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# Visual inspection of architectural faults and cracks

*Inspección visual de fallas y fisuras arquitectónicas*

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Civil constructions move, age, and breathe. Their movement is something that cannot be seen with the naked eye, but it is constant. At all times there are small changes in the same due to humidity, temperature, or movements in the ground, reaching the point where the materials with which the buildings are composed do not resist these movements and begin to appear cracks and fissures, which are considered important to examine to ensure the safety, durability, and viability of construction. For the inspection of this structural change, the training of a neural network will be used to inspect using images the appearance of cracks and classify them according to the stipulated categories.

*Keywords:* Categories, cracks, durability, fissures, images, inspection, materials, movements, neural network, safety

Las construcciones civiles se mueven, envejecen y respiran. Su movimiento es algo que a simple vista no se puede apreciar, pero es constante. En todo momento se producen cambios pequeños en la misma a causa de la humedad, temperatura o por movimientos en el terreno, llegando al punto donde los materiales con los cuales están compuestos los edificios no resisten estos movimientos y empiezan aparecer las grietas y fisuras, las cuales se consideran importantes de examinar para garantizar la seguridad, durabilidad y viabilidad de una construcción. Para la inspección de este cambio estructural se hará uso del entrenamiento de una red neuronal para inspeccionar por medio de imágenes la aparición de las grietas y clasificarlas según las categorías estipuladas.

*Palabras clave:* Categorías, durabilidad, fisuras, imágenes, inspección, grietas, materiales, movimientos, red neuronal, seguridad

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## Introduction

Crack detection is a crucial aspect of civil engineering infrastructure management, as it plays a vital role in ensuring the durability, integrity, and safety of structures (Carrasco et al., 2021). These structures are exposed to a wide range of factors that can cause partial or complete collapse, making it imperative to quickly identify the direction, location, and extent of any cracks that may develop.

The early detection of cracks allows for prompt repairs to be made, preventing further damage and ensuring the continued safe operation of the structure. Additionally, identifying the cause of the crack, whether it be due to poor construction, overloading, or exposure to extreme weather conditions, can help prevent similar issues from arising in the future (Ercolani et al., 2018).

There are a variety of methods that can be used to detect cracks in structures, including visual inspections, ultrasonic testing, and x-ray imaging. Each method has its strengths and weaknesses, and the choice of which method to use will depend on the specific structure and the type of crack being sought. In addition to traditional crack detection methods, there has been an increasing interest in the use of advanced technologies such as artificial intelligence and machine learning to aid in crack detection. These technologies can help automate the process, reducing the time and cost of inspections, and allowing for more accurate and efficient detection of cracks.

The process of detecting failures in structures has undergone significant evolution over time, with the initial method being manual inspections using a crack width comparator gauge (CWCG). However, this technique had several limitations, including being time-consuming and prone to a high level of error. To overcome these limitations, research and development in crack detection technology have been ongoing, to automate the process and improve its accuracy (Orozco R & Mendoza P, 2017). A variety of different analysis techniques have been explored, some of which include:

- Non Destructive Testing (NDT).
- Resistivity test (Shamsudin et al., 2021).
- Incremental dynamic analysis, considered a powerful tool for assessing vulnerability and seismic risk of buildings (Barbat et al., 2016).
- 3D visualization by means of a climbing robot with sensors that send the information to a ground station in real time (La et al., 2019).
- Inspection in unmanned aerial vehicles (UAV) (Woo et al., 2022), among others.

These studies and tests were carried out on concrete structures analyzing aspects of fracture propagation in concrete (Zárate & Oñate, 2018), cracks in low permeability structures (Donini, 2016), comparisons between preconstructed and constructed (Bernat et al., 2014), and column reinforcement (Naom & Mohammad, 2022); because it is a self-repairing material that can heal itself when cracked, protecting the interior matrix as well as the reinforcing steel, resulting in a longer service life (Mullem et al., 2020).

