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ON THE USE OF DIFFERENT IMAGE FILTERS FOR DAMAGE DETECTION IN CONCRETE-LIKE STRUCTURES USING AERIAL PHOTOGRAPHS FROM UAV

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Abstract. Structural health monitoring is vital for ensuring the safety and longevity of civil infrastructure. In this study, we evaluate the performance of three commonly used filters, namely the Gaussian filter, mean filter, and median filter, in pre-processing aerial images obtained by UAVs for crack detection in concrete structures. By comparing their performance using metrics such as precision, recall, F1-score, and accuracy, we aim to determine the most effective filter for crack detection applications. The evaluation is based on a dataset of aerial images containing both cracked and non-cracked regions. Our results demonstrate the suitability of each filter for different scenarios, highlighting their distinct advantages and limitations. The findings contribute to the field of structural health monitoring by providing insights into the optimal pre-processing technique for accurate and efficient crack detection. This research enables improved structural assessment and maintenance, leading to enhanced safety and cost-effective infrastructure management.

Keywords: Damage detection and structural health monitoring, Computer Vision, Artificial Intelligent Applications, Unmanned aerial vehicle, image processing.

1. INTRODUCCION

Ensuring the safety and longevity of civil infrastructures is paramount, and structural health monitoring (SHM) plays a important role in this process (Chandrasekaran, 2019). Based on the advancements in technology, the integration of computational-based techniques has gained significant attention in SHM, particularly in damage detection in concrete structures.

The typical basic SHM process includes pre-processing input data, and this is a relevant step in enhancing the performance of computational-based approaches. In particular, damage detection in concrete structures can be achieved by applying filters when using images, mainly to noise removal, and improve overall accuracy of the damage detection algorithms.

The present article introduces an investigation to evaluate different image filters focused on establishing a SHM process using aerial images obtained from unmanned aerial vehicles (UAVs). UAVs have been employed in different applications in engineering, and they are interesting vehicles to take photographs of large structures such as those typical concrete-base ones. The study considers the Gaussian filter, Mean filter, and Median filter to evaluate spatial filters. Their main characteristics, advantages, and limitations are introduced.

The Gaussian filter is described by Fisher *et al.* (2014), and it is a widely used linear smoothing filter that effectively eliminates Gaussian noise and preserves the image edge details. The Mean filter is explained by Solomon and Breckon (2011) and it simplifies the image by replacing pixel values with the mean of neighboring pixels, effectively reducing noise and maintaining homogeneity. On the other hand, the Median filter is highlighted by Solomon and Breckon (2011) and Mohtasham Khani *et al.* (2020), and it excels in noise reduction whereas preserving edges and fine details, making it

particularly effective in suppressing “salt and pepper” noise.

In this context, the present articles introduces a comparative study to demonstrate spatial filters applied to pre-process aerial images focused on establishing a SHM process for damage detection in concrete-like structures. The results demonstrate that the selection of an appropriate filter can significantly impact the accuracy and efficiency SHM process which uses images from UAVs. They contribute to the field of structural health monitoring by improving the accuracy and efficiency of damage detection algorithms which involves aerial images.

2. METHODOLOGY

A typical SHM process which involves UAV and aerial images for damage detection in concrete-like structures considers the following steps: 1) data preparation, which is the data-set composed of aerial images taken by UAVs, with and without cracks. The images are standardized in terms of size and resolution to ensure consistency in the results; 2) application of different image filters; 3) edge detection, such as the Canny edge detector to highlight the damage; 4) use of artificial intelligent algorithm to detect damage; 5) results analysis, such that the accuracy of the damage detection procedure is assessed for each a set of filtered images. These steps are indicated through the flowchart shown in Figure 1.

