





Spray Quality Assessment on Water-Sensitive Paper Comparing AI and Classical Computer Vision Methods

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Abstract: Over recent decades, precision agriculture has revolutionized farming by optimizing crop yields and reducing resource use through targeted applications. Existing portable spray quality assessors lack precision, especially in detecting overlapping droplets on water-sensitive paper. This proposal aims to develop a smartphone application that uses the integrated camera to assess spray quality. Two approaches were implemented for segmentation and evaluation of both the water-sensitive paper and the individual droplets: classical computer vision techniques and a pre-trained YOLOv8 deep learning model. Due to the labor-intensive nature of annotating real datasets, a synthetic dataset was created for model training through sim-to-real transfer. Results show YOLOv8 achieves commendable metrics and efficient processing times but struggles with low image resolution and small droplet sizes, scoring an average Intersection over Union of 97.76% for water-sensitive spray segmentation and 60.77% for droplet segmentation. Classical computer vision techniques demonstrate high precision but lower recall with a precision of 36.64% for water-sensitive paper and 90.85% for droplets. This study highlights the potential of advanced computer vision and deep learning in enhancing spray quality assessors, emphasizing the need for ongoing refinement to improve precision agriculture tools.


1 INTRODUCTION


Accurate evaluation of agricultural spray applications is critical for ensuring optimal pesticide usage and minimizing environmental impact. Although visual assessment of Water-Sensitive Papers (WSPs) is the norm for spray application of pesticides, it has shown to be an unreliable method for correctly assessing the paper's density and distribution of droplets. These challenges call for the development of improved methods for analyzing WSP data to enhance the precision and reliability of agricultural spray assessments.


The use of pesticides in crop management is crucial but can have significant economic, environmental, and health consequences if not applied correctly. The effectiveness of pesticides relies heavily on the application method to achieve an optimal droplet pat-


tern, reducing drift and ensuring precise product deposition on the target (Privitera et al., 2023). However, inconsistent pesticide spray coverage often results in unequal protection across fields, leading to numerous issues, such as the need for repeating pesticide applications, the development of weed resistance, and potential shifts in pest behavior. These shortcomings impose not only economic burdens but also amplify environmental and health risks (Machado et al., 2018). Moreover, factors such as the variability in weather conditions, equipment, and applicators further contribute to this inconsistency, posing significant challenges for effective and sustainable field crop protection (Nansen et al., 2021).

Precision spraying can be optimized by knowing the values of certain metrics such as Volume Median Diameter (VMD), which is measured by multiple image analyzers and stands as a key factor in reducing wasted spray and thereby minimizing environmental damage and cutting operational costs (Privitera et al., 2023). There are already a few methods available to assess the performance of pesticide

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applications with sophisticated imaging analyses and water-sensitive spray cards, which are able to quantify spray coverage and evaluate the efficiency of the pesticide distribution (Nansen et al., 2021). Techniques have evolved to calculate these metrics in the last few years, from manual processes to automated solutions such as DropletScan (Machado et al., 2018) and SmartSpray (Nansen et al., 2021). This signifies a growing need for more precise and efficient assessment tools (Xun and Gil, 2024). The integration of artificial intelligence and machine learning in agriculture can also make significant advancements in assessing spray quality (Privitera et al., 2023).

This research addresses the challenges described by developing a dual-method framework integrating both classical computer vision and advanced machine learning solutions for accurate WSP and droplet segmentation. To allow real-time image processing and statistical analysis of WSP in a practical tool for field use, an Android application was developed that is ready to be used for photography and analysis of the WSP. Additionally, a synthetic dataset for images of WSP with droplets was created to augment the training data as a means to improve the accuracy and generalization of the machine-learning models, given the limited number of annotated WSP images available.

This paper reviews existing methodologies for Water Spray Pattern (WSP) analysis, identifying their limitations through a gap analysis. It presents the primary metrics for evaluating spray quality and introduces an innovative approach to enhance model training using synthetic datasets. The methodology describes both classical computer vision and machine learning techniques for WSP and droplet segmentation, alongside the development of an Android application and web service. The results demonstrate the efficacy of the proposed solutions, comparing performance metrics across real and synthetic datasets. The study concludes with a summary of findings, implications for future research, and potential directions for further work.

2 LITERATURE REVIEW ON WATER-SENSITIVE SPRAY ASSESSMENT

Water Sensitive Papers (WSPs) have been a fundamental tool for agricultural spray evaluation for over 40 years, used in both aerial and ground applications (Cerruto et al., 2019; Marçal and Cunha, 2008). WSPs are semi-rigid papers coated with bromoethyl blue on one side and are available in various sizes.

