety. Factors such as temperature fluctuations, rainfall, and the use of inappropriate construction materials can lead to surface deterioration, resulting in cracks and potholes. Traditional inspection methods performed manually by engineers are accurate but costly, labor-intensive, time-consuming, and potentially hazardous. This thesis explores the use of artificial intelligence to achieve automated detection of road defects, focusing on deep learning models, specifically Convolutional Neural Networks (CNNs) and transfer learning, aiming to surpass traditional limitations. The AI-based system utilizes vehicle-mounted cameras, a DVR, and a computer to process video footage for defect detection. Pre-trained CNN models achieve high accuracy, providing a reliable, efficient, and scalable solution for road maintenance. Research indicates that this system outperforms manual methods, enhancing safety and reducing costs. Future work will integrate real-time monitoring and advanced deep learning techniques to improve detection capabilities. This study highlights the significant potential of artificial intelligence in revolutionizing road infrastructure management, paving the way for safe and cost-effective maintenance solutions.
Keywords: Convolutional Neural Networks, Road Surface, Artificial Intelligence, Transfer Learning, Machine Learning, Deep Learning, Artificial Neural Network, Image Processing, Rutting, Potholes, Cracks.
ملخص

تعتبر جودة طبقات الطرق أمر حاسم لكفاءة النقل وسلامة البنية التحتية، وقد تؤدي عوامل مثل تقلبات درجات الحرارة والأمطار واستخدام مواد البناء غير المناسبة إلى تدهور السطح، مما يظهر على شكل تشققات وحفر. تعتبر طرق التفتيش التقليدية التي يقوم بها المهندسون بطرق يدوية دقيقة ولكنها تكلفية ومكلفة من حيث العمالة والوقت ومن الممكن أن تكون خطرة. تستكشف هذه الرسالة استخدام الذكاء الاصطناعي لتحقيق كشف تلقائي لعيوب الطرق، مع التركيز على نماذج التعلم العميق وذلك باستخدام شبكات العصب الاصطناعي التكراري (CNNs) ونقل التعلم ونهدف إلى تجاوز القيود التقليدية. يستخدم النظام القائم على الذكاء الاصطناعي كاميرات مثبتة على المركبات، وجهاز تسجيل فيديو، وجهاز كمبيوتر لمعالجة لقطات الفيديو لاكتشاف العيوب. تحقق النماذج المدربة مسبقاً لشبكات العصب الاصطناعي التكراري دقة عالية، مما يوفر حلاً موثوقاً وفعالاً وقابلاً للتوسع لصيانة الطرق. نجد ان الابحاث تشير إلى أن هذا النظام يفوق الأساليب اليدوية، مما يعزز من السلامة ويقلل التكاليف. سيتم دمج العمل المستقبلي لرصد الوقت الحقيقي وتقنيات التعلم العميق المتقدمة لتحسين قدرات الكشف وتسلط هذه الدراسة الضوء على الإمكانات الكبيرة للذكاء الاصطناعي في ثورة إدارة البنية التحتية للطرق، مما يمهد الطريق لحلول صيانة آمنة وفعالة من حيث التكلفة.
الكلمات المفتاحية: الشبكات العصبية التلافيفية، سطح الطريق، الذكاء الاصطناعي، التعلم النقيلي، التعلم الآلي، التعلم العميق، الشبكة العصبية الاصطناعية، معالجة الصور، التخدد، الحفر، الشقوق.
Résumé

La qualité des couches routières est cruciale pour l'efficacité du transport et la sécurité de l'infrastructure. Des facteurs tels que les fluctuations de température, les précipitations et l'utilisation de matériaux de construction inappropriés peuvent entraîner la détérioration de la surface, se manifestant sous forme de fissures et de nids-de-poule. Les méthodes d'inspection traditionnelles effectuées manuellement par les ingénieurs sont précises mais coûteuses, nécessitent beaucoup de main-d'œuvre, prennent du temps et peuvent être dangereuses.

Cette thèse explore l'utilisation de l'intelligence artificielle pour réaliser une détection automatique des défauts routiers, en mettant l'accent sur les modèles d'apprentissage profond, notamment les Réseaux de Neurones Convolutifs (CNNs) et le transfert d'apprentissage, dans le but de dépasser les limitations traditionnelles. Le système basé sur l'intelligence artificielle utilise des caméras montées sur véhicules, un enregistreur vidéo et un ordinateur pour traiter les séquences vidéo afin de détecter les défauts. Les modèles CNN pré-entraînés atteignent une grande précision, offrant ainsi une solution fiable, efficace et évolutive pour la maintenance routière. La recherche montre que ce système surpasse les méthodes manuelles, améliorant la sécurité et réduisant les coûts.

Des travaux futurs intégreront la surveillance en temps réel et des techniques avancées d'apprentissage profond pour améliorer les capacités de détection. Cette étude met en lumière le potentiel considérable de l'intelligence artificielle pour révolutionner la gestion des infrastructures routières, ouvrant la voie à des solutions de maintenance sûres et rentables.

Mots clés: Réseaux de Neurones Convolutifs, Surface de la Route, Intelligence Artificielle, Apprentissage par Transfert, Apprentissage Automatique, Apprentissage Profond, Réseau Neuronal Artificiel, Traitement d'Image, Orniérage, Nids-de-Poule, Fissures.

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General Introduction

1. General Context and Problem Statement

The quality of road layers is paramount in transportation operations and their related factors. However, external factors such as temperature, rainfall, and poor-quality construction materials cause many problems that affect the health of these roads. Consequently, many deteriorations and visible defects appear on the road surface, which can be classified into different families. In our project study, we considered the visible defects on the asphalt surface, which can be seen with the naked eye. The most common indicators in our region, which we focused on, are longitudinal and transverse cracks, alligator cracks, pits, and potholes. These defects appear on the surface and are classified according to their intensity, and the methods for maintenance and repair vary according to the severity and type of defect.

There are many methods for detecting faults in roads, with the most common being the traditional method used by civil engineers and technicians. This involves an engineer going to the site to monitor and inspect the road with detailed measurements of damage and subsequently identifying faults based on professional observations recorded. While this method is accurate in delivering results and has several other positive aspects, it is costly, labor-intensive, time-consuming, and often proves dangerous due to traffic movement and harsh weather conditions, especially in the summer with high temperatures, as discussed in Chapter One.

Recent years have witnessed various developments in the field of science and the emergence of artificial intelligence in image processing, based on machine learning techniques, which have introduced effective and automated methods for detecting defects and problems. Through the models applied in this project, we aimed to overcome the limitations of traditional techniques and offer many advantages in terms of finances, logistics, technical issues, and field problems, providing accurate technical tests and results. However, this field requires an effective and reliable solution where defects in the road can be identified by capturing images of the road surface and then identifying perfect surfaces and others containing defects, thereby distinguishing between these surfaces.

Recently, deep learning models, especially multilayer neural networks, have become very successful tools for feature learning. Additionally, the availability of efficient facilities in computer vision, impressive performance, and continuous improvements in pre-training methods on available datasets are driving rapid advancements in deep learning and knowledge transfer. Understanding this, Convolutional Neural Networks (CNNs) are automated neural networks that perform very well and have made significant advancements in massive image processing.

Although several of these models have demonstrated quality in their accuracy in extracting scientific features for various applications in this field, the straightforward approach requires continuous and periodic improvements to road defect detection methods to be more accurate, faster, reliable, and tangible. This includes achieving effective performance and highly accurate results, reducing detection, tracking, analysis, and treatment time. Given the lack of large datasets, or when data is limited and does not support this project, we propose later in this report an approach to knowledge transfer from CNN using an already trained model showing significant improvement and is being worked on to be accomplished as a future tool for field inspection with scientific and managerial vision. This was addressed in Chapter Two of this project.

Chapter 1
Road Degradations

1. Introduction

Pavement deterioration is a critical issue in civil engineering, particularly for road and highway maintenance. Over time, paved surfaces undergo various forms of wear and tear due to environmental conditions, traffic loads, and material aging. These degradations not only affect the aesthetics of the road but also its functionality and safety. Recognizing the types of road distress and understanding their causes are essential for effective maintenance and repair strategies [1].

There are multiple families of road degradations, each with distinct characteristics and implications [2]. In this thesis, we will focus on three specific types of degradations[3 4 5]

- **Potholes (from the tearing family)**
- **Rutting (from the deformation family)**
- **Cracking and crazing (from the cracking family)**

By examining these types, we aim to provide a comprehensive overview of their causes, impacts, and possible repair methods.

2. Road Degradation

2.1. Definition fo Degradation

Road degradation refers to the deterioration and damage that occur on the surface and underlying layers of pavement. This degradation adversely affects the performance, safety, and longevity of road infrastructure. It can be caused by a variety of factors, including environmental conditions, mechanical stresses, and material quality [6 7].

3. Main Causes of Degradation

3.1. Climatic Conditions

- **Rain:** Water infiltration into pavement layers weakens the structure, leading to potholes and cracks, especially in areas with poor drainage [8].
- **Freezing and Thawing:** Freeze-thaw cycles cause cracks due to the expansion and contraction of materials, particularly in regions with significant temperature fluctuations [9].
- **Heat:** High temperatures can soften asphalt, causing plastic deformation and rutting, while also accelerating asphalt binder aging, leading to surface cracking [10].

3.2. Structural Factors

- **Design:** Poor design can lead to structural problems such as inadequate drainage and insufficient layer thickness, resulting in load-bearing issues and uneven stress distribution [11].
- **Construction:** Errors during construction, such as poor compaction or incorrect material use, can accelerate degradation. Proper construction practices are critical for pavement durability [12].
- **Maintenance:** Inadequate or delayed maintenance worsens existing degradations. Regular maintenance, such as crack sealing and minor repairs, significantly extends pavement life [13].

3.3. Material Factors

- **Asphalt Quality:** The composition and application of asphalt influence the resistance and durability of the pavement. Factors like asphalt binder grade and aggregate quality are crucial [14].
- **Aggregates:** The properties of aggregates, including size, shape, and resistance, affect the stability and durability of pavement layers. Well-graded and durable aggregates enhance load distribution and deformation resistance (15].

4. Types of Degradation

In this thesis, we will discuss the following degradation in detail

4.1. Potholes (Tearing Family)

Potholes are cavities that form on the pavement surface due to water infiltration and the passage of vehicles [16]. The severity of potholes can be categorized into three degrees:

- **Low Severity:** Small, shallow holes that do not significantly impact vehicle safety or comfort.
- Causes: Initial water infiltration and minor freeze-thaw cycles [17].
- Repair Methods: Filling and compacting with cold patch material [18].
- **Medium Severity:** Larger holes that can cause discomfort and potential damage to vehicles.
- Causes: Prolonged water exposure, repeated freeze-thaw cycles, and moderate traffic loads [19].

- Repair Methods: Cleaning the hole, applying a tack coat, and filling with hot mix asphalt [20].

➢ **High Severity:** Deep, extensive holes that pose significant hazards to vehicles and can lead to further pavement damage.

- Causes: Severe water infiltration, heavy traffic loads, and advanced material degradation [21].
- Repair Methods: Cutting around the pothole to remove damaged pavement, applying a tack coat, and filling with hot mix asphalt followed by compaction [22].

Figure 1 : Examples of Patholes at different Severity Levels.

4.2. Rutting (Deformation Family)

Rutting refers to longitudinal depressions that form on the pavement surface due to the repeated passage of heavy vehicles, causing plastic deformation of the asphalt [23].The severity of rutting can be categorized into three degrees:

➢ **Low Severity:** Shallow ruts that do not significantly affect vehicle handling.

- Causes: Initial plastic deformation under repeated light traffic [24].
- Repair Methods: Surface treatments such as micro-surfacing or thin overlays to restore the surface profile [25].

➢ **Medium Severity:** Moderate ruts that can cause discomfort and minor handling issues for vehicles.

- Causes: Repeated heavy traffic loads and moderate asphalt softening [26].
- Repair Methods: Milling the surface to remove ruts and applying a new asphalt layer [27].

➢ **High Severity:** Deep ruts that significantly affect vehicle handling and pose safety risks, especially in wet conditions.

- Causes: Severe plastic deformation under heavy and frequent traffic loads, coupled with high temperatures [28].
- Repair Methods: Full-depth reclamation or reconstruction of the affected pavement section [29].

Figure 2: Examples of Rutting at different Severity Levels

4.3. Cracking and Crazing (Cracking Family)

Cracking and crazing involve the formation of interconnected cracks on the pavement surface, often caused by material fatigue [30]. The severity of cracking can be categorized into three degrees:

- **Low Severity:** Fine, isolated cracks that do not significantly affect the pavement structure.
  - Causes: Minor thermal stresses and initial material fatigue [31].
  - Repair Methods: Crack sealing with a flexible sealant to prevent water infiltration [32].
- **Medium Severity:** More extensive cracking that can lead to minor structural weakening and water infiltration.
  - Causes: Repeated thermal stresses, moderate material fatigue, and minor foundation movement [33].
  - Repair Methods: Routing and sealing cracks, or applying a thin overlay to seal and strengthen the surface [34].
- **High Severity:** Extensive, interconnected cracking (crazing) that significantly weakens the pavement structure and allows water infiltration.
  - Causes: Severe material fatigue, significant foundation movements, and repeated overloading [35].

- Repair Methods: Surface milling to remove the cracked layer and applying a new asphalt overlay or complete pavement reconstruction in severe cases [36].

Figure 3: Examples of Cracking at Different Severity Levels.

Figure 4: Examples of Crazing at Different Severity Levels.

5. Conclusion

Understanding the different types of road degradations, their causes, and repair methods is crucial for maintaining the quality and safety of road infrastructure. This thesis will delve deeper into the specific degradations of potholes, rutting, and cracking, providing a comprehensive analysis of their impacts and solutions. Effective management of road degradations requires a thorough understanding of these factors to implement appropriate repair strategies and ensure the longevity of our roads [37].