In the last ten years, advances in photogrammetry and image processing have begun to change the construction industry, as it is possible to capture fast and remote digital records of objects and features, taking into account an important aspect that when modeling the mechanical behavior of existing structures the accuracy in which the geometry of the actual structure is transferred into the numerical model to make its analysis relevant (Loverdos et al., 2021). However, there remains some uncertainty as to how to develop appropriate and cost-effective evaluation procedures that take into account the inherent advantages and disadvantages of various available tools and technologies (Lacroix et al., 2021).

The dangers of cracks in constructions, severely decrease the reliability and safety of structures, due to this receiving increasing attention to mitigate these failures (Yang & Xu, 2020), within the area of deep learning has been used in training to neural networks with Kohonen-type algorithms (Carreño et al., 2011), Canny algorithm, Decision Tree type algorithms, K-neighborhoods (Jitendra et al., 2020), deep convolutional neural network (DCNN) (Manjurul & Kim, 2019) to increase the accuracy and precision in the preliminary results of the digital images, evaluating finite aspects and methods (Zárate & Oñate, 2018) of reliability factor in a stipulated time (Ruiz et al., 2014).

The problem of accurately detecting and classifying cracks in structures is a critical one in the field of civil engineering. To address this problem, the use of neural networks for image recognition has been proposed as a potential solution. By training a neural network to identify and classify images of cracks, it is possible to improve the efficiency and accuracy of crack detection. The neural network is trained to classify cracks into two main categories: those of physical origin, such as those caused by humidity and temperature changes, and those of mechanical origin, such as those caused by movements on the surface, vibrations, or loads. Additionally, the network can also classify images without any cracks for reference.

The methodology for this project involves collecting a dataset of images of cracks, both of physical and mechanical origin, along with images without cracks. The dataset is then used to train the neural network. Once the network is trained, it can be applied to new images to detect and classify cracks. The results of this project will be evaluated through various metrics such as accuracy, precision, and recall. The performance of the neural network will be compared to traditional methods of crack detection and classification to determine its effectiveness.

## Problem statement

As buildings age and undergo wear and tear, cracks may begin to appear in their structures. These cracks can be a serious issue, as they can compromise the integrity of the building and put the lives of those who use it at risk. To address this problem, it is desirable to develop a neural network-based system for the identification of cracks in buildings.

This system would use the classifications outlined in relevant documents to automatically detect cracks, saving time and reducing the potential for human error in manual inspections. By identifying cracks promptly, it would also be possible to take preventative measures to mitigate any further damage to the building, ensuring the safety of those who use it.

The neural network-based system would use image recognition and classification techniques to analyze images of buildings and identify cracks. These images could be captured using a variety of methods, such as drones or cameras mounted on building exteriors. The neural network would be trained on a dataset of images of buildings with known cracks, allowing it to learn to identify cracks based on specific patterns and features.

Once the neural network is trained, it could be used in real-time inspections of buildings to quickly and accurately identify cracks. The system could also be integrated with existing building management systems, allowing building managers to track the condition of their buildings over time and take proactive measures to address any issues that are identified.

## Methods

The proposed methodology for detecting cracks in structures through a neural network involves several key steps. The first step is to gain an understanding of the available data. This includes analyzing the type of data that will be used to train and test the neural network, such as images of buildings with known cracks.

Once a clear understanding of the available data has been established, the next step is to test various segmentation models. Segmentation models are used to identify specific regions or objects within an image, such as cracks in a building. These models can be based on different techniques, such as convolutional neural networks (CNNs) or U-Net.

After testing and evaluating the performance of different segmentation models, the most appropriate one will be chosen and used to develop the computational model necessary for the automatic detection of cracks in structures. This computational model will be based on the chosen segmentation model and will be trained on the available data using techniques such as supervised learning.

Once the computational model has been developed, it will be applied to the available data (images) and the results will be checked. This will involve evaluating the model's performance in detecting and quantifying cracks in the images, and comparing the results to the known ground truth.

During this process, it is important to continually monitor and evaluate the performance of the computational model. As the model is being trained, it will become more accurate in identifying and quantifying cracks, but it may not reach optimal performance immediately. To achieve optimal results, the model will need to be constantly trained and fine-tuned, until an acceptable percentage in the identification and quantification of cracks is reached.

For this detection process it is of great importance to take into account the proposed categories, which are:

- Cracks of physical origin.
- Cracks of mechanical origin.
- Crack-free construction.

