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Pavement damage image classification using deep learning with inspection system: a case study in Morocco

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ABSTRACT

Road and highway authorities rely on pavement management systems (PMS), in particular regular pavement condition inspections, to manage and preserve this infrastructural heritage. To this end, visual surveys are regularly conducted to detect and classify pavement damage, assess pavement condition, and derive performance indicators. However, manual pavement inspection can be a subjective and time-consuming process that requires a high level of skill from those responsible for inspection and monitoring. This study proposes a machine learning (ML) technique to automatically classifying digital images of national road surfaces captured by a camera mounted on a smart vehicle equipped with a multifunctional road inspection system (SMAC). The image dataset, captured on different roads in Morocco, includes five classes of pavement damage and one class of no damage. The experimental results indicate that the ResNet50 model achieves superior classification accuracy of approximately 94%. This research contributes to the automation of road monitoring processes and provides road managers with an effective tool for planning and executing maintenance operations with enhanced reliability and efficiency.

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1. INTRODUCTION

Road infrastructure projects significantly impact economic development by enhancing connectivity, facilitating trade, and attracting foreign investment. Additionally, robust road networks underpin governmental strategic initiatives across diverse sectors such as health, education, and agriculture, thus fostering comprehensive socio-economic development. They ensure civilizational progress and promote greater territorial cohesion [1]. In Morocco, transportation of goods and passengers is the leading driver of economic growth, and the country ranks fifth in Africa and first in the Maghreb region for the quality of its road infrastructure [2]. The country currently has a road network spanning over 57,330 km, comprising national, regional, and provincial roads. Several major development projects are being planned. The aim is to increase the total length of expressways from 1,100 to 3,380 km by 2030, with an additional 2,092 km planned based Ministry of Equipment and Water of Morocco [3], [4].

Road network management is a crucial task that requires special attention from the relevant departments. One of these tasks is to perform a visual inspection to identify and classify the different types of pavement surface deterioration. The objective is to evaluate them in order to make the right decisions regarding maintenance and reinforcement methods, based on performance indicators calculated from the classification. However, if this classification work is done manually, based on human vision, it can be subject to subjectivity, generate errors, and represent a high cost, as it requires time and professional skills [5]. This is why it is necessary to use automated methods of roadway inspection based on computer vision, which offer numerous advantages: speed, high reliability, and reduced costs [6].

The integration of intelligent techniques for pavement inspection is one of the areas of scientific research that is attracting a great deal of interest. Intelligent vehicles such as WayLink and AMES are some of the most widely used data collection vehicles equipped with pavement imaging systems [7], [8]. On the other hand, computer vision algorithms based on deep learning offer significant advantages over traditional methods for damage recognition [9], [10]. In a literature review of pavement practices, Zhang *et al.* [11] showed that deep learning algorithms were present in 42.2% of the pavement damage recognition methods cited in the literature between 2010 and 2023.

The majority of studies have concentrated on detecting and classifying of pavement images using DL approaches. Unfortunately, many of these previous research studies have explored on the classification and detection of a few types of defects that are very common in pavement, such as cracks, which generally have a limited number of classes [12]. For example, despite the excellence of the comparative study between ten convolutional neural networks (CNN) architectures for the purpose of detecting and classifying road cracks, carried out by Matarneh *et al*. [13], who concluded that the DenseNet201 model performed best in terms of accuracy, and despite exploiting two databases, the authors only addressed three degradation classes in this work. On the other hand, the literature is full of studies exploiting public datasets like GAPs [14], CFD, EdmCrack600, and CRACK500 [15], which have several limitations, including excessive standardization of data and a lack of representativeness in real-life conditions. Research using private datasets collected by intelligent vehicles allows for adapting the study and evaluation contexts to homogeneous conditions [16], if the data set is controlled, as is the case in our study, but also to directly apply the results obtained to decision-makers, which strengthens the link between practice and research. Wang *et al*. [17] benefited from image processing and machine learning techniques to create an automatic system based on CNNs to detect road damage. However, to improve representativeness, they expanded the study area of private data collection to four Chinese regions (Shanxi, Sichuan, Zhejiang, and Jiangsu) using the LUKUN3D system, equipped with an imaging system.

The literature on CNN-based pavement degradation image classification distinguishes between comparative studies, which implement several models and provide an overview of performance, and research focused on a single model, whose scope remains limited and partial. Comparative work allows for the identification of relative strengths and weaknesses of the models, while single-model approaches do not allow for direct comparisons. This distinction highlights the value of multiple analyses for assessing the robustness and generalization of CNNs. The U-Net ResNext-101 model, presented by Garita-Durán *et al*. [18], is a CNN that extracts features from crack images to quantify and localize this type of degradation. First, CNNs are used to identify and localize degraded areas. Once the areas are delineated, traditional computer vision approaches, such as edge extraction and Hough Transform, are used to refine the measurements and provide accurate results. Another work to quantify the severity of cracks in Virginia (USA), in accordance with the Fault Identification Manual, and from a dataset containing approximately 4,000 pavement images, was done. Four types of pavement degradation were detected and classified by a four-layer CNN, which gave very good results. After 30 epochs, the model achieved a classification accuracy of more than 96% for the presence of cracks and more than 96.7% for the severity [19].