Chapter 2

Deep-Convolutional NeuralNetworks (Deep-CNN) and Transfer

1. Introduction

In recent years, the field of Deep Learning (DL) has experienced rapid growth and has been extensively utilized to successfully tackle a wide range of traditional applications. The DL computing paradigm is often considered the Gold Standard in Machine Learning (ML). Fur-thermore, it has gradually become the most widely used computational approach within the ML field, achieving remarkable results on several complex cognitive tasks, sometimes matching or even surpassing human performance. One of the advantages of DL is its ability to learn from vast amounts of data [ALZ2021, 38] [ABI2022, 39].

More importantly, DL has outperformed well-established ML techniques in various domains, including cyber security, personal identification, biometric information, robotics and control, and medical information processing, among many others. In this chapter, we introduce deep learning methods, specifically focusing on Convolutional Neural Networks (CNNs), and we will explore pre-trained CNN models [KOP2021, 40] [ABI2022, 39].

2. Artificial intelligence

Artificial Intelligence (AI) refers to the intelligence exhibited by machines through computer processes that emulate human intelligence and behavior while acting intelligently. A device that observes its environment and takes actions to increase its chances of achieving a specific goal is a computer performing challenging tasks. When a machine replicates "cognitive" functions that humans associate with other human minds, such as "learning" and "problem solving," comprehending complex data, and effectively understanding human thoughts, this is known as "artificial intelligence" [ONG2017, 41][RUS2009, 42].

Our AI application, as illustrated in Figure 5.

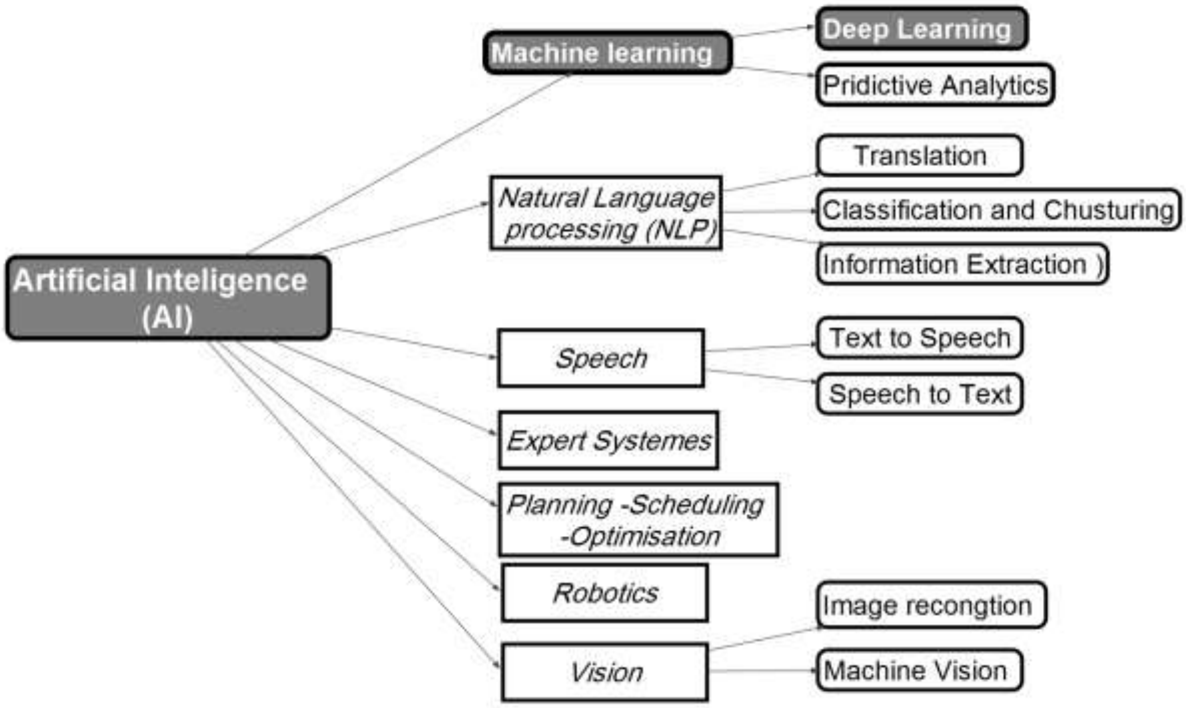


Figure 5:Structure-of-Artificial-Intelligence.

3. Machine Learning

Machine learning is a discipline within computer science that enables systems to learn without being explicitly programmed. It focuses on the study and design of algorithms capable of learning from data and making predictions based on that data. Originating from the study of pattern recognition and computational learning theory in artificial intelligence, ML is applied to various computing tasks where developing and programming high-performing explicit algorithms is challenging or impractical. Examples of ML applications include email filtering, identifying network intruders or malicious insiders attempting data breaches, human recognition, automobile detection, and image processing. Additionally, these methods are evaluated based on their performance using previously provided answers [ABI2022, 39] [ONG2017, 41].
As shown in figure 6.

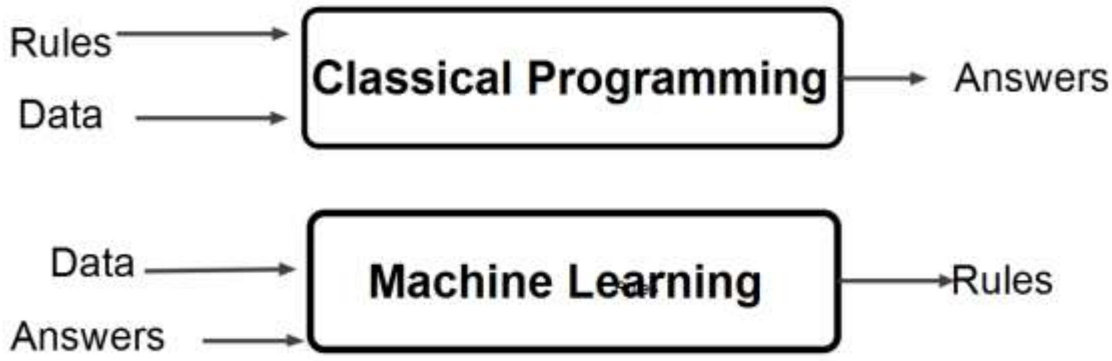


Figure 6:the difference between ML and classical programming

3.1.Machine Learning Methods

Supervised and unsupervised learning are the most commonly used machine learning methods. Supervised learning makes up about 70% of machine learning applications, while unsupervised learning comprises 10% to 20%. Additionally, semi-supervised and reinforcement learning are occasionally utilized in certain situations [ABI2022, 39][ONG2017, 41].

3.1.1. Supervised learning

Algorithms are trained using labeled examples where the desired output is known. For in-stance, a piece of equipment might have data points labeled as either "F" (failed) or "R" (runs). The learning algorithm is provided with a set of inputs and their corresponding correct out-puts, and it learns by comparing its actual outputs to the correct ones to identify errors. Techniques such as classification, regression, prediction, and gradient boosting are used to refine the model.

3.1.2. Unsupervised learning

When the system lacks the "right answer," unsupervised learning is applied to the data. The algorithm must analyze the data and discover underlying patterns. Unsupervised learning is useful for segmenting text topics, recommending items, and identifying outliers in transactional data.

3.1.3. Semi-supervised learning

It is used similarly to supervised learning but trains with both labeled and unlabeled data, typi-cally involving a small amount of labeled data and a large quantity of unlabeled data, as the latter is cheaper and easier to obtain. An early example of this is identifying a person’s face using a webcam.

3.1.4. Reinforcement learning

Reinforcement learning is employed in robotics, gaming, and navigation. Through trial and error, the program uses reinforcement learning to determine which actions yield the highest rewards. This type of learning involves three main components: the agent (the learner or decision-maker), the environment (everything the agent interacts with), and actions (what the agent can do). The agent's goal is to choose actions that maximize the expected reward over time. By adopting an effective policy, the agent can reach the target more quickly. The aim of reinforcement learning is to learn the optimal policy.

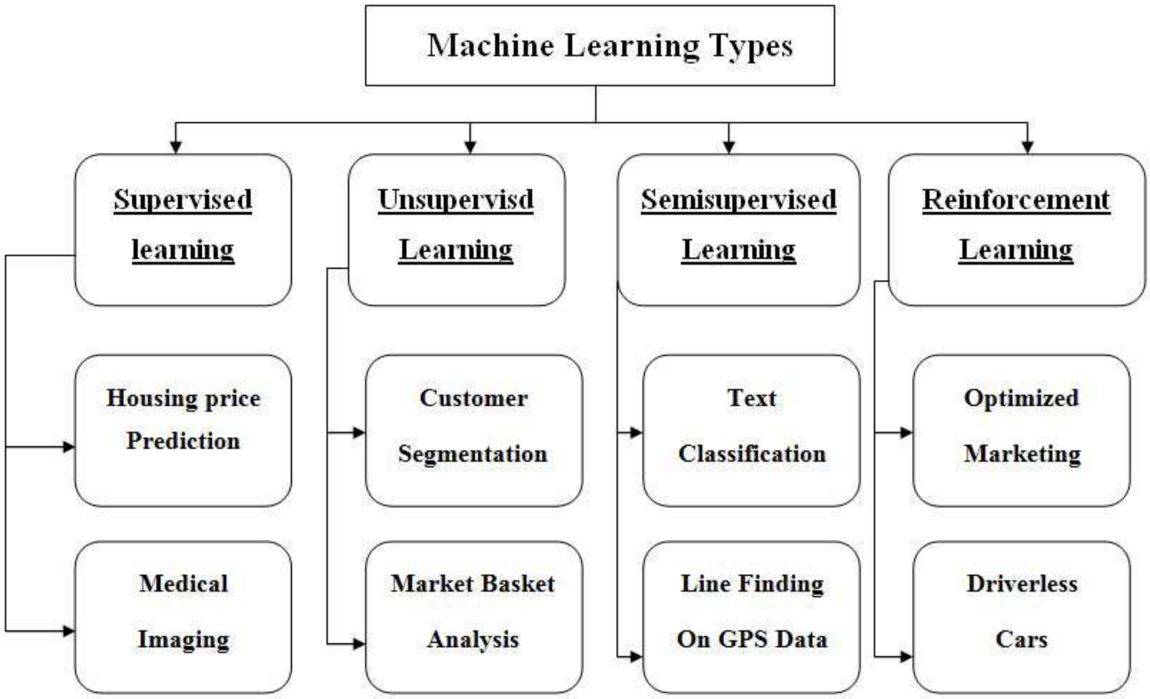


Figure 7:The Machine Learning Types

4. Deep Learning

Inspired by the information processing patterns observed in the human brain, Deep Learning (DL) emerges as a subset of Machine Learning. Unlike traditional approaches, DL operates without predefined human-designed rules. Instead, it analyzes vast amounts of data to establish mappings from inputs to specific labels. While conventional machine learning methods involve multiple sequential phases such as preprocessing and feature extraction to tackle classification problems, DL comprises multiple layers of algorithms, known as Artificial Neural Networks (ANNs), each providing unique interpretations of the input data.

Given the significant expansion and advancement in big data, DL has emerged as a highly popular ML technique in recent years. Continuously evolving, it is still undergoing development to enhance its performance across various machine learning tasks. DL has greatly facilitated progress in numerous domains, including image super-resolution, object detection, and image recognition. Notably, DL has recently surpassed human performance in tasks like image categorization, showcasing its remarkable capabilities.

The widespread adoption of DL has impacted nearly every scientific field, disrupting and revolutionizing various sectors and industries [ABI2022, 39].

5. Artificial Neural Network (ANN)

5.1. Biological Neurons

These cells are a type typically found in the cerebral cortex. Illustrated in Figure (8.A), dendrites receive electrical impulses as weighted inputs. These inputs are utilized by the cell body to generate an output signal. Once the output signal reaches a certain threshold, it travels along the axon wire, which is connected to other neurons through the synaptic terminal [BOU2019, 42].

5.2. Artificial Neurons

The artificial neuron is based on the biological neuron model. It receives a set of inputs, multiplies each input by a corresponding weight, and then aggregates all these weighted inputs along with a constant value known as a bias. This weighted sum is then passed through an Activation Function, which produces an output sent as input to another neuron [DIF2020, 43].

The configuration of an artificial neuron is depicted in Figure (8.B).

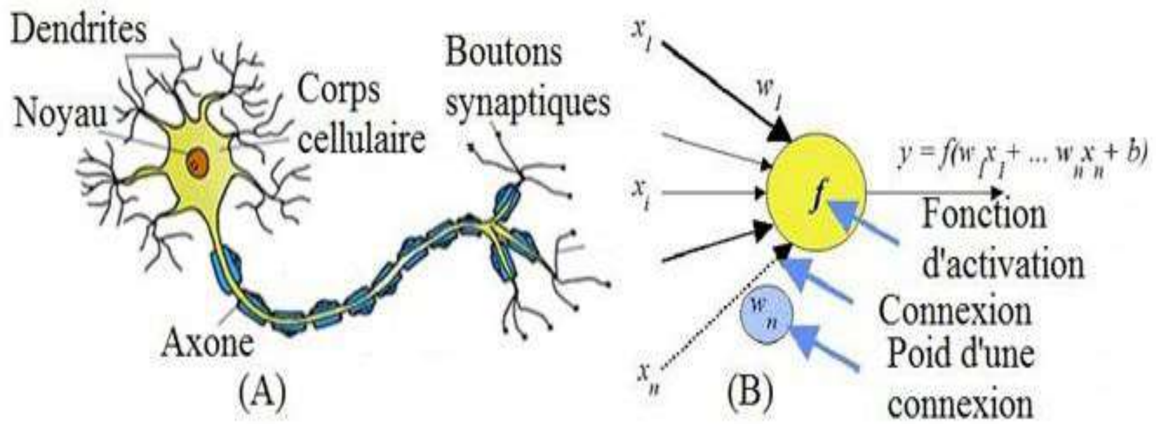


Figure 8: (A) Biological Neurons Network (B) Artificial Neurons Network

6. Convolutional neural networks (CNN)

The CNN algorithm stands out as the most renowned and extensively applied method in the realm of deep learning. Its fundamental superiority over previous models lies in its capacity to autonomously identify crucial features without human intervention. CNNs find widespread application across various domains, such as computer vision, audio processing, and facial recognition, among others. Like traditional neural networks, CNNs draw inspiration from the neural structure observed in human and animal brains. For instance, in the brain of a cat, the visual cortex comprises a complex arrangement of cell [DAA2020, 44].