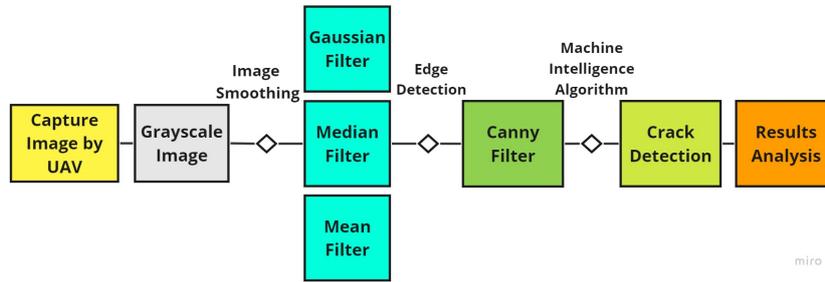


Figure 1. Flowchart of the damage detection process using aerial images.

The evaluation of image filters for damage detection necessitates a range of metrics that offer insights into their effectiveness. These metrics detail the algorithm’s capacity to correctly identify and categorize data points. To offer a comprehensive understanding, we delve deeper into the metrics as follows:

- **Precision** : Represents the agreement of the data class labels with those of a classifier (as illustrated in the formulas provided by (Powers, 2020)). Essentially, precision quantifies the number of correct positive predictions and indicates the purity of positive predictions. The formula for precision is:

$$\text{Precision} = \frac{tp}{tp + fp} \quad (1)$$

where tp and fp represent the counts of true positives and false positives, respectively.

- **Recall**: Also termed as sensitivity, it’s the effectiveness of a classifier to identify class labels as deduced from the summation of per-text decisions (Powers, 2020). Recall measures the fraction of the total amount of relevant instances that were retrieved. Its formula is:

$$\text{Recall} = \frac{tp}{tp + fn} \quad (2)$$

where fn represents the count of false negatives.

- **F1 Score**: The harmonic mean of precision and recall. This metric is useful because it gives a more comprehensive view than accuracy, particularly when classes are imbalanced (Sokolova and Lapalme, 2009). Its formula is:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

- **Support**: Represents the number of actual occurrences of the class in the dataset. It’s crucial for assessing the relevance of the performance metric against the actual frequency of the label.

- **Accuracy**: The proportion of predictions that a model gets right, providing an average effectiveness across all classes. This is mathematically defined by the ratio of correctly predicted observation to the total observations (Powers, 2020). As per (Sokolova and Lapalme, 2009), the formula for accuracy in binary classification is:

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn} \quad (4)$$

and for multi-class classification, the average per-class effectiveness is represented as:

$$\text{Average Accuracy} = \frac{1}{L} \sum_{i=1}^L \frac{tp_i}{tp_i + fn_i} \quad (5)$$

where L is the number of classes.

- **Macro Avg and Weighted Avg:** These offer insights into the unweighted and support-weighted mean per label, respectively. While Macro Average considers all classes equally, Weighted Average takes the size of the classes into account (Sokolova and Lapalme, 2009).
- **Confusion Matrix:** A foundational tool in machine learning and classification, the confusion matrix offers a visualization contrasting actual versus predicted classifications (Powers, 2020; Susmaga, 2004; Deng *et al.*, 2016). This matrix provides insights into the correct and incorrect predictions made by the model.

For binary classification, it can be mathematically represented as:

Table 1. Confusion matrix representation for binary classification.

	Predicted Positive	Predicted Negative
Actual Positive	a	b
Actual Negative	c	d

where:

- a and d are the numbers of correct predictions (true positives and true negatives respectively).
- b and c represent incorrect predictions (false negatives and false positives respectively).

The matrix can extend to multi-class classification problems, resulting in a $N \times N$ table where N denotes the number of classes (Deng *et al.*, 2016).

Additionally, confusion matrices are sometimes employed in feature selection. For example, wrapper methods might use classifiers, such as the decision tree algorithm, to gauge the importance of specific attributes or subsets thereof (Visa *et al.*, 2011).

2.1 Dataset

In this study, a total of 5,830 images were utilized, categorized into those depicting cracks and those without. To ensure the robustness of our model, we split the dataset into training and testing sets:

- Training set: 80% (equivalent to 4,664 images)
- Testing and validation set: 20% (equivalent to 1,166 images)

This 80-20 division ensured that the model was trained on a substantial majority of the dataset while still being validated on a significant, separate subset that remained unseen during the training phase.