This study proposes an in-depth comparative examination of eight fundamental CNN architectures for the classification of six classes of pavement images containing a multitude of pavement degradation classes: no distress (ND), potholes (P), transversal cracking (TC), raveling (R), longitudinal cracking (LC), and alligator cracks (AC). Its objective is to determine the best model for classification for the classification of pavement degradations while using a new and real dataset collected in Morocco, which contains a large number of pavement images in a real environment. Therefore, this research provides an indication for researchers and practitioners for the choice of DL models suitable for pavement condition monitoring. The following is the structure of this document: the preceding work in this context is discussed in section 2. The suggested classification approach is detailed in section 3. Section 4 provides an overview of the processing findings and associated discussions. The major conclusions can be found in section 5.

2. RELATED WORKS

Using DL to detect pavement damage is an area of research that has seen significant advances. It includes methods for classification, semantic segmentation, and detection of road damage [20]. The classification section is very important compared to any previous research. For example, the term "crack classification" is the most cited, with a longer burst duration between 2016 and 2023 [21].

In the literature, Ijari and Patermina-Arboleda [22] have used machine learning techniques to develop a GAN-enhanced pavement damage detection and classification system by evaluating the EfficientNetB3, ResNet18, ResNet50, and SwinGAN models. Li *et al.* [23] obtained an accuracy of over 94% for the CNN models used for classifying four classes of pavement cracking and one class of no damage. To improve accuracy and efficiency, the researchers set out to compare the CNN models to derive the best-performing models. Eslami and Yun [24] compared several CNN models for the classification of pavement objects and obtained very good results with the M-VGG19 model, with a very high F-score compared to the other models.

For pavement condition assessment, Zhang *et al.* [20] introduced an innovative hybrid approach combining an object detector with semantic segmentation. This integrated method effectively classified and quantified the severity levels in a comprehensive dataset of 7,237 pavement damage images, thereby providing a more detailed and nuanced evaluation compared to traditional methods. The you look only once (YOLO) model is then trained to recognize damage (potholes and cracks) and train a U-Net model using fully convolutional layers to classify the severity of fracture damage. Matarneh *et al.* [13] concluded that DenseNet201 and the grey wolf optimizer (GWO) are the best models for classifying 2,139 pavement images in three classes (diagonal cracking, longitudinal cracking, and transversal cracking) using three databases (GAP, CrackTree, and CRACK500). Comes with ten pre-trained CNN architectures. The model achieved an accuracy of 94.12%, and the execution time was optimized, which can increase reliability and reduce the cost of manual inspection. The study used a dataset of 7,453 images taken of various types of roads in Ireland and rated them according to pavement condition index (PSCI) [5]. The researchers then used a deep learning architecture to segment roads and classify their condition. The PSCI automated evaluation results showed an average Cohen's Kappa value and F1 value of 0.9 and 0.85, respectively, on a rating scale of 1 to 10. Overall, models using ConvNeXt and SwinV2 outperformed models based on ResNet50. In another paper, Li *et al.* [25] developed deep learning models to automatically classify pavement damage quickly and accurately. They first built a large database containing 18,637 images of four asphalt roads from three provinces in China, divided into 9,017 images of damaged roads and 9,620 images of undamaged roads. They then implemented several neural architectures, including ResNet and VGG, as binary classifiers to distinguish damaged from undamaged pavements. After evaluating four different CNNs, they found that ResNet 50 outperformed the other architectures, achieving an accuracy of 96.243%. This performance demonstrates the superior effectiveness of ResNet 50 for this specific road inspection computer vision application.

Comparative studies between different CNN architectures have taken a very important place in the literature. Jiang *et al.* [26] proposed the enhanced YOLOv5s-Road model, incorporating a CNN-Transformer architecture and adaptive spatial feature fusion. This model is optimized for the detection and classification of road surface defects, such as cracks, potholes, and rutting, in real-world construction environments. Evaluation, performed on a well-annotated pavement defect dataset, demonstrated that the YOLOv5s-Road model outperforms several other common detection methods in terms of robustness and classification accuracy, achieving over 76%, a significant improvement (+15.3%) compared to the basic YOLOv5s model. In a second work, to automate the recognition of road defects. Eslami and Yun [27] compared the A+MCNN model with four deep classifiers commonly used in road and transportation engineering applications, as well as a generic CNN classifier. The results indicate that the A+MCNN approach outperforms the other models, with an average gain ranging from 1% to 26% in terms of F-score. The experiments show that SqueezeNet is more sensitive when validating the data. In their study, Meftah *et al.* [28] combined a random forest machine learning classifier with three state-of-the-art models: MobileNet, InceptionV3, and Xception. These models were used to confirm the effectiveness of their ability to recognize road cracks on real concrete pavements. The performance and robustness of the training architectures were tested using around 6000 pictures. Table 1 (in Appendix) [5], [13], [16], [22], [23], [25], [29]-[34] lists several methods for classifying pavement distress using deep learning.