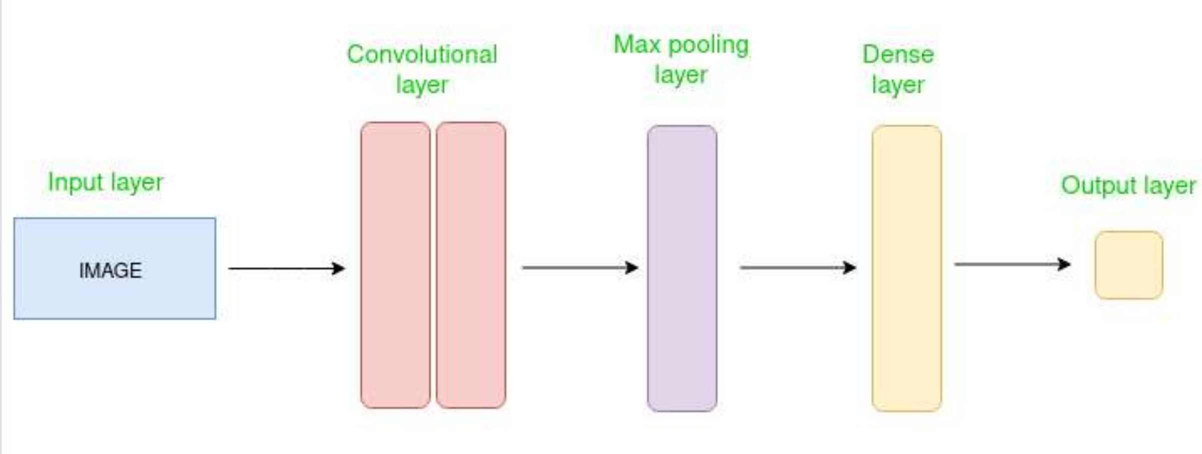


Figure 9: CNN Architecture

6.1.General architecture of a Convolutional neural network

In a CNN model, the input x of each layer is structured in three dimensions: height, width, and depth, or m mr, where the height (m) equals the width. The channel number is another name for the depth. The depth (r) of an Red Green Bleu (RGB) picture, for example, is three. Each convolutional layer's available kernels (filters) are designated by k and have three dimensions (n×n×q) to the input image. Figure2.5 shows an example of the CNN architecture for image categorization [DAA2020, 44][ABI2022, 39].

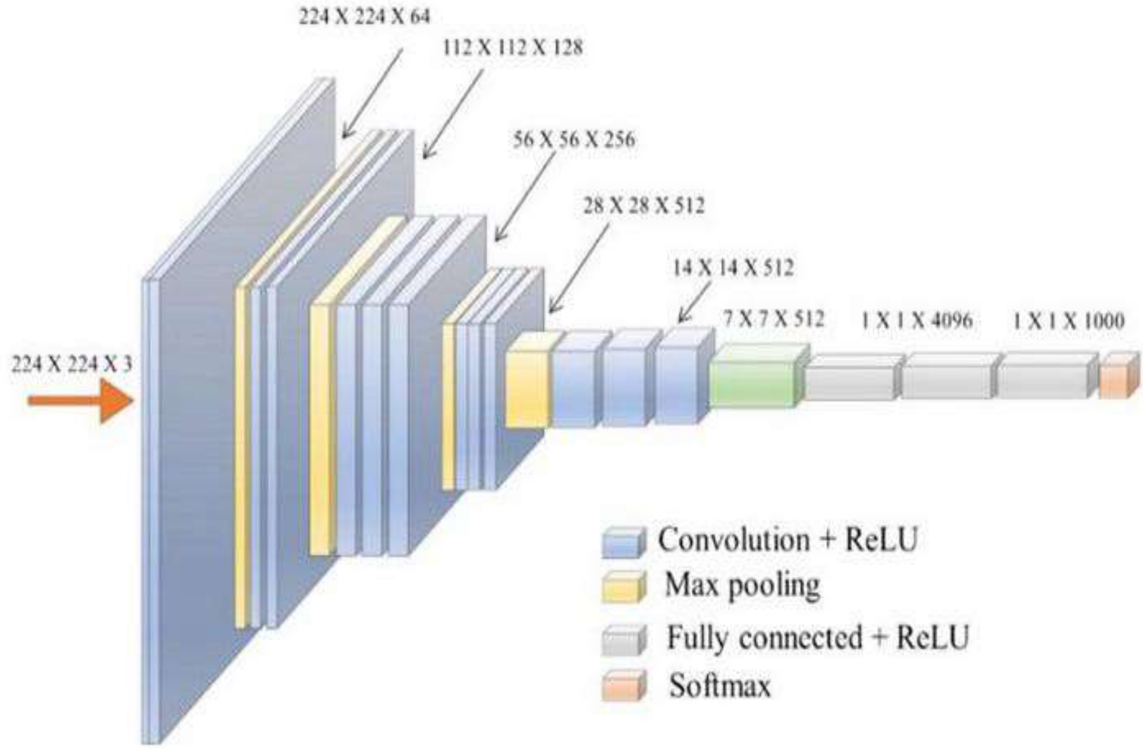


Figure 10: General architecture of a Convolutional neural network

7. CNN layers

Nowadays, CNNs stand out as the most proficient models for image recognition tasks. They consist of four primary types of layers: the convolution layer, the pooling layer, the Rectified Linear Unit (ReLU) layer, and the fully connected layer. Subsequent subsections will delve into a detailed explanation of the various layers within a CNN.

7.1.Convolution Layer

It constitutes the core of CNN architecture, serving as its most fundamental component. This layer is positioned as the initial one in CNN structures, with at least one Conv layer mandated. In image processing, the convolution layer aims to extract features from images through two-dimensional convolution operations between the input maps $Z^m$and the filters denoted by the kernels K^m with indices n and m, where m and n represent the level and map indices respectively, and l signifies the filter index. The calculation of output map f^m for Layer L is detailed in equation (7, 1) [ABI2022, 39] [DAA2020, 44].

$$[H]f_l^m = \sum_n^{N^{m-1}} k_{1,n}^m * z_n^m + b_l^m \ldots\ldots\ldots\ldots\ldots\ldots (7, 1)$$

Where: N^m Represents the number of input maps, $*$ denotes convolution

b^m Indicates the bias of the m-th level's output map L.

The parameters defining the kernels and biases are established through the process illustrated in figure 11.

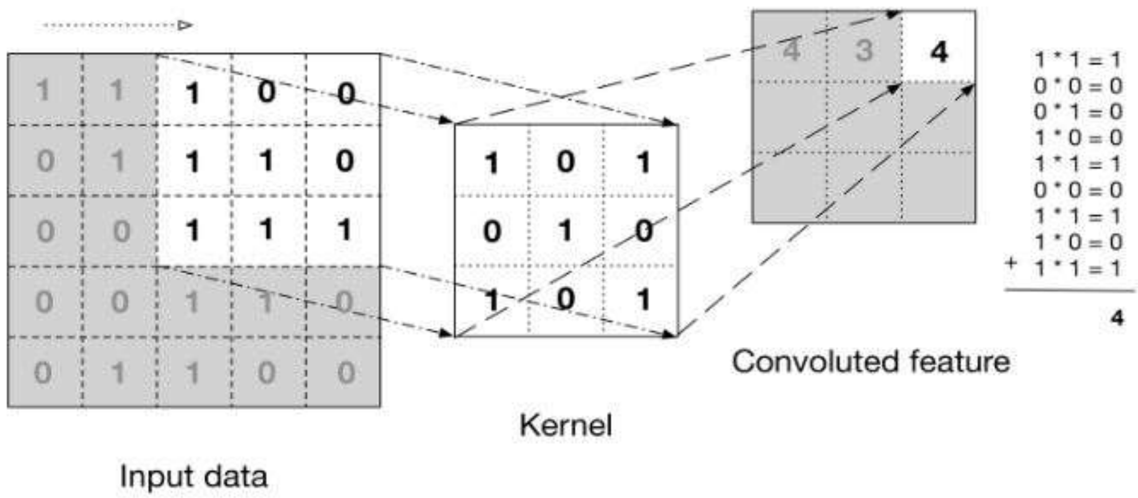


Figure 11:The convolution operation

7.2.ReLU layer

The ReLU layer, also referred to as the activation layer, is a non-linear component often employed following the Conv layer. Utilizing the function f(y) =max (0, y), the ReLU layer effectively sets all negative activations to zero. Because CNNs lack feedback, this layer introduces non-linearity to the network without altering the receptive fields of the Conv layer [ABI2022, 39].

7.3.Pooling layer

The pooling layer takes numerous feature maps as input and consolidates them. By utilizing a filter, typically of size 2×2 with a stride of the same length, the pooling method reduces the dimensions of the images while preserving their significant characteristics. The most common pooling layer is max pooling, which scans the input volume and outputs the maximum value within each sub region that the filter covers. Alternatively, pooling layers can use methods such as average pooling or L2-norm pooling. These techniques help prevent overfitting by reducing the number of parameters in the feature maps, thereby decreasing network computations. Max-pooling selects the maximum value from the receptive field, while avg-pooling returns the average of the values [DAA2020, 44] [ABI2022, 39].

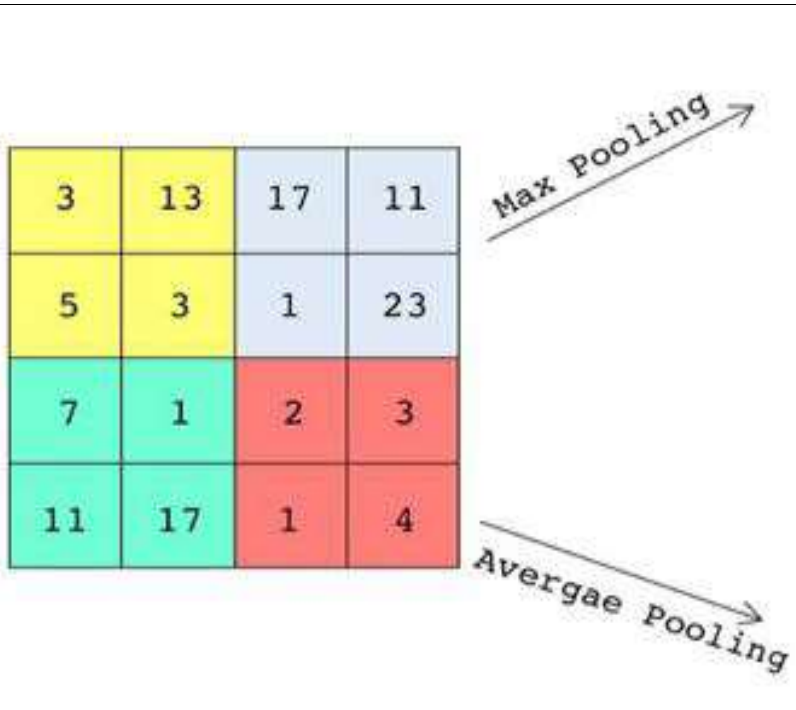


Figure 12: the Pooling operation

7.4.Fully connected (FC) layer

The Fully Connected (FC) layer, also known as the feed-forward neural network, is the final layer of a CNN. It can take input from the convolution layer, pooling layer, or ReLU layer. The characteristics of the FC input layers are analyzed, with the output from the final pooling or convolutional layer being flattened before being passed to the fully connected layer. Flattening is the process of converting the values of a three-dimensional matrix into a vector. Selected features are then pooled and used for data classification [DAA2020, 44] [ABI2022, 39].

8. Transfer Learning

Transfer learning is a technique that allows you to apply knowledge gained from previous learning experiences to your current task. Specifically, the parameters of a previously trained CNN (using an earlier database) can be adjusted using a newly acquired database.

The primary advantage of this approach is that it saves time by leveraging fresh data to update the parameter model, rather than requiring a completely new database with both old and new data. This strategy is particularly effective when working with a pre-trained model that lacks access to a comprehensive training database. In essence, transfer learning is crucial in deep learning for addressing the challenge of insufficient training data.

A common transfer learning technique is fine-tuning, which involves using pre-trained models such as AlexNet, VGG16, and VGG19[ABI2022, 39].

9. Pre-trained CNN networks

Several pre-trained CNN architectures have been proposed over the last decade. The architecture of a model plays a crucial role in enhancing the performance of various applications. Since 1989, numerous modifications have been made to CNN architectures, including structural reformulations, regularization techniques, parameter optimizations, and more. However, the most significant improvements in CNN performance have primarily resulted from the restructuring of processing units and the development of new blocks. The utilization of network depth has been a key factor in the most innovative advancements in CNN design.

CNN architectures have made significant contributions across various domains, leading to the prominence of models such as AlexNet, VGG16, and VGG19, as shown in Table 1. These networks are currently employed in a wide range of recognition tasks [ABI2022, 39].

As a result, we will go through their designs in detail.

Networks	Year	Depth Size	Image Input	Size
AlexNet	2012	25	227MB	227 ×227×3
VGG16	2015	47	515MB	224×224×3
VGG19	2015	47	515MB	224 × 224×3

Table 1:Information about Pre-trained Models used.

9.1.AlexNet

AlexNet is a renowned deep CNN architecture that has achieved groundbreaking success in the fields of image recognition and classification. This design marked a significant leap in CNN performance, earning first place in the 2012 ILSVRC competition, one of the most challenging image recognition and classification tasks to date.

Developed at the University of Toronto by Krizhevsky and his team, AlexNet consists of five convolutional (Conv) layers, each followed by Rectified Linear Unit (ReLU) activation, three max-pooling layers, and three fully connected (FC) layers.