2.2 Support Vector Machine (SVM) Application in AI-based Structural Analysis

Support Vector Machines (SVM) have been established as a compelling method for both classification and regression in a wide array of applications, especially in the realm of Artificial Intelligence (AI). SVM's strength lies in its unique global solution derived from the principle of *Structural Risk Minimization* (SRM) (Mavroforakis and Theodoridis, 2006).

The SVM's primary objective is to discern the optimal hyperplane that can best separate or fit the data in a high-dimensional feature space. This is mathematically articulated by the linear discriminant function:

$$f(x) = \langle w, x \rangle + b \quad (6)$$

where w represents the weight vector and b is the bias (Mavroforakis and Theodoridis, 2006).

However, in scenarios where the data isn't linearly separable in its native space, SVM, as detailed by (Wu *et al.*, 2023), utilizes the "kernel trick". This involves mapping the data into a different feature space, allowing it to become linearly separable. Such a transformation accentuates the importance of judiciously selecting parameters, predominantly the penalty factor C and the kernel function, to ensure the model's optimal performance (Wu *et al.*, 2023).

Given the sophisticated mathematical foundation and its versatility in addressing non-linear challenges, SVM was employed in this study for detecting cracks in concrete structures, aligning with the overarching objective to identify the most efficacious smoothing filter for the task (Ding *et al.*, 2023).

2.3 Smoothing Filters

Smoothing filters are commonly used for blurring and noise reduction in image processing. They help in pre-processing tasks, such as removing small details and connecting discontinuities in lines and curves (Gonzales and Woods, 2010). Linear smoothing filters can be applied in the spatial domain by defining appropriate weights in the convolution mask, or in the frequency domain by attenuating high frequencies. These filters play a crucial role in achieving smoother images and reducing noise (Distante and Distante, 2020).

2.3.1 Mean Filter

The mean filter, also known as the box filter due to its application of a local neighborhood where all pixels share the same weight (Fisher *et al.*, 2014), is a prevalent technique in image processing due to its simplicity and effectiveness. According to (Solomon and Breckon, 2011), this spatial processing technique operates by replacing the value of each pixel with the mean of the intensity levels of neighboring pixels, ensuring equal weight for all pixels within the considered neighborhood. As pointed out by (Pedrini and Schwartz, 2007), this approach helps preserve the average value of the image and maintain the homogeneity of gray levels in constant regions of the image. Nevertheless, (Zhang, 2014) highlights that this method can lead to a loss of image sharpness, particularly at its edges and details, a drawback compensated by its simplicity and swift computation time. Furthermore, (Gonzales and Woods, 2010) emphasized that by reducing the abrupt transitions of intensities, the mean filter serves as an effective method for noise suppression.

Let's consider an input image represented by the matrix $M \times N$ $F[x, y]$ and a kernel, or smoothing mask, represented by the matrix $m \times n$, $W[i, j]$. The objective is to apply the mask $W[i, j]$ to the input image $F[x, y]$ in order to produce a smoothed image, which is represented by the matrix $M \times N$ $G[x, y]$.

$$g[x, y] = \frac{\sum_{s=-a}^a \sum_{t=-b}^b w[s+i, t+j] \cdot f[x+s, y+t]}{\sum_{s=-a}^a \sum_{t=-b}^b w[s+i, t+j]} \quad (7)$$

such that for a mask size of W , a $m \times n$ matrix are considered $m = 2a + 1$ and $n = 2b + 1$. Furthermore, $g[x, y]$, $f[x, y]$ and $w[i, j]$ correspond to the individual elements within their respective matrices.

2.3.2 Median Filter

The Median filter is another widely used technique in image processing, recognized for its capability to effectively reduce noise, especially the so-called 'salt and pepper' noise, while maintaining the edges and fine details of the image (Solomon and Breckon, 2011; Mohtasham Khani *et al.*, 2020; Rahim and Maitheen, 2019). The term "median" in the context of the median filter refers to the midpoint value in an ordered sequence of pixel values (Zhang, 2014). When applying a median filter, a window slides along the image, and the median intensity value of the pixels within the window becomes the output intensity of the pixel being processed (Malothu Nagu, 2014).