3. METHOD

This study aims to classify pavement images into six categories: ND, TC, LC, AC, P, and R with high accuracy. Accurate classification of distressed and non-distressed pavements is critical for optimizing the pavement inspection and road management process. The methodological framework covers dataset preparation, model selection, training and validation strategies, and hyperparameter tuning and evaluation. Figure 1 illustrates the flow chart of the research methodology.

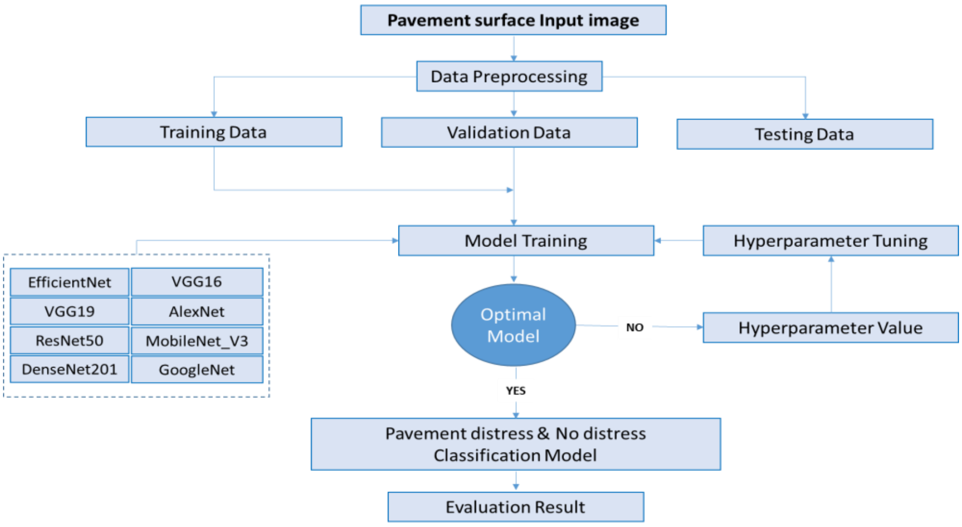

Figure 1. Research method

3.1. Datasets

The study investigates pavement conditions across multiple geographically diverse Moroccan provinces, including Jerada, Taourirt, Oujda-Angad, and Berkane (Oriental region), Midelt (Drâa Tafilalet region), and Al Haouz (Marrakech Safi region). This expansive geographic coverage ensures variability and robustness in data, thereby enhancing the applicability and accuracy of the proposed classification method, see Figure 2.