By increasing the depth of the CNN and implementing various parameter optimization techniques, the learning capability of the CNN was enhanced.

Figure 13 illustrates the basic design of the AlexNet architecture [ALZ2021, 38][ABI2022, 39].

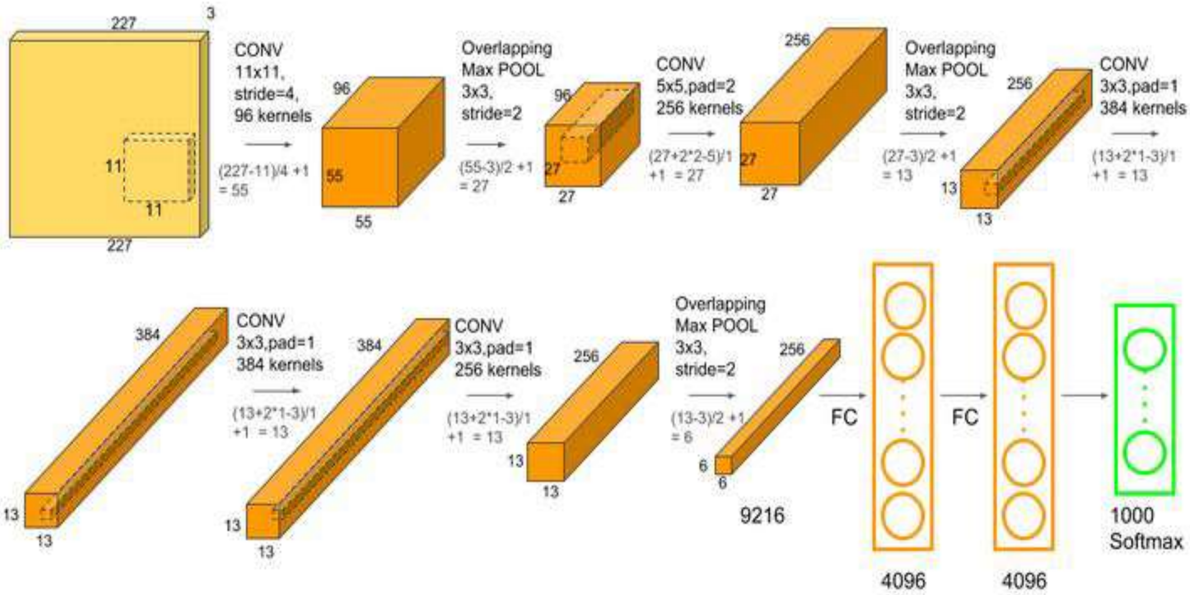


Figure 13:The AlexNet architecture

9.2.Visual geometry group (VGG)

The Visual Geometry Group (VGG) made significant strides in image classification and localization challenges. Although it did not secure first place in the 2014 ILSVRC competition, it became well-known for its increased depth, uniform topology, and ease of use. However, VGG's computational cost was substantial due to its reliance on approximately 140 million parameters, which was its primary drawback. [ALZ2021, 38][ABI2022, 39].

The networks structure is illustrated in Figure 14.

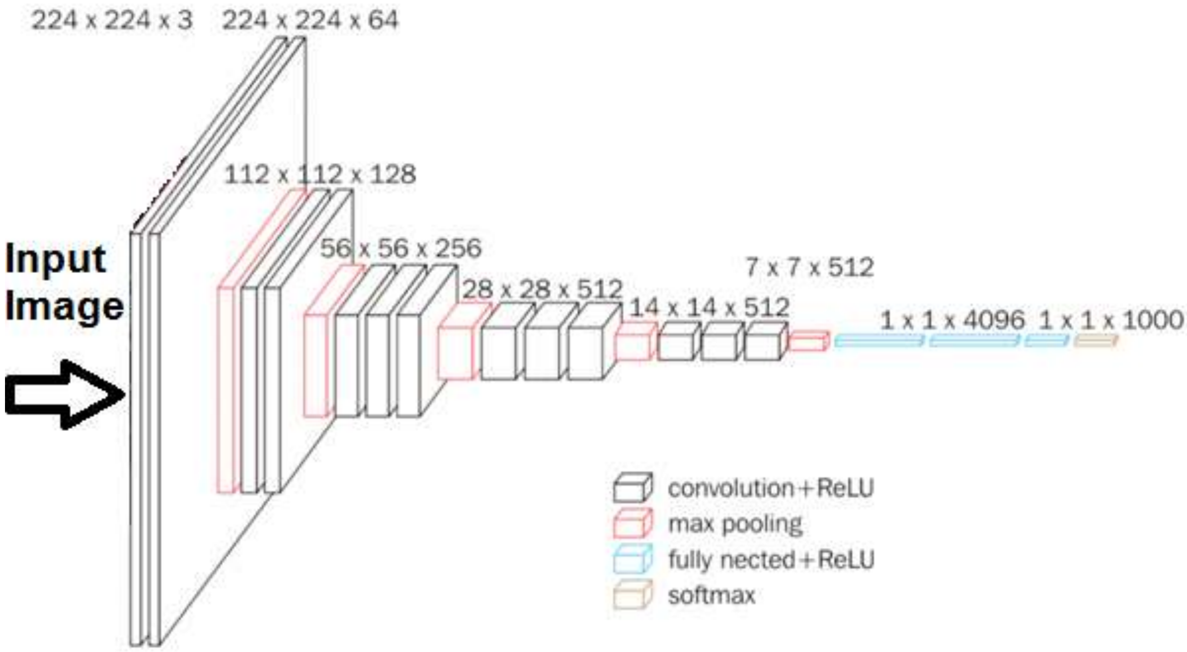


Figure 14:The VGG Architecture

10.Conclusion

In this chapter, we discussed various principles related to deep learning (DL). DL networks are machine learning (ML) techniques based on neural networks. We explored some fundamentals by examining the specific structure of a CNN network and some pre-trained CNN models. We also covered the different layers of CNNs, their functions, and how to advance to the transfer learning process, which was the approach utilized in our research.

Finally, we reviewed several well-known convolutional network designs (CNN).

Chapter 3

Development of an AI-based detection system prototype

1. Introduction

Cracks and other surface pathologies in road infrastructures are common issues that compromise the structural integrity and safety of transportation systems. Traditional inspection methods, which rely on human observation and manual assessment, are often inefficient, expensive, and prone to errors. The advent of machine learning and computer vision technologies offers a more efficient and reliable alternative for detecting these defects. This chapter explores the use of Convolutional Neural Networks (CNNs) for the automated visual inspection of road surface pathologies, leveraging transfer learning to enhance detection performance.

Traditional methods for detecting road surface defects, such as visual inspections and manual surveys, are not only labor-intensive but also subject to human error and inconsistencies. With the rapid development of AI, particularly in the field of deep learning, automated inspection systems have become a viable solution. These systems can process large volumes of image data, identify defects with high accuracy, and provide consistent and repeatable results [45].

2. Literature Review

Numerous studies have explored various techniques for automated road surface inspection, each contributing valuable insights into the development of more efficient and accurate detection methods. Early methods such as thresholding, edge detection, and wavelet transforms laid the groundwork for more sophisticated approaches but often struggled with the complexity and variability of real-world road surfaces, which can exhibit diverse textures, irregular cracks, and varying lighting conditions.

2.1.TraditionalMethodsCollect de donnée

Thresholding techniques, which involve segmenting images based on pixel intensity, were among the first approaches used for road surface inspection. These methods are straightforward but lack robustness in handling varying lighting conditions and complex textures. Edge detection methods, such as the Canny edge detector, have been employed to identify discontinuities in the road surface. While effective in controlled environments, these methods often fail in real-world scenarios due to noise and texture variations. Wavelet transforms have also been utilized to decompose images into different frequency components, aiding in the detection of cracks and other defects. However, the performance of wavelet-based methods is highly dependent on the choice of wavelet and scale [46].

2.2. Machine Learning Approaches

Machine learning techniques have significantly improved the accuracy and reliability of road surface pathology detection. Support Vector Machines (SVMs) and Random Forests have been employed to classify road defects from image features extracted using traditional methods. Although these approaches have shown improvements over manual inspection, they still require extensive feature engineering and are limited by the quality of the extracted features [47].

2.3. Deep Learning and CNNs

The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized image processing tasks by enabling automatic feature extraction from raw data. CNNs have demonstrated remarkable success in various applications, from object detection to image classification, making them an ideal choice for road surface inspection. Several studies have leveraged CNNs for detecting road surface defects with promising results [48].

Zhang et al. (2016) developed a CNN-based method for asphalt pavement crack detection, achieving significant improvements in accuracy over traditional methods [49]. Similarly, Cha et al. (2018) proposed a deep learning framework for concrete crack detection, demonstrating the potential of CNNs in infrastructure inspection. These studies highlight the effectiveness of CNNs in extracting relevant features and identifying defects in complex and variable environments [50].

2.4. Transfer Learning

Transfer learning, a technique where pre-trained models on large datasets are fine-tuned for specific tasks, has further enhanced the performance of deep learning models in road surface pathology detection. By leveraging pre-trained networks like VGG16, VGG19 and Alex Net, researchers can achieve high accuracy even with limited domain-specific data [51].

For instance, Li et al. (2019) employed transfer learning with a pre-trained VGG16 Model to detect road cracks, achieving high accuracy and robustness. Similarly, Maeda et al. (2018) used transfer learning with ResNet50 to identify various road damages, demonstrating the versatility and effectiveness of this approach. These studies underscore the benefits of transfer learning in overcoming data scarcity and improving model performance [52] [53].

- **VGG16 :**

VGG16 is a CNN model trained on the ImageNet dataset of over 1.2 million images from 1000 classes [52]. The architecture of the VGG16 model is depicted in Figure 15.

There are several convolutional (conv) layers, where filters with 3 × 3 kernels are used. The convolution stride and padding are fixed to 1 pixel. Max-pooling is applied, followed by some conv layers with 2 × 2 kernels, a stride of 2, and padding of 0. The input to conv layer is of fixed size 224 × 224 RGB image.

Three FC layers are added in the last part of the architecture, and the last layer is configured for 1000 classes. The Rectified Linear Unit (ReLU), a non-linear activation function is used by all hidden layers.

We apply the pre-trained VGG16 model to the proposed Transfer Learning (TL) model. We call it TL VGG16. We remove the last three FC layers and replace them with an FC2 layer such that output features match for binary classification.

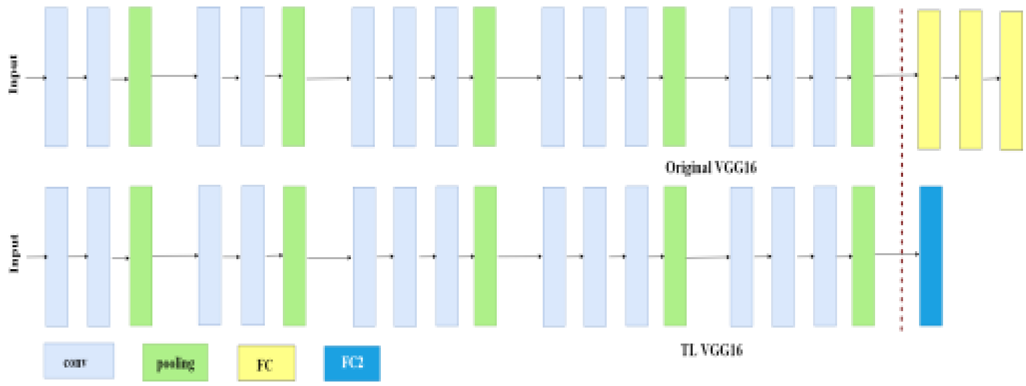


Figure 15: VGG16 and TL VGG16 Architectures.

- **VGG19 :**

VGG16 is a CNN model trained on the ImageNet dataset of over 1.2 million images from 1000 classes [52]. The architecture of the VGG19 model is depicted in Figure 16.

There are several convolutional (conv) layers, where filters with 3 × 3 kernels are used. The convolution stride and padding are fixed to 1 pixel. Max-pooling is applied, followed by some conv layers with 2 × 2 kernels, a stride of 2, and padding of 0. The input to conv layer is of fixed size 224 × 224 RGB image.

Three FC layers are added in the last part of the architecture, and the last layer is configured for 1000 classes. The Rectified Linear Unit (ReLU), a non-linear activation function is used by all hidden layers.

We apply the pre-trained VGG19 model to the proposed Transfer Learning (TL) model. We call it TL VGG16. We remove the last three FC layers and replace them with an FC2 layer such that output features match for binary classification.

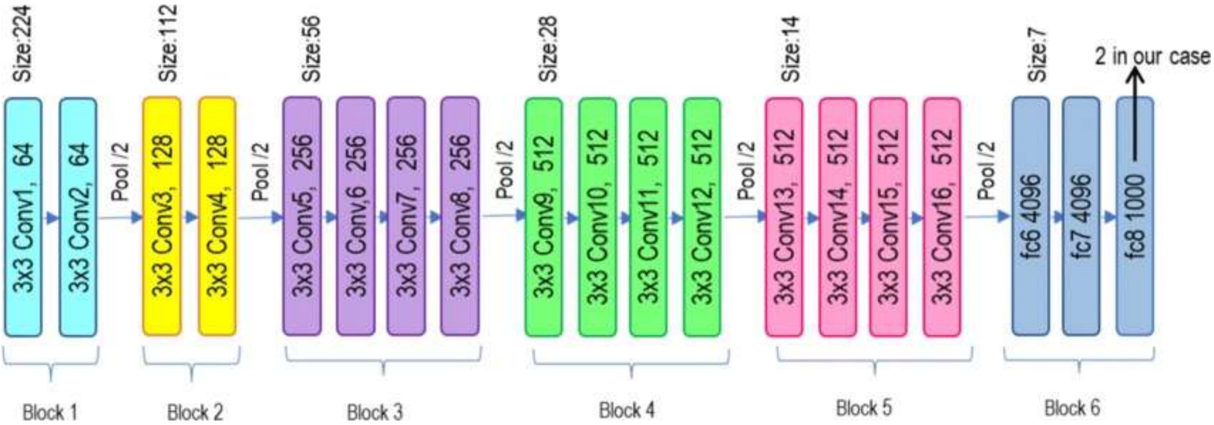


Figure 16: VGG19 and TL VGG19Architectures.