The computation of the median filter includes ordering the pixel values within a neighborhood and selecting the median value as the new pixel value (Szeliski, 2021; Chang *et al.*, 2008). For an odd number of entries, the median is the value at the center of the ordered sequence; for an even number of entries, the median is the average of the two central values (Kumar and Sodhi, 2020). Median filters are particularly popular due to their excellent noise reduction capabilities with less blurring compared to linear smoothing filters of similar size (Gupta, 2011). However, the computational cost of median filters can be greater than that of mean filters, which may limit their usage (Solomon and Breckon, 2011; Szeliski, 2021).

$$g[x, y] = \text{median} (\{f[x+i, y+j] : (i, j) \in w\}) \quad (8)$$

where $F[x, y]$ is the input matrix that represents the original image, $G[x, y]$ is the output matrix that represents the image after the application of the median filter and W is the set of all ordered pairs (i, j) representing the location of all pixels in the kernel window.

2.3.3 Gaussian Filter

The Gaussian filter, a linear smoothing filter that utilizes the Gaussian function, is highly efficient in image processing, capable of performing fast and robust two-dimensional convolutions (Smith, 2003). Its kernel is based on the Normal distribution, adapting its behavior according to the Gaussian weight parameter (Jain and Gupta, 2015). The key properties include rotational symmetry, separability, and optimal location in time and frequency (Charalampidis, 2016; Wang *et al.*, 2014).

Despite its advantages, including the effectiveness in eliminating Gaussian noise and maintaining the same characteristics irrespective of the orientation (Das *et al.*, 2015), the Gaussian filter has certain drawbacks. It is computationally intensive and tends to reduce the level of image detail, which can impact the sharpness and intricacies (Das *et al.*, 2015; Seddik *et al.*, 2014). The width of the filter, governed by the parameter σ , can control the balance between excessive smoothing and insufficient smoothing (Wang *et al.*, 2014; Seddik *et al.*, 2014).

Gaussian filters exhibit the same degree of smoothness in all directions, an advantage when dealing with images with an unknown edge direction (Fude *et al.*, 2008). However, the filter processes the whole image uniformly, which can create dissimilarities due to the non-linear distribution of image intensities (Seddik *et al.*, 2014). In this paper, a two-dimensional discrete Gaussian function with zero mean value is adopted as a smoothing filter. According to (Gonzales and Woods, 2010), the equation adapted from the Gaussian filter in 2 dimensions is given by

$$w[i, j] = e^{-(i^2+j^2)/(2\sigma^2)} \quad (9)$$

where $w[i, j]$ is the kernel value at a given position and σ (sigma) is the standard deviation of the Gaussian distribution.

2.4 Edge Detection

Edge detection, an integral part of image processing, aids in image segmentation by efficiently partitioning an image into its components (Shubhashree Savant, 2014). It simplifies image representation by filtering out non-critical data while maintaining essential structural features (Ganesan and Sajiv, 2018). Canny edge detector, renowned for its efficiency, will be the focus of this work, as it adeptly identifies areas with a high change rate in pixel intensities, thus defining object boundaries (Shrivakshan and Chandrasekar, 2012).

2.4.1 Canny Filter

The Canny filter is introduced by John Canny in 1986, and it is recognized as a robust and widely employed technique for edge detection in digital images (Canny, 1986; Sekehravani *et al.*, 2020). This algorithm was developed based on three crucial criteria: low error rate, accurate location, and single response for each edge (Hussain and Agarwal, 2015; Pedrini and Schwartz, 2007). Following these criteria, Canny sought optimal solutions through mathematical formulations and numerical optimization, identifying a principle of uncertainty between the detection and location of noisy edges (Canny, 1986; Distanto and Distanto, 2020).