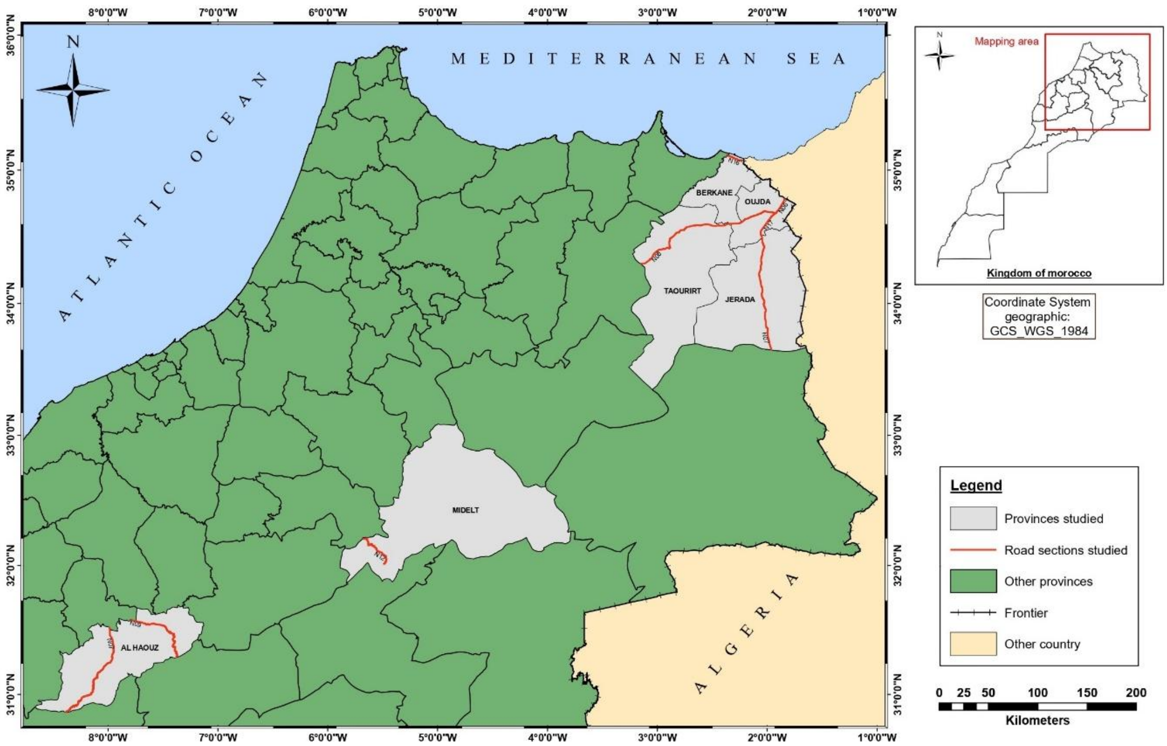

Figure 2. Study area

As part of the 2022 road inspection conducted by the Major Moroccan Center Specializing in Road and Bridge Studies (CNER), as shown in Figure 3, the company used the vehicle-mounted multifunctional pavement evaluation system (SMAC) to visually inspect the study areas, which is equipped with three rear cameras whose respective field of view is perpendicular to the pavement surface.

Figure 3. Pavement inspection vehicle equipped with multifunctional pavement assessment system (SMAC)

As shown in Figure 4, the dataset used for this Moroccan pavement image classification study comprises a total of 19,430 images. The data set comprises 3,150 raveling images, 6,329 alligator cracks images, 5,311 Longitudinal cracks images, 2008 transverse cracks images, 768 potholes images, and 1,864 no deterioration images. The images have a size of 640×472 pixels and capture a section of 1 meter by 1.5 meters with a resolution of 2.34 mm/px by 2.12 mm/px. To ensure robust evaluation, the dataset was split into 80% training and 20% testing. From the training portion, 10% was further reserved as a validation set, ensuring stratified sampling across all six classes to preserve class balance. It should be noted that our dataset clearly reflects the actual distribution of road damage classes observed in the field. In real-life situations on Moroccan road networks, some types of damage, such as potholes, are naturally very rare compared to other types. This imbalance is common in real pavement classification datasets and can lead to errors when training models. However, the CNN architecture used enabled the efficient extraction of discriminative features while maintaining high performance, even for minority classes. This imbalance is therefore representative of the network under study and was taken into account when analyzing the results.

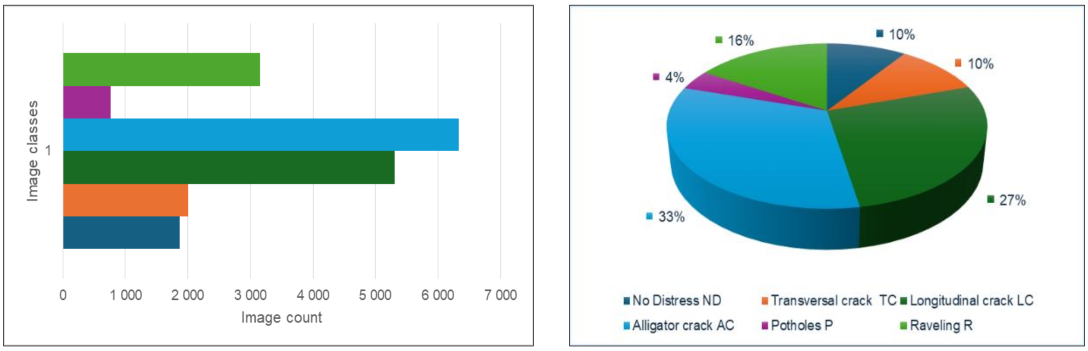

Figure 4. Number and percentage of each class of pavement images

The Moroccan method is based on several classes of pavement damage to calculate the surface quality indicator: the crack family includes LC, TC, and AL, as well as R and P [35]. Figure 5 shows some sample images of the classes studied in this paper: one class of ND, indicating very good pavement condition, and five classes of damage. To clearly distinguish between the different classes studied in this research, Figure 6 shows descriptive diagrams allowing a clear understanding of the different forms of existing damage.

3.2. Model selection

Eight widely used CNNs models were selected for comparative evaluation: ResNet50, DenseNet201, VGG16, VGG19, MobileNet, EfficientNet, GoogleNet, and AlexNet. The rationale for this selection is threefold:

- Baseline coverage: AlexNet and VGG models provide classical benchmarks.
- Advanced architectures: ResNet and DenseNet address vanishing gradients via residual and dense connections.

- Lightweight models: MobileNet and EfficientNet are optimized for deployment in real-time and resource-constrained environments (e.g., vehicle-mounted systems).
- Multi-scale extraction: GoogleNet leverages inception modules for efficient hierarchical feature learning.

This mix of heavy and lightweight models enables both research benchmarking and practical recommendations for road inspection systems. The ResNet50, MobileNet, EfficientNet, GoogleNet, VGG16, DenseNet201, VGG19, and AlexNet architectures were chosen in this study for their proven performance in feature extraction and classification in roadway imagery [36].