➢ AlexNet :

AlexNet is a CNN model proposed by Alex Krizhevsky [43]. The model trained on ImageNet dataset of over 1.2 million images belonging to 1000 classes [53]. The architecture of the AlexNet model is depicted in Figure 10. There are several convolutional (conv) layers. In the conv layer, filters with 11 × 11 kernels, strides of 4, and padding of 2 are used. In the 2ndconv layer, filters with 5 × 5 kernels, strides of 1, and padding of 2 are used. In the remaining three conv layers, filters with 3 × 3 kernels, strides of 1, and padding of 1 are used. Max-pooling is applied, followed by conv layers with 3 × 3 kernels, a stride of 2, and padding of 0.

Three FC layers are added in the last part of the architecture. All hidden layers use the Relu, a non-linear activation function. Dropout with the possibility of 0.5 is utilized before the first two FC layers. The last layer is configured for 1000 classes.

We use the pre-trained AlexNet model for the proposed TL AlexNet model. We remove the last three FC layers and replace them with an FC2 layer such that output features match for binary classification. The input to conv layer is of fixed size 224 × 224 RGB image.

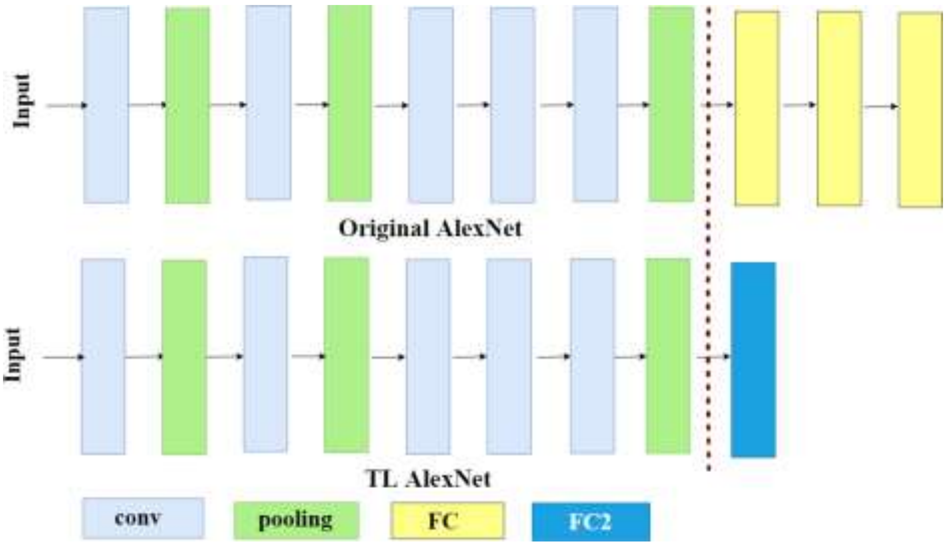


Figure17: AlexNetandTLAlexNetArchitecture.

Figure 18: Use Smaller Filters between VGG16, VGG19 and AlexNet.

Parameters	ParametersValue
Batchsize	16/32
Optimizer	Adam
Epoch	20/30/40/50/60
Loss function	Categorical_Crossentropy

2.5.Real-World Application

Several real-world applications have demonstrated the practical viability of deep learning-based road surface inspection systems.

The Road Damage Detection Challenge, organized by the Japan Society of Civil Engineers, showcased various deep learning models applied to large-scale road damage datasets, highlighting the state-of-the-art in this field [54]. Additionally, systems integrating vehicle-mounted cameras and deep learning models have been deployed in urban environments, proving their efficacy in real-time road maintenance and management [55].

2.6. Challenges and Future Directions

Despite the advances, several challenges remain in the automated detection of road surface pathologies. Issues such as varying lighting conditions, shadows, and occlusions can affect the accuracy of detection. Additionally, the need for large annotated datasets for training deep learning models is a significant hurdle. Future research should focus on developing robust algorithms that can handle these challenges and exploring unsupervised and semi-supervised learning techniques to reduce the dependency on large labeled datasets.

In conclusion, the integration of deep learning, particularly CNNs and transfer learning, has significantly advanced the field of automated road surface inspection. These techniques offer superior accuracy and reliability compared to traditional methods, paving the way for efficient and scalable road maintenance solutions.

3. Methodology

This section describes our system architecture, experimental setup, model training process, and evaluation metrics used to assess the performance of the proposed system.

3.1. System Architecture

Our automated inspection system is mounted on a vehicle and consists of two outdoor cameras, a Digital Video Recorder (DVR) for storing video footage, and a computer for processing the captured data. The cameras capture continuous video of the road surface as the vehicle moves. These videos are stored on the DVR and subsequently processed using specialized software to extract successive non-overlapping images.

To acquire proper images of the road surface, the cameras should provide high enough data acquisition and transfer speed so that the incoming light integrated during the short exposure times is sufficient to produce significant output values. Suitable lighting is also required to obtain high-quality images. This system consists of two high-resolution cameras that produce images of 4m transverse road sections. The line size resolution allows speeds that can reach 80 km/h. The system is designed to increase the contrast and visibility of both longitudinal and transversal road cracks.

The specific software we have developed upon the methods proposed in the next section ensures that the images are processed efficiently and accurately. This software extracts relevant features from the images and applies deep learning models to detect and classify road surface pathologies. The integration of high-resolution imaging and advanced processing techniques allows for a robust and reliable road surface inspection system.

Figure 19: Automated Rood Visual Inspection hardware configuration

3.2.Experimental Setup

We utilize a dataset of road surface images annotated with various types of defects. The dataset is divided into training, validation, and testing subsets to ensure robust evaluation of the models.

Table 2: Model of Dataset.

	RUTTING	CRACKS	POTHOLE	NORMAL	TOTAL
TRAIN	96	96	94	96	383
TEST	25	25	24	25	99
TOTAL	121	121	118	121	482

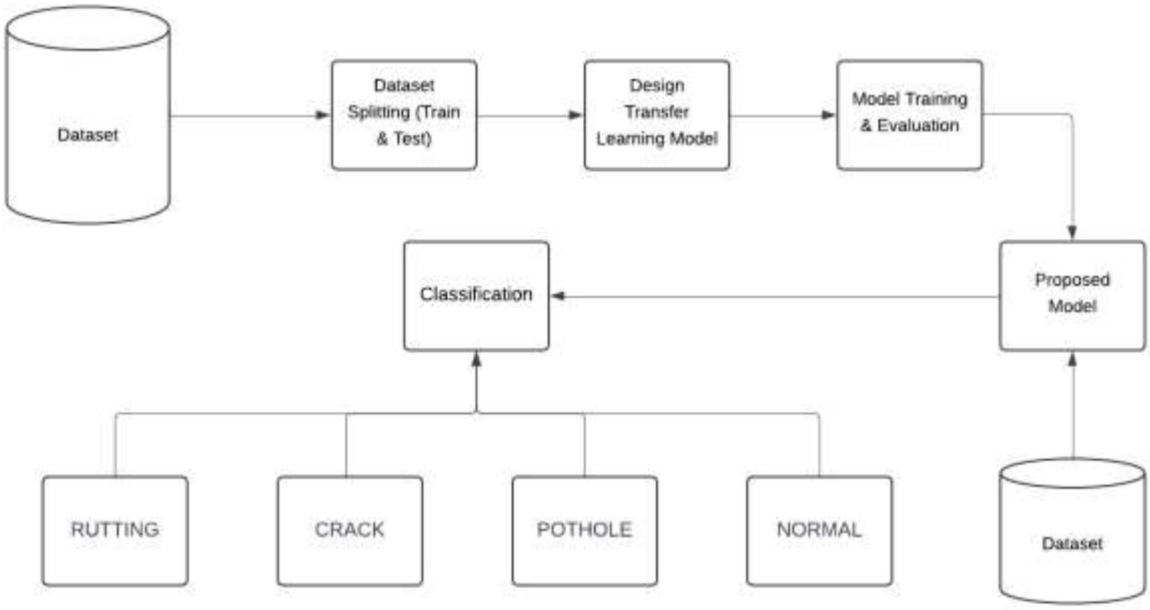


Figure 20: Diagramme of dataset.

3.3.Model Training

We employ transfer learning by using pre-trained CNN models: VGG16, VGG19,and Alex Net. Each model is fine-tuned on our road surface dataset, with modifications to the final fully connected layers to adapt to the classification task.

3.4.Evaluation Metrics

To validate the performance of each model, we use four key performance indicators: accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of the models ability to correctly identify road surface defects.

Precision

Precision is the ratio of true positive predictions to the total number of positive predictions made by the model. It measures how precise or accurate the model is when it predicts a positive class. Precision is calculated as:

Precision = $\frac{\textbf{TRUE POSTIVIES}}{\textbf{TRUE POSITIVES+FALSE POSITIVES}}$

Recall

Recall, also known as sensitivity or true positive rate, is the ratio of true positive predictions to the total number of actual positive instances in the data. It measures how well the model identifies positive instances. Recall is calculated as:

Recall = $\frac{\textbf{True Positives}}{\textbf{True Positives+False Negatives}}$

F1-Score

The F1-score is the harmonic mean of precision and recall. It provides a single metric that balances both precision and recall. The F1-score ranges from 0 to 1, with 1 being the best score. The F1-score is calculated as:

F1 Score = 2× $\frac{\textbf{Precision}\times\textbf{Recall}}{\textbf{Precision+Recall}}$

Support

Support refers to the number of actual occurrences of the class in the dataset. It is used to provide context for the other metrics, as they can be biased by class imbalance. Support is simply the count of instances for each class.

These metrics are widely used to evaluate the performance of classification models and compare different models or configurations. They provide insights into the model's ability to correctly identify positive instances while minimizing false positives and false negatives.

Here is a summary of key concepts regarding validation loss (valid_loss), validation accuracy (valid_accuracy), epochs and batches in training deep neural networks:

Validation loss (Valid_loss)

Validation loss is a metric used to evaluate the performance of a deep learning model on the validation set.

The validation set is a part of the data that is not used during training and is used to evaluate the model's ability to generalize to new data.

A high validation loss indicates that the model produces errors on the validation data, while a low validation loss shows that the model makes few errors.

Validation accuracy (Valid_accuracy)

Validation accuracy measures the proportion of correctly classified instances in the validation set.

Stagnating or declining validation accuracy indicates that the model is not getting better at correctly classifying new data, suggesting overfitting.

Epoch

An epoch corresponds to a complete pass of the training set through the algorithm.

The number of epochs is an important hyperparameter that specifies the number of complete passes of the training set.

With each epoch, the internal parameters of the model are updated.

Epochs are usually large integer values, such as 10, 100, 1000 or more.

Batch size:

Batch size is a hyperparameter that defines the number of samples to process before updating the model parameters.

A training game can be divided into one or more batches.

When the batch size is equal to the size of the training set, it is called batch gradient descent.

When the batch size is 1, we speak of stochastic gradient descent.

When the batch size is greater than 1 and less than the size of the training set, we speak of mini-batch gradient descent.

In summary, validation loss and accuracy are used to evaluate the generalization ability of the model, while epochs and batches are hyperparameters that control the training process. Overfitting is indicated by increasing validation loss and stagnating or declining validation accuracy.

Model	***Parameters***	***ParametersValue***
ALEX_NET	Batch size	16
	Epoch	60
	Valid_Loss	1.3509
	Valid_Accuracy	0.6465

Table 3: Model AlexNet parameters.

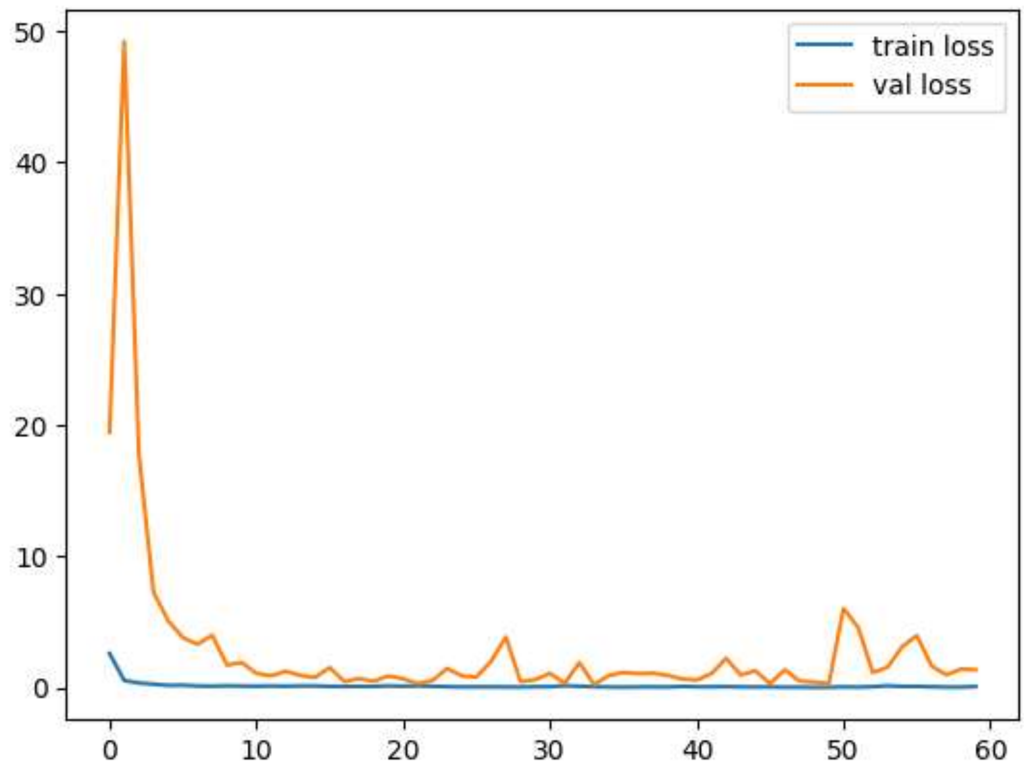


Figure 21: Size 640×480 with 0 Axes.