The Canny algorithm is implemented in several stages: smoothing of the image using a Gaussian filter; calculation of the image gradient to determine the strength of the edge; non-maximum suppression to keep only locally maximum gradient magnitude points as edges; and finally, the application of a double threshold that identifies potential edges through the use of two thresholds - high and low (Sekehravani *et al.*, 2020; Hussain and Agarwal, 2015). (Distanto and Distanto, 2020) emphasized that the Canny's approach is highly effective in accurately detecting edges and minimizing the effect of noise, thus being considered a standard for edge detection in digital images.

3. RESULTS AND DISCUSSION

This section presents the results obtained by considering the images shown in Figure 2. The first step before applying the filters is to transform the colored image into gray-scale. Then, the three smoothing filters are evaluated (Mean, Median, and Gaussian). The resulting images are depicted in Figure 3.



Figure 2. Original image with crack.

The Canny edge detection filter is applied. Note that the smoothing filters effectively reduce the noise in the image, resulting in a more accurate edge detection, as depicted in Figure 4.

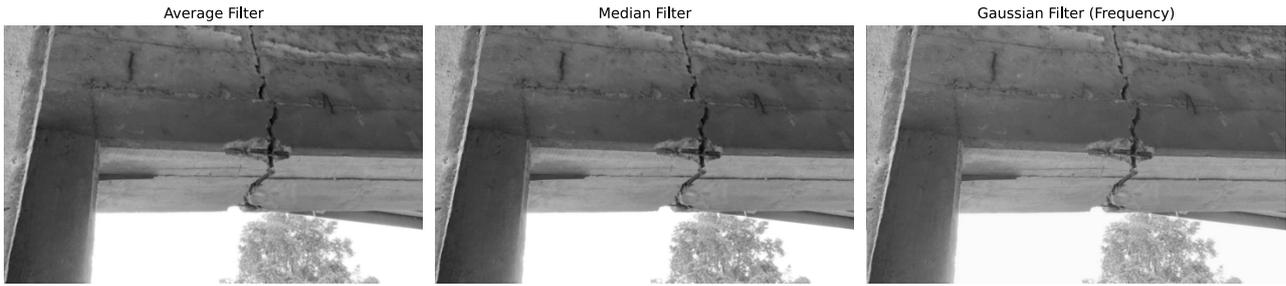


Figure 3. Images smoothed using different filters. From top to bottom: mean, median, and Gaussian.

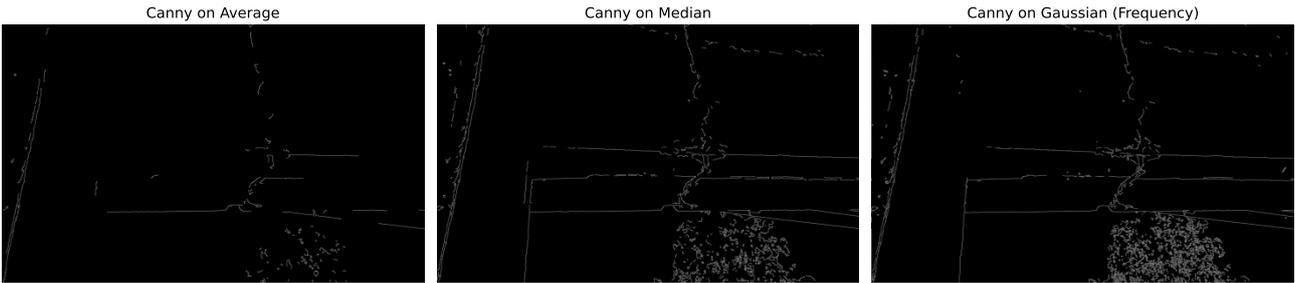


Figure 4. Result of Canny edge detection after the application of the smoothing filters. From top to bottom: mean, median, and Gaussian.

Each filter is separately applied to evaluate its effect on the image. The Gaussian filter (Table 2) demonstrates satisfactory precision, with 0.90 for the negative class and 0.87 for the positive class. However, considering its overall accuracy (0.88) in Figure 7, this filter is not the most efficient among the three analyzed.