Once the Keras-based computational model for detecting cracks in structures has been developed and fine-tuned to an optimal or acceptable level using the proposed categories and the available databases, the next step is to generate conclusions and measure the failure rates of the model.

To generate conclusions, the model will be evaluated using various metrics such as accuracy, precision, recall, and F1 score. These metrics provide a quantitative measure of the model's performance in identifying and quantifying cracks in the images. Additionally, qualitative analysis can be performed by visualizing the model's predictions on the images and comparing them to the ground truth.

The failure rate is also an important metric to evaluate the model's performance. The failure rate is the percentage of images in which the model failed to detect or quantify cracks correctly. This metric indicates how often the model makes mistakes and how reliable it is. The failure rate of the model can be used to identify areas where the model is struggling and make adjustments to improve its performance. For example, if the model is failing to detect cracks in certain types of images or specific regions of the images, additional data or fine-tuning of the model may be needed in those areas.

In addition, it's important to evaluate the model's performance with a diverse set of data to test the robustness of the model. This includes testing the model on images taken under different lighting conditions, angles, and resolutions.

## Results

The proposed methodology in this case involved the constant training of two different neural models using varying amounts of images. The goal of this approach was to observe the learning process of the models and how it is affected by the number of images used. However, the results of this methodology revealed that both models struggled to accurately identify more than one or two of the three proposed categories.

This outcome highlights the importance of having a sufficient amount of diverse images for training a neural model. Without a sufficient number of images, the model is unable to learn and generalize to new images effectively. Furthermore, it also indicates that having a diverse set of images is equally important, as it allows the model to learn from different examples of the same category and improve its ability to generalize to unseen examples.

Additionally, it also suggests that the quality of images used for training is an important factor that should be taken into consideration. A model trained on low-resolution images may struggle to identify features in the images and thus, fail to classify them correctly.

Furthermore, it also raises questions about the architecture of the neural models used. Different architectures have different strengths and weaknesses when it comes to image classification tasks. It may be beneficial to experiment with different architectures to find the best one for the specific application.

The attached images (Figs. 1 to 4) demonstrate the training of a ResNet neural network in comparison to a DenseNet model. The ResNet model was able to achieve a better performance in terms of image classification, compared to the DenseNet model which only recognized a single category. This outcome highlights the superiority of the ResNet architecture in this specific application, in comparison to the DenseNet architecture.

An analysis of the images loaded in the database revealed that a large percentage of the images belonged to category 2 (Mechanical). This indicates that the database was heavily skewed towards this category, which could have potentially contributed to the better performance of the ResNet model in recognizing images within this category. A well-balanced dataset with equal distribution of images across all categories would have been ideal to evaluate the performance of the models in a more accurate way.

Furthermore, it also suggests that the quality of images used for training is an important factor that should be taken into consideration. A model trained on a skewed dataset may struggle to identify features in the images belonging to the under-represented categories and thus, fail to classify them correctly.

## Conclusion

The training of a neural network is a crucial step in the development of any machine learning system. In this case, the DenseNet model was utilized as the initial implementation for training a neuron. Two training tests were conducted using a small database of captured images, which were classified into three different categories. The

**Figure 1**

*Metrics obtained in 10 epochs*

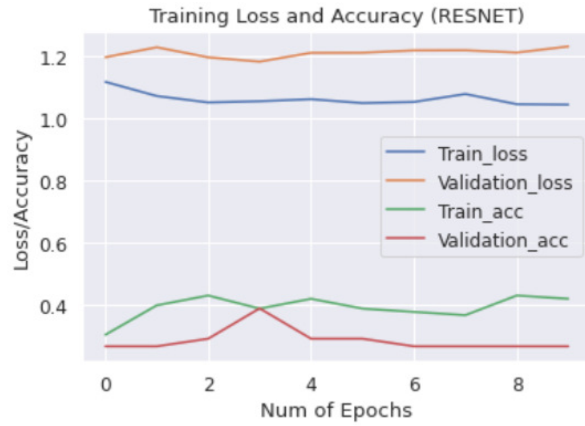
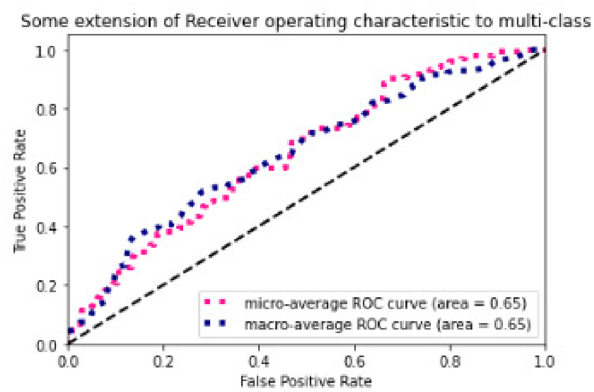