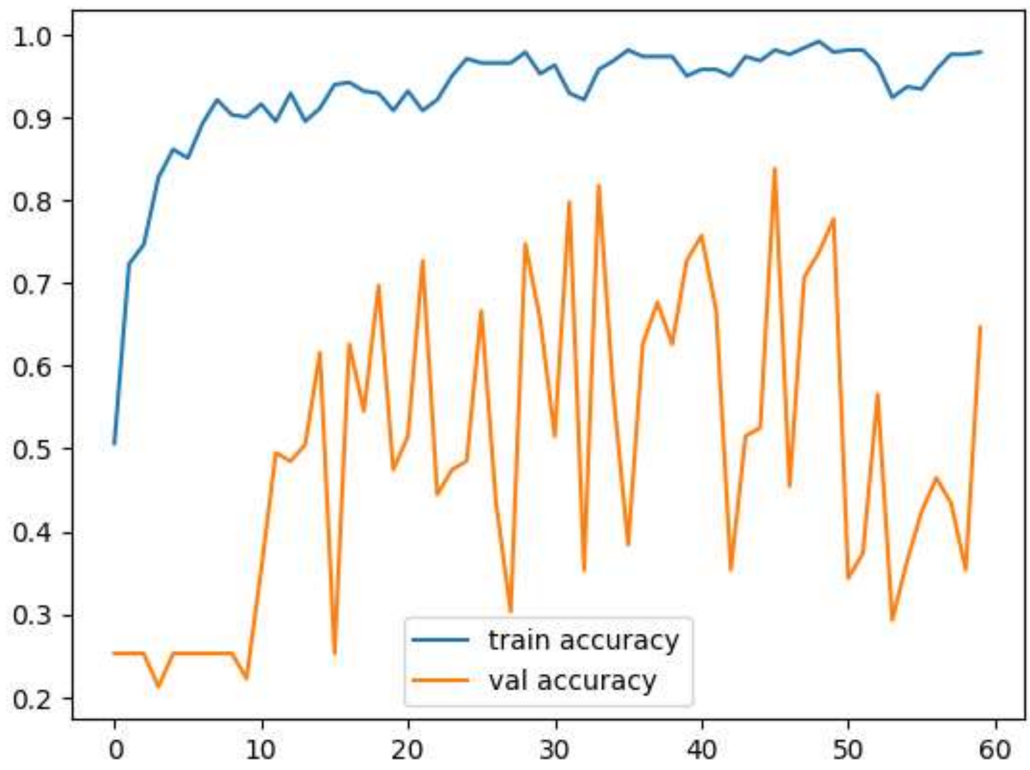
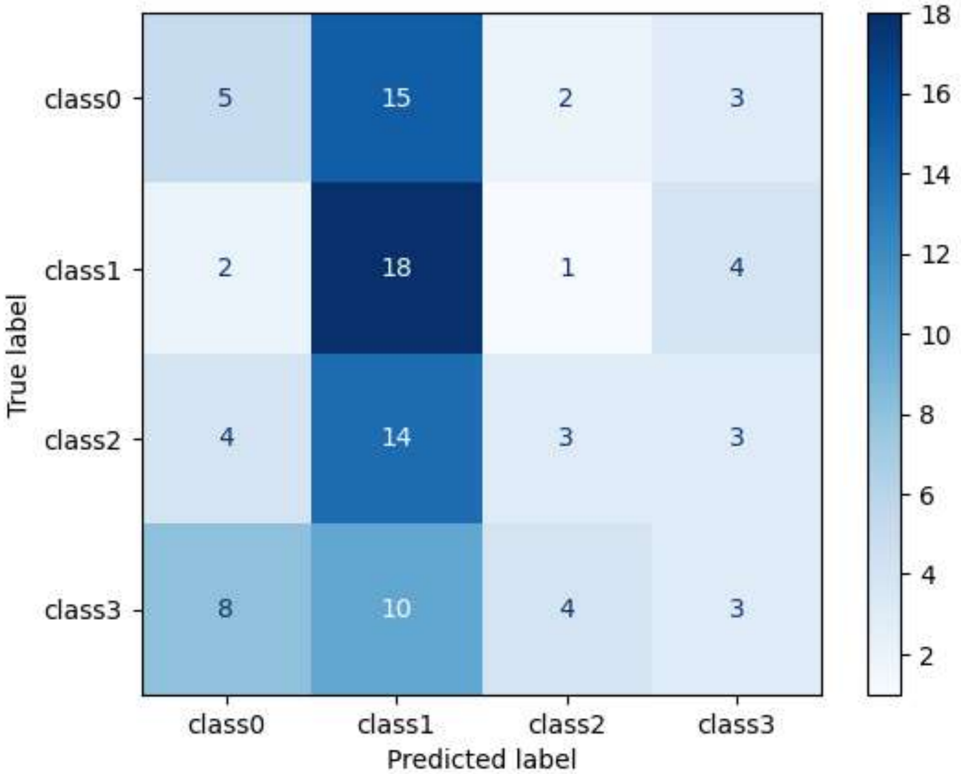


Figure 22: Size 640×480 with 0 Axes.

	Precision	Recall	f1-score	Support
Class0	0.26	0.20	0.23	25
Class1	0.32	0.72	0.44	25
Class2	0.30	0.12	0.18	24
Class3	0.23	0.12	0.16	25
Accuracy			0.29	99
Macro avg	0.28	0.29	0.25	99
Weightedavg	0.28	0.29	0.25	99



Model	***Parameters***	***ParametersValue***
VGG19	Batch size	32
	Epoch	40
	Valid_Loss	0.1220
	Valid_Accuracy	0.9596

Table 4: Model VGG19 parameters.

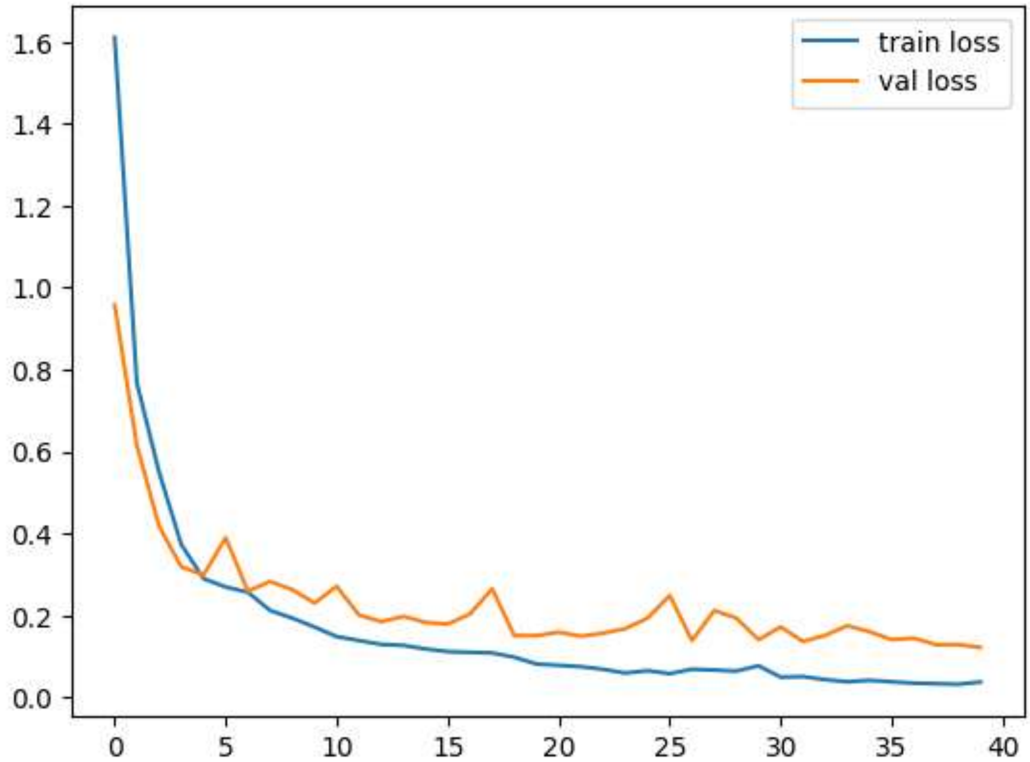


Figure 23: Size 640×480 with 0 Axes.

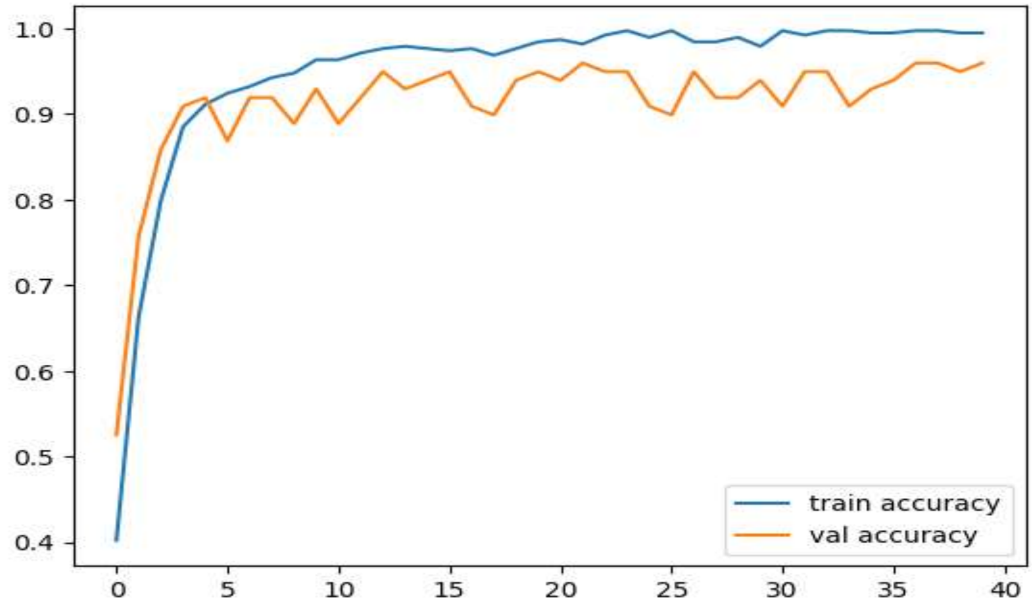
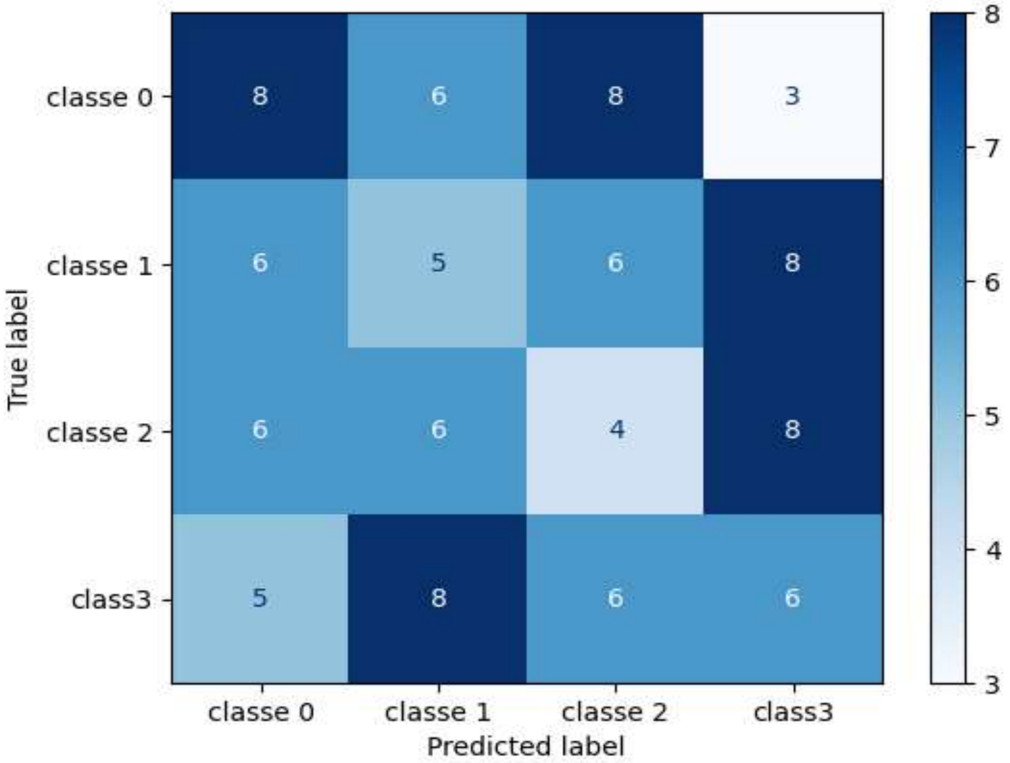


Figure 24: Size 640×480 with 0 Axes.