Table 2. Classification Report - Gaussian Filter

Class	Precision	Recall	F1-score	Support
Negative	0.90	0.83	0.86	528
Positive	0.87	0.92	0.89	638
Average/Total	0.88	0.88	0.88	1166

In the context of aerial images obtained from UAVs (Unmanned Aerial Vehicles), the Gaussian filter might not adequately handle noise caused by varying environmental conditions, thereby impacting its performance. Additionally, its F1-score (Figure 5), which seeks a balance between precision and recall, indicates lower values than the other filters, particularly for the negative class.

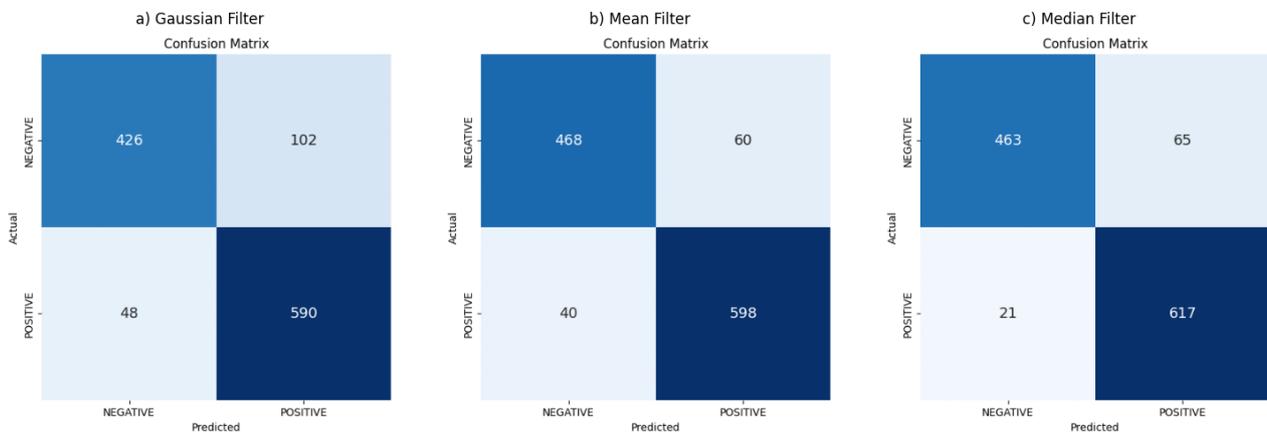


Figure 5. Confusion matrices for the analysis of Gaussian, Mean, and Median filters

The Mean filter (Table 3) shows slightly better performance than the Gaussian filter, with a precision of 0.92 for the NEGATIVE class and 0.88 for the positive class. For aerial images, this filter may be more adept at handling inconsis-

tencies in image quality, leading to improved performance. Its F1-score for the negative and positive classes are 0.88 and 0.91, respectively, showing a more significant balance between precision and recall compared to the Gaussian filter. Its overall accuracy is 0.90 (Figure 7), indicating a more efficient performance than the Gaussian filter, but it is still not the most efficient among the three filters under analysis (Figure 5).

Table 3. Rating Report - Mean Filter

Class	Precision	Recall	F1-score	Support
Negative	0.92	0.85	0.88	528
Positive	0.88	0.94	0.91	638
Average/Total	0.90	0.90	0.90	1166

The Median filter (Table 4) presents the best performance among the three filters. It achieves a precision of 0.98 for the negative class and 0.97 for the positive class. It's particularly effective for dealing with 'salt and pepper' noise, often found in aerial imagery due to various external factors. Moreover, its F1-score offers the best values, with 0.96 for the NEGATIVE class and 0.98 for the POSITIVE class, indicating an excellent balance between precision and recall. The overall accuracy of this filter is 0.97 (Figure 7), making it the most efficient in classifying the images (Figure5).