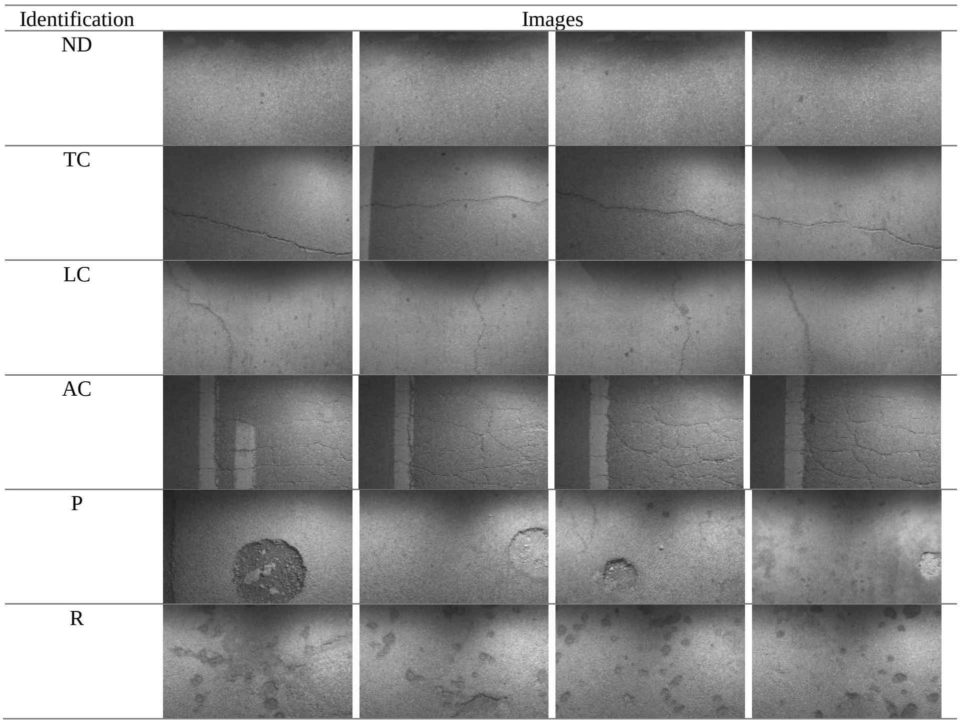

Figure 5. Six classes of pavement images

Figure 6. Graphical representation of the six image classes

3.3. Transfer learning

All models were initialized with ImageNet-pretrained weights. For lightweight architectures (MobileNet and EfficientNet), the entire network was fine-tuned to adapt features to pavement textures. For deeper architectures (ResNet, DenseNet, and VGG), we applied two-stage training: i) freezing convolutional layers and training only the classifier head for 10 epochs and ii) fine-tuning all layers with a reduced learning rate. This strategy accelerated convergence and improved generalization.

3.3. Hyperparameter tuning

Hyperparameters were optimized through grid search over a predefined space. The final settings were:

- Optimizer: Adam optimizer (β1=0.9 and β2=0.999).
- Learning rate: 0.001 with step decay (factor 0.1 every 15 epochs).
- Batch size: 32.
- Epochs: 20 with early stopping (patience=5) based on validation loss.
- Regularization: L2 weight decay (1e-4) and dropout (0.5 in fully connected layers).

4. RESULTS AND DISCUSSION
4.1. Performance evaluation

A confusion matrix was created to evaluate the classification performance. The confusion matrix is an important tool for evaluating classification performance and can visualize the model's performance in more detail. It provides information on how well the classification model predictions match the actual values. The components of the confusion matrix include [37]:
TP_{road}: road images that are correctly classified (predicted) as roads.
TN_{road}: road images that are incorrectly classified (predicted) as non-roads.
FP_{road}: non-road images that are correctly classified as non-roads.
FN_{road}: non-road images that are incorrectly classified as roads.
Several important classification evaluation metrics can be calculated from these components:

$$Accuracy = \frac{(TP_{road}+TN_{road})}{(TP_{road}+TN_{road}+FP_{road}+FN_{road})} \quad (1)$$

$$\text{Precision} = \frac{TP_{road}}{(TP_{road}+FP_{road})} \quad (2)$$

$$\text{Recall} = \frac{TP_{road}}{(TP_{road}+FN_{road})} \quad (3)$$

$$\text{F1\_ Score} = 2 \times \frac{(\text{Precision}*\text{Recall})}{(\text{Precision}+\text{Recall})} \quad (4)$$

4.2. Experimental results

The accuracy graph illustrates the model's capacity for making correct predictions, and the loss graph reveals the extent to which the model reduces the loss value, see Figure 7. An increase in accuracy across multiple epochs suggests that the model is improving its predictive ability. Conversely, an increase in loss may indicate overfitting. Conversely, a reduction in accuracy may suggest that the model has reached its performance threshold. A reduction in loss over several epochs indicates effective learning.