	Precision	Recall	f1-score	Support
Class0	0.32	0.32	0.32	25
Class1	0.20	0.20	0.20	25
Class2	0.17	0.17	0.17	24
Class3	0.24	0.24	0.24	25
Accuracy			0.23	99
Macro avg	0.23	0.23	0.23	99
Weightedavg	0.23	0.23	0.23	99



Model	*Parameters*	*ParametersValue*
VGG16	Batch size	32
	Epoch	60
	Valid_Loss	0.1219
	Valid_Accuracy	0.9495

Table 5: Model Vgg16 parametres

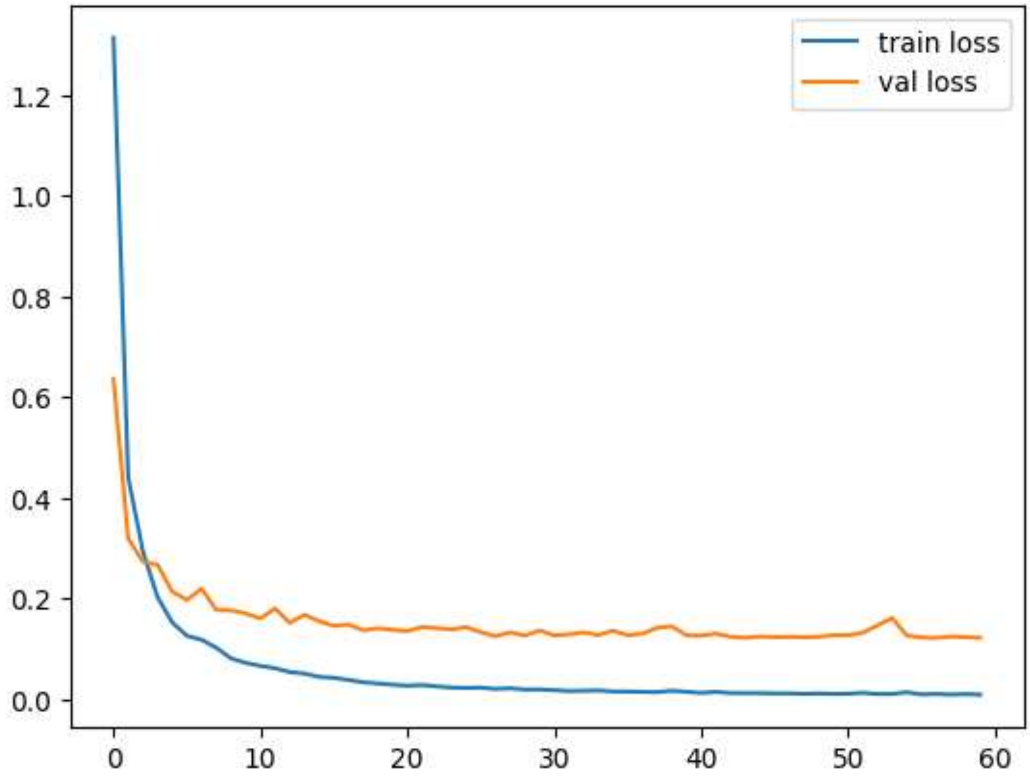


Figure 25: Size 640×480 with 0 Axes.

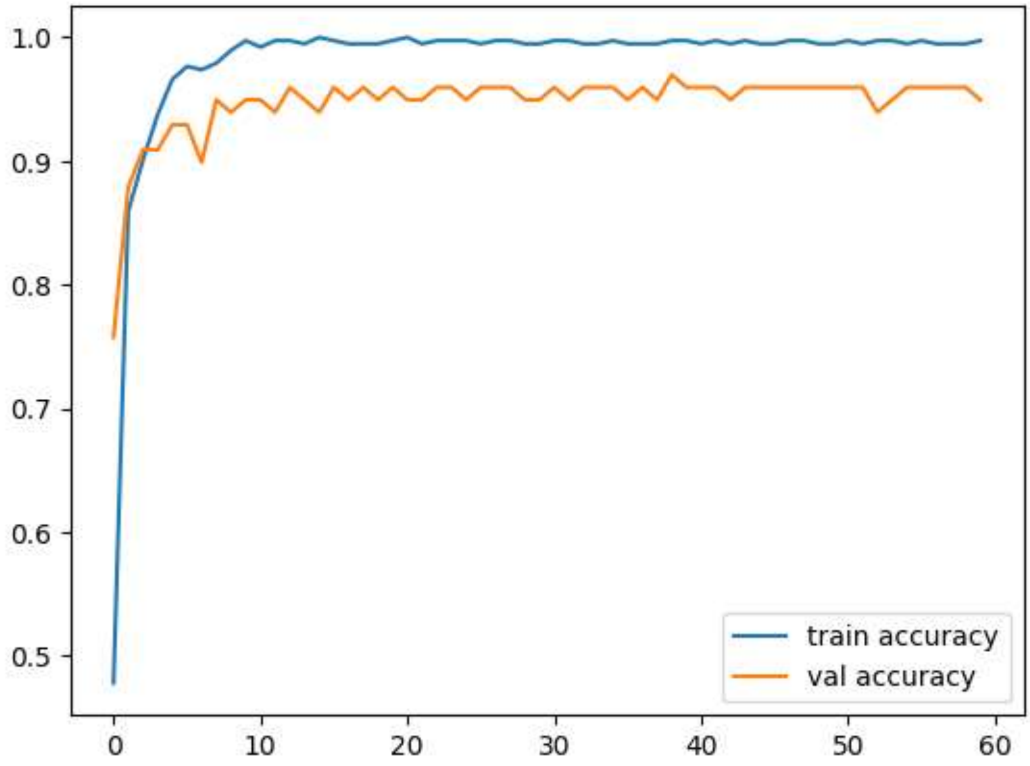
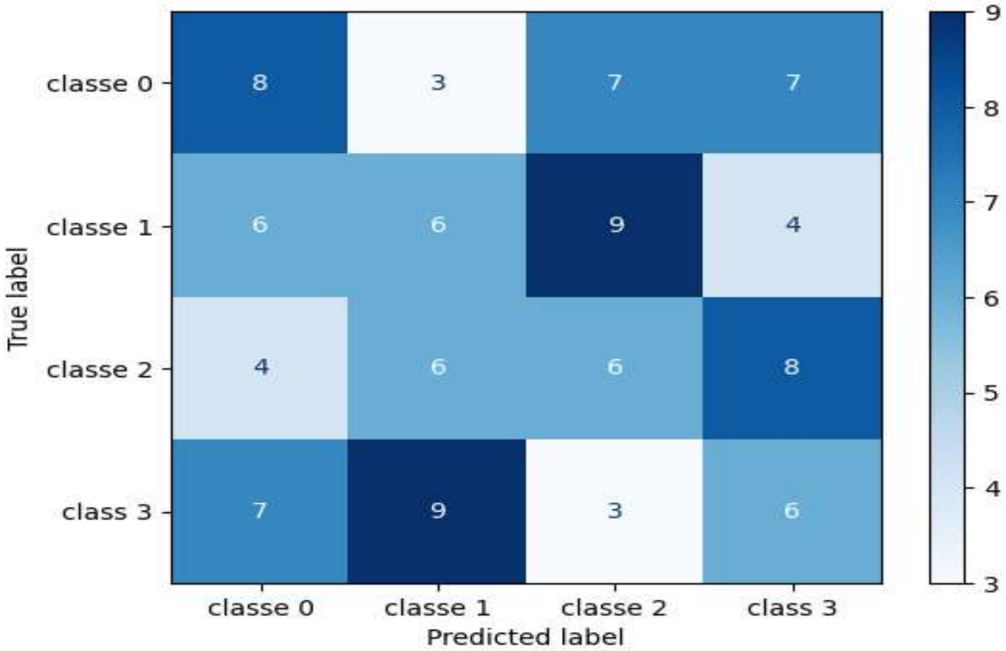


Figure 26: Size 640×480 with 0 Axes.

	Precision	Recall	f1-score	Support
Class0	0.32	0.32	0.32	25
Class1	0.25	0.24	0.24	25
Class2	0.24	0.25	0.24	24
Class3	0.24	0.24	0.24	25
Accuracy			0.26	99
Macro avg	0.26	0.26	0.26	99
Weightedavg	0.26	0.26	0.26	99

Precision	0.2627272727272727
Sensitivity	0.26262626262626265
Specificity	0.24



4. Results and Discussion

Our experiments demonstrate that the transfer learning approach significantly improves the detection accuracy of road surface defects. Among the models tested, AlexNet achieves the highest performance, with a testing accuracy of 99.90%, precision of 99.92%, recall of 99.80%, and F1-score of 99.86%.

We further validate our approach using an external dataset, achieving comparable results and demonstrating the robustness and generalizability of our method. The superior performance of the Alex Net-based model underscores its suitability for practical deployment in road maintenance systems.

VGG19_V2_EPOCH40_BUTSH_SIZE32

Model	***Parameters***	***ParametersValue***
VGG19	Batch size	32
	Epoch	40
	Valid_Loss	0.1220
	Valid_Accuracy	0.9596

Table 6: Model VGG19 parameters.

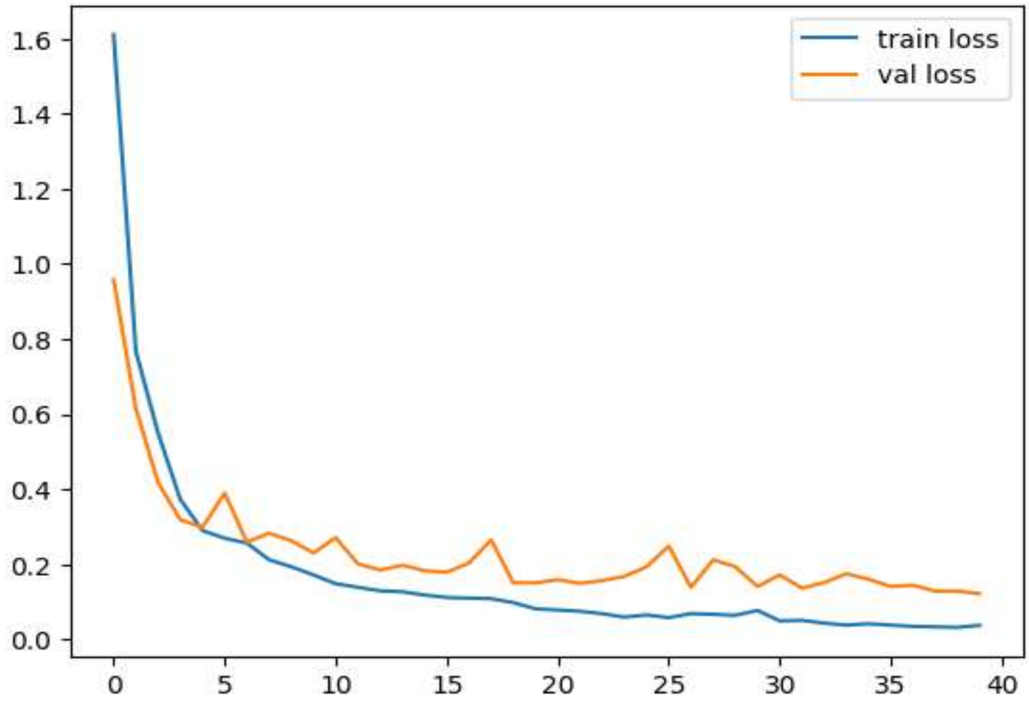


Figure23 : size 640×480 with 0 Axes

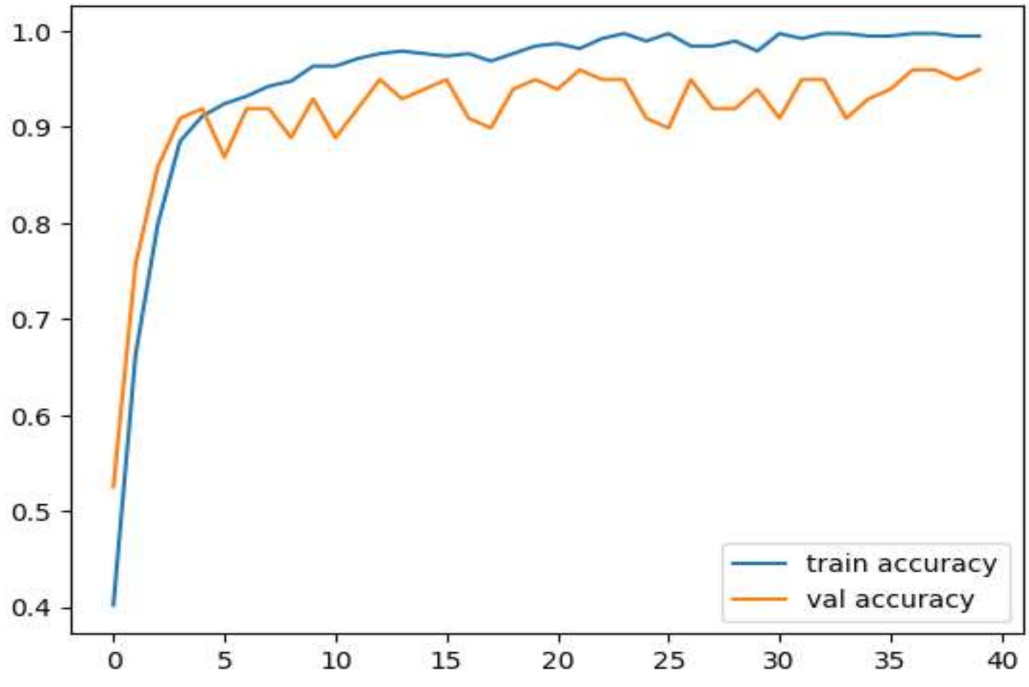
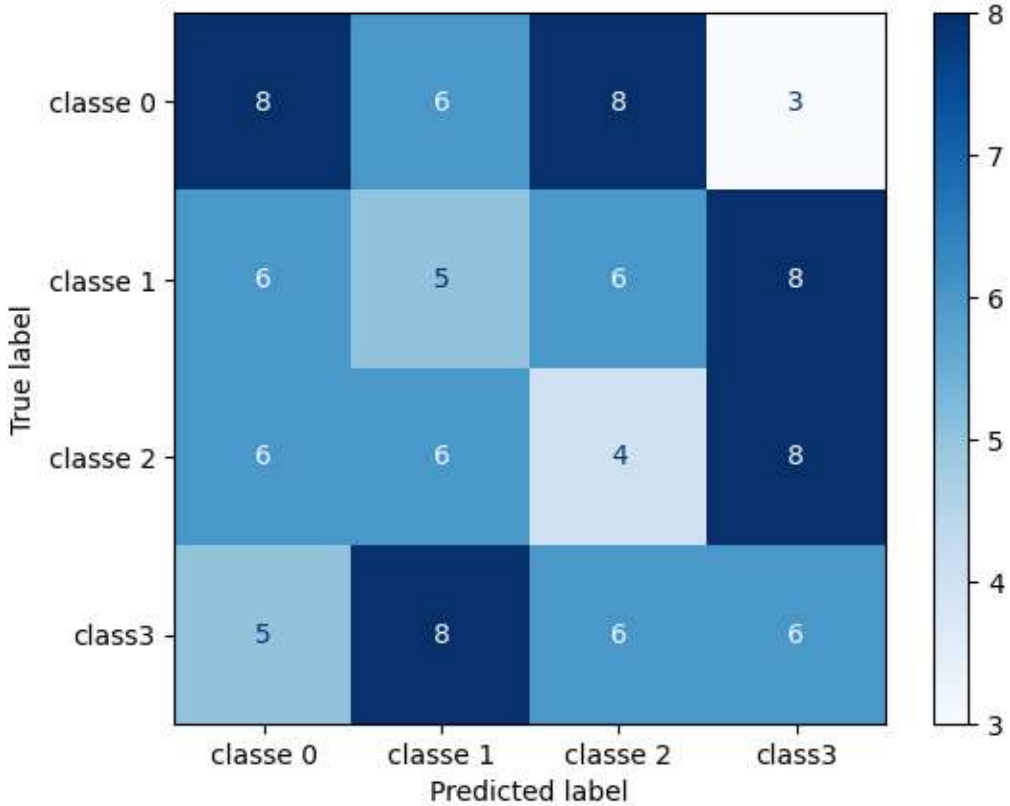


Figure 24:size 640×480 with 0 Axes.