Table 4. Rating Report - Median Filter

Class	Precision	Recall	F1-score	Support
Negative	0.98	0.95	0.96	421
Positive	0.97	0.99	0.98	640
Average/Total	0.97	0.97	0.97	1061

When comparing the three filters 6, the Median filter emerges with the highest hit rates for both classes. This outcome aligns with our individual analyses, where the median filter also demonstrated the best results. In the context of aerial images from UAVs, it's crucial to note that this filter's superior performance may be attributed to its effectiveness in handling specific types of noise and inconsistencies that are common in such images. Moreover, the median filter not only stands out for its accuracy but also for its F1-score, representing a balanced metric considering both precision and recall.

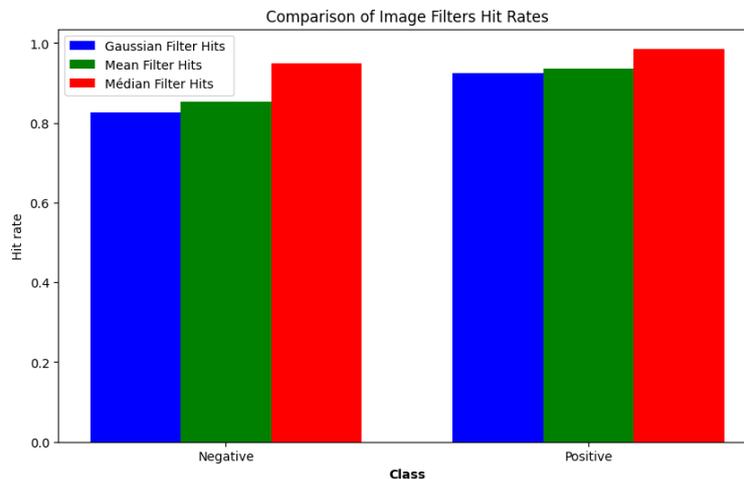


Figure 6. Comparison of the correctness of the filters according to the confusing matrix.

Figure 7 shows the superiority of the Median filter in overall accuracy. The results clarify that, for this specific image classification task, the Median filter is the most suitable among the analyzed options. However, it is important to highlight that the choice of an ideal filter can vary depending on the context and the specific characteristics of each image set. In UAV-based aerial imaging, different parameters such as altitude, camera quality, and environmental conditions can impact image quality and thus the effectiveness of different filters. Therefore, based on this study is crucial to determine which filter offers the best results in each specific scenario.

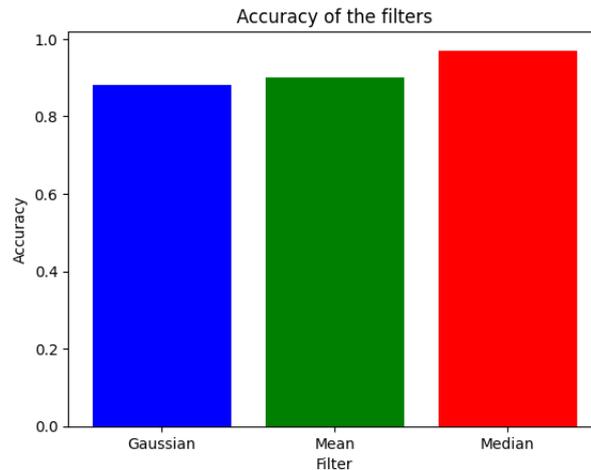


Figure 7. Accuracy of image filters

4. CONCLUSIONS

This study aimed to evaluate and compare the effectiveness of three different spatial filters for image pre-processing focused on damage detection in concrete-based structures. The Gaussian filter, Mean filter, and Median filter were evaluated. The results revealed important insights for this type of application involving image processing techniques to establish a structural health monitoring approach.

Among those three filters, the Median filter stood out as the most suitable choice for pre-processing. It demonstrated superior precision, recall, and overall accuracy in detecting crack-like damage in concrete structures. These findings have significant implications for SHM processes, mainly in terms of accurate and efficient.

This article introduced that the choice of an ideal filter may vary depending on the image specific characteristics for each particular application. In this sense, further research can explore additional image processing techniques and different algorithms to enhance the damage detection accuracy and efficiency.

5. ACKNOWLEDGMENT

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