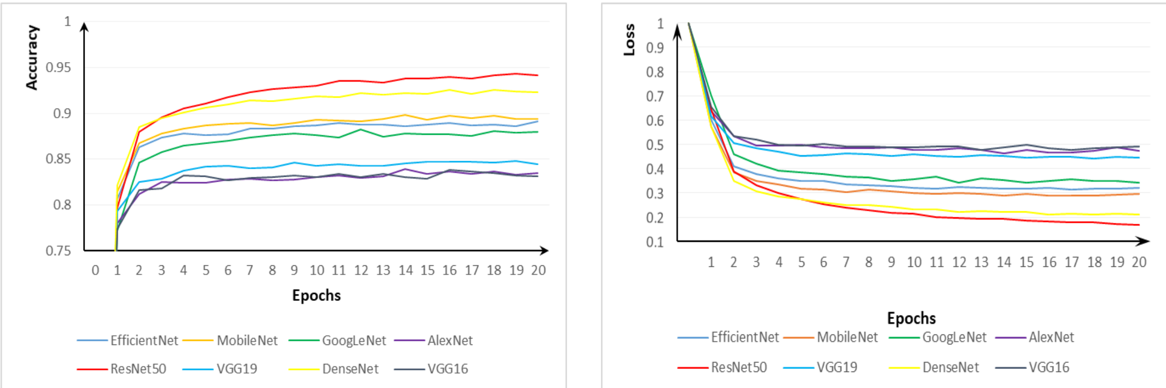

Figure 7. Loss function and accuracy for each learning model

The performance of the architectures is compared in Table 2 on both the validation and test databases. ResNet50, MobileNet, EfficientNet, GoogleNet, VGG16, DenseNet201, VGG19, and AlexNet performed well in both the testing and validating phases, attaining accuracies close to 94%. The ResNet50 model performed well, although not as well as the above models. In particular, the AlexNet, VGG16, and VGG19 models had significant differences in loss rates when comparing the validation and the test dataset, although the other architectures (ResNet50, MobileNet, DenseNet201, EfficientNet, and GoogleNet) achieved high accuracies on the test data.

As demonstrated in Table 2, which illustrates the performance of eight CNN architectures for roadway image classification, ResNet50 had a minimal loss value (0.1688) and the most accurate results (over 94%) on a set of training data. Good performance was also demonstrated by the other models, achieving relatively minimal loss values and accuracies over 89%. The majority of the models performed well in regard to recall, precision, and the F1 score, among which ResNet50 achieved a higher score (0.9077). This indicates that these models have high accuracy and consistent classification capabilities.

ResNet50 performs best in regard to the loss function and accuracy, but other architectures, especially MobileNet and EfficientNet, also perform well in terms of the last three metrics. The architectures that can attain the highest levels of accuracy (over 90%) on testing databases show exceptional predictive capabilities, indicating that they can detect patterns outside of the training dataset. In addition, architectural effectiveness and complication are also key factors, particularly in environments such as real-time applications or resource-constrained mobile devices. Models like MobileNet (1, 524,006) have fewer parameters and lower complexity, and can classify road damage more efficiently.

Table 2. Performance of eight architectures of convolutional neural networks for road surface classification

Model	Total of parameters	Training		Testing		Precision (%)	Recall (%)	F1_Score (%)
		Loss (%)	Accuracy (%)	Loss (%)	Accuracy (%)			
AlexNet	57,028,422	47.24	83.51	42.04	85.32	87.79	85.26	84.69
VGG16	134,285,126	49.08	83.13	36.55	87.17	87.92	87.11	86.04
VGG19	139,594,822	44.42	84.44	50.37	82.90	85.33	82.82	81.59
GoogleNet	5,606,054	34.34	88.02	29.02	90.65	91.14	90.61	90.74
EfficientNet	4,015,234	31.98	89.13	26.04	90.88	90.80	90.84	90.79
MobileNet_V3	1,524,006	29.44	89.38	29.05	89.98	90.01	89.94	89.94
DenseNet201	18,104,454	20.99	92.30	24.76	**92.01**	**91.95**	**91.98**	**91.92**
ResNet50	23,520,326	16.88	**94.19**	25.69	90.68	91.16	90.64	90.77

The confusion matrices provided in Figure 8 demonstrate the performance accuracy of the ResNet50 architecture across various pavement damage categories. Notably, the model demonstrated strong capabilities in accurately classifying AC and LC. However, challenges were identified in distinguishing transversal cracks (TC), highlighting the need for further refinement or alternative model exploration for this specific category. ResNet50 and obtained perfect classification in the majority of classes compared with the other models.