**Figure 2**

*ROC curve*




results of this training revealed that the number of images used was insufficient for the neural model, as it could only identify a single category out of the three proposed. This highlights the importance of having a larger and more diverse image database for training, to improve the efficiency and accuracy of the neuron's learning.

In addition to the DenseNet model, the ResNet neural model was also used for training. The image database was expanded in an attempt to improve the training process, but the neuron still struggled to recognize all the proposed categories. This suggests that the images used in the database may not have had the appropriate resolution for the model to effectively learn and classify the images.

Crack identification and classification is an important aspects in both industry and everyday life. Knowing the origin and type of a crack can greatly impact the safety and durability of a building. The application of a neural model in this field can greatly aid in the efficient identification

**Figure 3**

*Confusion matrix*

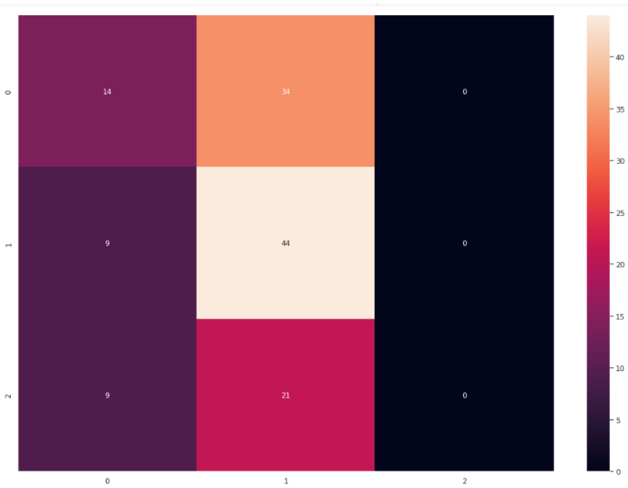



**Figure 4**

*Metrics by category*

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.44 | 0.29 | 0.35 | 48 |
| 1 | 0.44 | 0.83 | 0.58 | 53 |
| 2 | 0.00 | 0.00 | 0.00 | 30 |
| accuracy | | | 0.44 | 131 |
| macro avg | 0.29 | 0.37 | 0.31 | 131 |
| weighted avg | 0.34 | 0.44 | 0.36 | 131 |

and classification of cracks, providing valuable insights to building engineers and contractors.

To improve the performance of the neural model in identifying and classifying cracks, several steps can be taken. One of the most important is to increase the size and diversity of the image database used for training. This will allow the neuron to learn from a larger and more representative sample of images, which will improve its ability to generalize to new images. Additionally, it is important to ensure that the images used in the database have adequate resolution and quality, as this will allow the model to more accurately identify and classify the different types of cracks.

Another important factor to consider is the architecture of the neural model itself. Different architectures, such as DenseNet and ResNet, have different strengths and weaknesses when it comes to image classification tasks. It may be beneficial to experiment with different architectures to find the best one for the specific application of crack identification and classification.

Finally, it is important to fine-tune the parameters of the neural model through techniques such as hyperparameter tuning to optimize its performance. This can involve adjusting the number of layers, the number of neurons in each layer, the learning rate, and other parameters to find the optimal configuration for the specific task at hand.

Overall, the application of neural models in the field of crack identification and classification has the potential to greatly improve the efficiency and accuracy of this task. However, to achieve this, it is important to consider factors such as image database size and quality, neural model architecture, and fine-tuning of parameters.

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