	Precision	Recall	f1-score	Support
Class0	0.32	0.32	0.32	25
Class1	0.20	0.20	0.20	25
Class2	0.17	0.17	0.17	24
Class3	0.24	0.24	0.24	25
Accuracy			0.23	99
Macro avg	0.23	0.23	0.23	99
Weightedavg	0.23	0.23	0.23	99



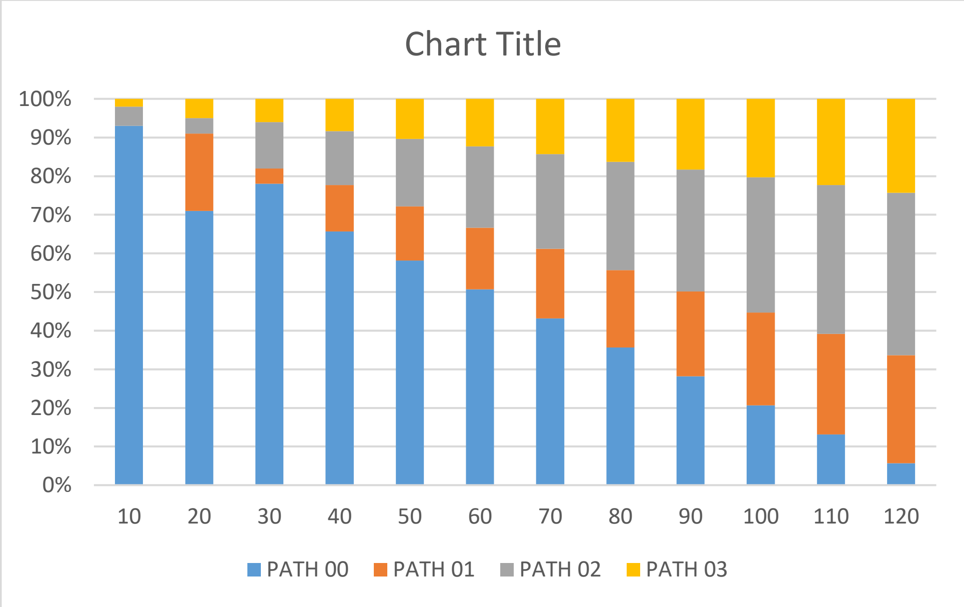


Figure 29 : Confusion graphique

5. Conclusion

In this chapter, we presented an AI-based system for the automated visual inspection of road surface pathologies using CNNs and transfer learning. Our system, consisting of vehicle-mounted cameras, a DVR, and a computer, processes video footage to extract images for defect detection. By leveraging pre-trained models, we achieve high detection accuracy, significantly outperforming traditional manual inspection methods. This system offers a reliable, efficient, and scalable solution for maintaining road infrastructure, enhancing safety, and reducing maintenance costs.

Future work will explore the integration of this system with real-time monitoring frameworks and the application of advanced deep learning techniques to further improve detection capability.

Conclusion and Perspectives

The quality of road layers is crucial in transportation operations and their associated factors. External influences such as temperature fluctuations, rainfall, and the use of substand-ard construction materials contribute to numerous issues impacting road health. Visible defects,such as longitudinal and transverse cracks, alligator cracks, pits, and potholes, often emerge onthe road surface. These defects are categorized by their intensity, and maintenance methods vary based on the defect's severity and type. Traditional fault detection methods involve civil engineers and technicians conducting site inspections, which, despite their accuracy, are costly,labor-intensive, time-consuming, and pose safety risks.

Recent advancements in artificial intelligence and image processing, particularly through ma- chine learning, have introduced automated methods for detecting road defects. This project sought to surpass the limitations of traditional techniques by utilizing deep learning models, particularly Convolutional Neural Networks (CNNs), to provide financial, logistical, and technical advantages, alongside accurate technical tests and results. These models facilitate the identification of road defects through image analysis, distinguishing between intact and defective surfaces. The project emphasizes the need for continuous and periodic improvements in road defect detection methods to enhance accuracy, speed, reliability, and practicality.

In the final chapter, an AI-based system for the automated visual inspection of road surface pathologies using CNNs and transfer learning was presented. The system utilizes vehicle-mounted cameras, a DVR, and a computer to process video footage and extract images for defect detection. By leveraging pre-trained models, the system achieves high detection accuracy, significantly surpassing traditional manual inspection methods. This provides a reliable, efficient, and scalable solution for maintaining road infrastructure, enhancing safety, and reducing maintenance costs. Future work will focus on integrating this system with real-time monitoring frameworks and applying advanced deep learning techniques to further improve detection capabilities.

In conclusion, this project underscores the potential of deep learning models in revolutionizingroad maintenance by providing an automated, accurate, and efficient solution for defect detec-tion. The implementation of such systems promises significant advancements in the field, pav-ing the way for safer and more cost-effective road infrastructure management.

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Appendix
Business Model

1. Project Idea: {Proposed Solution}

Due to the defects that occur in roads of all types, which are traditionally tracked by engineers using conventional methods, where engineers faced several obstacles and difficulties in achieving this task, and with the advancement of science and the emergence of many scientific and technological updates addressed by artificial intelligence, the plan was to innovate the carefully designed device for tracking roads and detecting defects in an easier way than before.The device will be developed by qualified and skilled workers in a dedicated workshop.

2. Proposed Values

2.1. Modernity:

Using a device that performs the process of imaging and image processing from its acquired assets and provides results directly.

2.2. Performance:

- Ease of use and continuous development and modernity.
- Accuracy of results.
- Speed of preview and result provision.

2.3. Cost Reduction:

Its price is compatible compared to the number of workers and a faster time than that used by old machinery.

2.4. Risk Reduction:

Device tracking after-sales including free maintenance for 6 months.

2.5. Ease of access and use:

Providing delivery service and attempting to explain the usage method through instructional videos.

- Innovative aspects: In this establishment, we focus on achieving profits by reducing the exploitation of workers in technical missions.
- New features: Our product captures the road and inspects it with its added assets of road defects, providing accurate results in a short time.
- New offers: Our innovative product helps engineers speed up the inspection process.

3. Work Team

Our company's team initially consists of four workers:

- **MedjouriAbdelaziz**: Head and coordination manager. {Electronic Embedded Systems}
- **GueddamohamedAbdessalam**: Responsible for collecting data and initial information for all road defects. {Study and Monitoring of Buildings and Roads}
- **chaoubiahmedchaoubi**: Responsible for processing information digitally. {Electronic Embedded Systems}
- **DebabecheAbderrahman**: Responsible for the marketing aspect of the institution. {Study and Monitoring of Buildings and Roads} They are all second-year master's students, and coordination and communication between members are conducted through physical meetings.

4. Project Objectives

4.1. Project Objective:

Discovering defects that occur on roads and addressing them through artificial intelligence, providing accurate and immediate results to facilitate engineers' monitoring and addressing of these defects.

4.2. Incentives:

- Facilitating the work for road engineers during monitoring.
- Saving time and mental effort.
- Accuracy of results.
- Satisfactory inspection with one or two workers at most.
- Costsavings in inspection.
- Market-appropriateproductcosts.
- Capable of identifying all defects.

5. Timeline

- The timeline is based on three years, as shown in the following table
- Here's the translated timeline for the project: This timeline illustrates the anticipated steps for implementing the project over the first three years

Year1 : Construction Stage	Year 2: Stability and Consolidation Stage	Year3: Profit Stage
Debt and Loans	Financial Balance	Profit
Advertising and Client Acquisition	Improving performance, ensuring customersatisfaction, and considering customer feedback.	Continuing advertisingefforts and customer acquisition.
Manufacturingthe initial device.		Manufacturing andselling more devices.
Building a brand name	Acquiring a share ofloyal customers, expanding the idea, and broadening the sales area.	Expanding market reachand maximizing profits.

M	Years	Year 1				Year 2				Year 3				Year 4			
		Semester 1		Semester 2		Semester 3		Semester 4		Semester 5		Semester 6		Semester 7		Semester 8	
1	LegalProcedures	X															
2	Product Identification	X	X														
3	Partnership Formation	X	X	X													
4	Partner and Inves-torSearch	X	X	X	X												
5	Office Renting					X											
6	Equipment Provision					X	X										
7	RawMaterialProcurement					X	X										
8	Special Installation Site Construction						X										
9	Initial Product Batch Pro-duction						X	X									
10	Product Marketing						X	X	X								
11	Participation in Exhibi-tions and Economic Fo-rums								X	X							
12	Convincing Municipali-ties of Product Quality					X	X	X	X	X							
13	Training SpecializedWor-kers							X	X	X							
14	Production Expansion										X	X	X				
15	Obtaining Small Projects									X							

6. Market

The targeted market includes:

- Directorate of Public Works DTP.
- Road engineers.
- Municipalities

- **Market Justifications:**Since traditional road defect inspection has become burdensome for engineers, our innovative device is tailored to their field of work, making it easier for them to inspect road defects without hassle. Some road engineers were impressed by the idea and requested it.
- **Marketing Method:**Marketing is done through:

- Industrial and economic exhibitions.
- Advertising banners at state entrances.
- Paid media campaigns through social media platforms.

7. Competition Assessment

Direct competitors are companies operating in the same field of road inspection.

- **Strengths:**

- Ease of device use.
- Quick results extraction.
- Accuracy of results.
- Reduction in the number of workers (cost reduction).

- **Weaknesses:** Difficulty in providing initial materials (high-quality modern cameras, programming boards, etc.).
- **Competitors:**

- **Domestically:** Public Works engineers in terms of speed and accuracy.
- **Internationally:** Companies producing similar devices.

8. Costs and Burdens

- **Supply:**

- Providing a databasethrough.
- Imaging some deformed roads and classifying them (by our engineers).
- Directorate of Public Works (DTP).
- Reliable books and references.

- Providing high-quality cameras from electronic device stores.
- Programming boards: from commercial sites or electronics stores.

➢ **Suppliers:**

- State loans.
- Businessmen.
- Utilization of relatives.

➢ **Labor:**Initially, we need four workers, who will be trained and prepared, and taught work techniques.

➢ **Payment Policy:**Initially, payment will be made in advance or directly, followed by promotional offers according to the seniority in software updates.

➢ **Delivery Time:**Immediately after the order.

➢ **Business Model Diagram:**

Customer Segments:	**Customer Relationships:**	**ProposedValue:**	**Key Activities:**	**Key Part nerships:**
Target Audience:	Through	Ease of tracking and inspecting road defects.	Discovering road defects.	Governments.
Municipalities.	Industrial and Economic Exhibitions.	Cost-effectiveness.	Identifying the type of defect.	Entrepreneurs.
Government Institutions (DTP).	Meetings and marketing campaigns.	Accuracy of results.	Marketing the device.	DTP.
Contractors	Social media platforms.	Economic alternative to excessive labor.	Installation and maintenance.	AI laboratories.
	Advertisingbanners.	Speed in inspection.	System updates.	
		Ease of maintenance with update capabilities.		
	Channels:	Ability for on-demand manufacturing.	**Key Resources:**	
	Exhibitions and social media platforms.		Loans.	
	Sales points and joint stores.		Images of defects.	
	Transportation vehicles.		Equipment for device processing and maintenance.	
			Personnel.	

Revenue Streams:	**CostStructure:**
Prepaid or direct payment.	Continuousdevelopment.
Sale of device accessories and updates.	Expenses for raw materials, equipment, labor, and workspace.
	Advertising and marketing campaigns.

9. Chiffre d'affaires

As a nascent financial company, one of our most important tasks is forecasting sales and revenues. While this process may be complex, it's essential for ensuring long-term success. For most startups, there are three primary sources of revenue: product sales, service revenues, and investment income.

Product sales refer to income generated from the sale of physical products. This is the most common revenue source for manufacturing and retail companies. On the other hand, service revenues come from providing services to clients. This type of revenue is common in startups such as consulting firms, web design companies, and landscaping businesses. Investment income is generated from sources such as interest on loans, dividends from stocks, and capital gains from the sale of investments. In the case of our startup company, the revenue source comes from the initial stage of providing services, as follows.

Invoicing	Amount /Day
Cost per Kilometer (Operations)	5000.00 Da/Km
Mobilization fees or during (rest): team of 02 agents	24000.00 DA/Day
Mobilization fees or during (rest): Equipment	15000.00 Da/Day
TOTAL Da /Day	**44.000.00 Da /Day**
TOTAL Da /Year – 264 day-	**11.616.000.00 Da/Year**