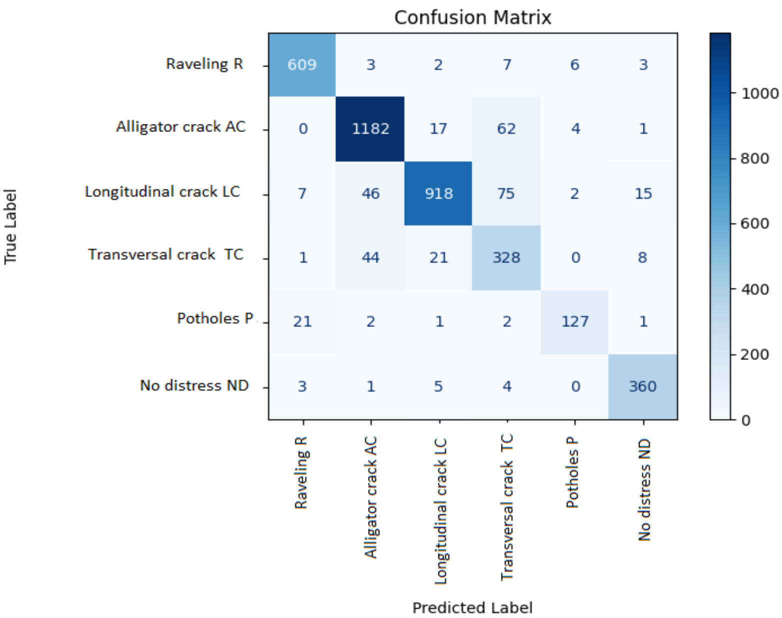

Figure 8. ResNet50 confusion matrix

4.3. Discussion

In consideration of the preceding studies that have been reviewed, it is evident that, although there has been considerable advancement, there is still room for improvement in the accuracy of pavement image recognition (including various potential performance degradations). Using a suitable transfer learning model, combined with a large real-world database and optimized hyperparameters, has the potential to produce improved performance. Within this framework, our study surpasses some similar works because it is based on sophisticated transfer learning architectures and carefully calibrated hyperparameters. By leveraging the following networks based on CNNs, like ResNet50, MobileNet, EfficientNet, GoogleNet, VGG16, VGG19, and AlexNet, we achieved superior classification accuracy. Combining these powerful models with Moroccan road imagery acquired directly from the national road network in Jerada, Taourirt, Oujda-Angad, and Berkane in the Eastern Region, Midelt in the Dratfilalet Region, and Haouz in the Marrakesh-Safi Region, we developed a system that can recognize road damage with greater accuracy and reliability. Our results highlight the significance of architecture selection to improve the effectiveness of classification systems, enabling fast and efficient road inspections and setting a new benchmark for road management systems.

This study applied deep learning architecture to cla²ssify road pavement images. Based on the training dataset, ResNet50 was the best model, with minimum training loss (0.1688) and the highest accuracy (over 94%). EfficientNet, GoogleNet and MobileNet also performed well, with accuracy over 0.90 and training loss around 0.03. Cross-testing results highlighted the consistent performance of ResNet50 in all areas, establishing it as the best-performing model. MobileNet, EfficientNet, and GoogleNet obtained consistent and accurate results, rendering them viable options. The value of 94.19% refers to the best training/validation accuracy obtained during cross-validation when the ResNet50 model was evaluated on the validation subset. In contrast, the value of 90.77% reported in Table 2 corresponds to the final test accuracy achieved on the independent test set, which was held out from the training and validation process. The higher validation accuracy compared to the test accuracy reflects the model's strong performance during training, but also highlights the expected generalization gap when applied to unseen data. This distinction is consistent with results reported in the literature [22], [38] where accuracies on validation sets are often slightly higher than on independent test sets. To maintain transparency, we emphasize that the 90.77% test accuracy should be considered the most reliable measure of real-world performance, while the 94.19% validation accuracy illustrates the model's potential under controlled conditions.

Although the overall performance metrics were strong, the dataset exhibited class imbalance, particularly with fewer pothole and transversal crack samples compared to longitudinal cracks and alligator cracks. This imbalance likely contributed to the relatively lower precision and recall observed for the transversal crack class in the confusion matrix. To mitigate this issue during training, we applied class weighting in the loss function and incorporated data augmentation to synthetically expand minority classes, thereby improving model robustness. Nevertheless, we acknowledge that imbalance remains a limiting factor, as minority classes are still underrepresented compared to real-world distributions. Future work will focus on constructing a purpose-balanced dataset with increased representation of potholes and transversal cracks, as well as exploring advanced strategies such as synthetic data generation (GANs), oversampling techniques (SMOTE), and focal loss functions. These approaches are expected to reduce bias toward majority classes and ensure fairer, more reliable classification performance across all pavement damage categories.

A closer inspection of the misclassified samples reveals that TC were the most challenging to classify accurately. This difficulty stems from their shorter length, subtle visual patterns, and similarity to surface artifacts such as shadows, seams, or minor raveling, which often mislead the model. In several cases, transversal cracks were either confused with longitudinal cracks when oriented diagonally, or with raveling due to surface texture overlaps. These qualitative errors highlight the inherent complexity of pavement damage recognition in real-world conditions. Future improvements could include the use of multi-scale feature extraction networks to capture finer crack details, attention mechanisms to focus on subtle structural cues, and integration of temporal data from sequential images to disambiguate transversal cracks from noise. Incorporating these enhancements would address the current model's limitations and provide a more reliable classification across all damage types.

This paragraph compares our method with previous work, as shown in Table 3. In the literature, remarkable efforts have been made to achieve high accuracy rates. Among these, Majidifard *et al.* [39] developed a pavement condition assessment system that aims to quantify the degree of degradation by detecting and classifying nine types of pavement degradation, using the combination of YOLO and U-Net. The results obtained showed an accuracy of 93% and a recall of 77%. To detect and classify damage on pavements. Ijari and Paternina-Arboleda [22] combined the EfficientNetB3 and SwinGAN architectures from the CQU-BPDD database, which achieved a learning accuracy rate close to 79.8%. On the other hand, Matarneh *et al.* [13] conducted a comparative study between ten CNN architectures for recognizing and classifying pavement cracks, using three public databases (CRACK500, GAP, and CrackTree). DenseNet201 obtained the best accuracy with 94.12%, preceded by ResNet101 and ShuffleNet and with 93.83% and 94.07% respectively. In June 2022 in Canada, Zhang *et al.* [12] used a GoPro Hero 7 camera in a system mounted on a pavement inspection vehicle to capture 12,000 images across five pavement image classes. The test set showed an accuracy of over 83% and a very high F1 score of about 0.916 of the crack class. With an accuracy rate of 94.19%, our approach outperforms all of the aforementioned models, regardless of the dataset. Our results show that a well-processed dataset enables the model to perform better without requiring a complex architecture.

Table 3. Results obtained compared to various literature methods

Method used	Author	Year	Dataset	Accuracy obtained (%)
YOLO and U-Net	Majidifard *et al.* [39]	2020	22 pavement sections (USA)	93.00
AlexNet	Dhakal *et al.* [40]	2022	-	93.00
CNN	Zhang *et al.* [12]	2022	This data was collected using a GoPro Hero 7 camera in Montreal.	88.3
YOLOv8	Roy and Bhaduri [41]	2023	RDD-2018	89.51
DCNN	Nhat-Duc and Van-Duc [38]	2023	-	92.60
EffNetB3+SwinGAN	Ijari and Paternina-Arboleda [22]	2024	CQU-BPDD	79.8
CNN	Li *et al.* [42]	2025	UAV-PDD2023	93.08
ShuffleNet	Matarneh *et al.* [13]	2025	CRACK500, GAP and CrackTree	94.07
DenseNet201				94.12
ResNet101				93.83
Proposed model (ResNet50)		2025	Our data set	94.19

5. CONCLUSION

This research highlights the remarkable effectiveness of advanced DL models in classifying pavement damage. The examined models ResNet50, DenseNet201, VGG16, VGG19, MobileNet, EfficientNet, GoogleNet, and AlexNet showed their ability to substantially improve the accuracy and reliability of classification compared to conventional visual inspection approaches. Our analysis reveals that ResNet50 performed particularly well, achieving the best accuracy coupled with the lowest validation loss throughout the initial evaluation and maintaining reliable and steady performance through the cross-validation testing. This highlights the transformative potential of deep learning in assessing pavement damage levels. Adopting these technological approaches provides precise, robust solutions to traditional manual inspection methods. In practical terms, implementing such models would significantly optimize pavement inspection efficiency and contribute to improved management of road and highway infrastructure assets. However, the computational complexity of the proposed model raises questions about its application in scenarios with limited resources. Furthermore, a larger dataset enriched with additional digital images of damaged asphalt pavements would facilitate the development of models with enhanced generalization capabilities. Therefore, future studies could focus on using multi-scale feature extraction networks with larger datasets and more advanced algorithms to capture finer crack details, detect depth-related characteristics, and achieve more accurate classification results, thereby improving our understanding of the variability inherent in pavement damage. This could transform the way transportation agencies assess pavements.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Souad El Moudni El Alami	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓		
Mohammed Berrahal	✓	✓	✓	✓	✓	✓	✓		✓	✓		✓		
Mohammed Boukabous	✓	✓	✓	✓	✓	✓	✓		✓	✓		✓		
Mohammed Qachar	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓			

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [initials: YA], upon reasonable request.

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APPENDIX

Table 1. Recent related works

Ref.	Year	Number of damaged images	Number of damage types	Method	Best acc. (%)
Li *et al*. [23]	2018	28,462	5	CNN	94.60
Maeda *et al*. [29]	2018	9,053	8	SSD MobileNet	95.00
Cheng *et al*. [30]	2019	20,000	5	CNN	94.89
Guo *et al*. [31]	2020	42,068	2	DWN	98.55
Wang *et al*. [32]	2021	4,650	3	ResNet-v2	97.41
Hammouch *et al*. [33]	2022	9,017	6	VGG-19	95.48
Liu *et al*. [34]	2022	2,211	3	EfficientNet-B4	95.00
Qureshi *et al*. [5]	2023	7,453	10	ConvNeXt	83,90
Li *et al*. [25]	2023	18,637	6	ResNet 50	96.24
Ijari and Paternina-Arboleda [22]	2024	60,059	6	EfficientNetB3	76.70
Matarneh *et al*. [13]	2024	2,139	3	DenseNet201	94.12
Lee *et al*. [16]	2024	-	5	MFCC40	96.84

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