The coating appears yellow when dry but turns different shades of brown, blue, and purple when it comes into contact with water droplets. These stains create a significant contrast with the dry yellow background, making it easier to assess the dispersion of the droplets (Privitera et al., 2023; Machado et al., 2018; Hoffmann and Hewitt, 2005). However, this method faces limitations such as the inability to measure droplets smaller than 50 μm (Machado et al., 2018; Cerruto et al. (2019), sensitivity to high humidity (Nansen et al., 2021; Hoffmann and Hewitt, 2005), and inaccuracies with high coverage (Marçal and Cunha, 2008). These limitations call for alternative methods for accurate spray analysis.

Rosin-Rammler distribution is a widely used function expressing drop size distribution with two parameters, representative diameter and a measure of drop size dispersion, and is useful for single-peaked results. Its simplicity and ability to extrapolate into difficult-to-measure ranges make it popular (Lefebvre and McDonell, 2017; Déchelette et al., 2011).

The evaluation of droplet sizes commonly uses Volume Median Diameter (VMD), which expresses drop size based on the volume of liquid sprayed. The spray is divided into two equal parts based on the sprayed volume, meaning that 50% of the total volume is made up of drops with diameters larger than the VMD value, and the other 50% by droplets with diameters smaller than the VMD value (Privitera et al., 2023; Schick, 2008). Relative Span Factor (RSF) is another metric commonly used. It is a dimensionless parameter indicative of the uniformity of the drop size distribution. RSF is a practical way of comparing various drop size distributions. High RSF values indicate wider drop size distributions and lower RSF values indicate less variation among drop sizes (Lefebvre and McDonell, 2017; Privitera et al., 2023; Machado et al., 2018; Schick, 2008).

YOLOv8, a state-of-the-art model in object detection, excels in efficiency and speed, making it suitable for real-time applications like precision agriculture.

There are an array of software solutions available to characterize spray quality. Zhu et al. (2011) created DepositScan, which is a portable scanner comprised of a handheld card scanner and a deposit collector. Nansen et al. (2015) presented SnapCard as an app available for both iOS and Android smartphones that offers two core functions: prediction of spray coverage based on pre-application weather data and spray settings, and post-application measurement for quality control. Machado et al. (2018) introduced DropLeaf, a smartphone app tailored to estimating pesticide amounts on WSPs, assisting farmers and agronomists in measuring spray coverage. Addi-

tionally, there are multiple other methodology solutions that although are not readily available and commercialized, they serve important contributions to the field. Ömer Barış Özlüoymak and Bolat (2020) developed a novel image processing software within Vision Acquisition Software (VAS) by National Instruments that aims to assess accurately spray coverage rates and droplet counts on WSP, including overlapped droplets. Xun and Gil (2024) developed a novel methodology that focuses on precisely segmenting overlapping droplets by utilizing concave point detection and ellipse fitting, ensuring optimal accuracy when the coverage is below 25%. Liu et al. (2024) presented a novel Optical Droplet Edge Imaging method that uses a device to acquire images from the top and bottom side of the droplet deposition surface to obtain the correct size measurement of the droplets.

3 DESIGN AND IMPLEMENTATION OF PROPOSED SOLUTION

The main goal of the system is to create an Android application tool for real-time assessment of spray quality on water-sensitive paper. The Android application, client-side, captures an image of the water-sensitive paper and sends it to the server side. The server analyzes the image, provides droplet statistics, and sends the results back to the client. The server-side application uses a dual-method algorithm that combines classical computer vision and machine learning techniques to accurately segment water-sensitive paper and droplets. The primary objective of both algorithms is to detect and separate overlapped droplets, ensuring that droplets that overlap are counted as separate entities for statistical purposes. Both methods developed follow an equivalent logic: detect the water-sensitive paper, remove distortion, segment individual droplets, and calculate the WSP statistics. This dual-algorithm approach allows to directly compare distinct methods of analyzing water-sensitive papers.

The standard WSP image contains over 1000 droplets that require manual labeling to establish accurate ground truth. This is challenging due to pixel-level segmentation requirements and the risk of incorrect labels. To overcome this, an algorithm was created to generate a simulation-based dataset, producing synthetic data that replicates real-world processes and automatically generates ground truth annotations. This approach saves time, ensures consistency, and

improves annotation accuracy, which is vital for effective machine learning model training.

Two distinct sets of images of water-sensitive paper were provided that form the basis for the analysis and study of the visual aspect of real spraying on a WSP. The images were also used to test the application’s algorithms implemented. Given the task of manually labeling each droplet, only two images were properly annotated for testing purposes.

Both datasets will be made available further into the future.

3.1 Synthetic Dataset

The synthetic dataset addresses the data acquisition and annotation challenges and was designed for transfer learning during the training of CNN models. Elements from real datasets, such as droplet colors, patterns, and shapes, were combined to enhance accuracy and simulate realistic conditions. The dataset represents a range of spraying scenarios with overlapped droplets. The Rosin-Rammler distribution was used to calculate droplet sizes, a method commonly used to describe particle sizes in sprays. The synthetic datasets were created with three different image resolutions to test model generalization across varying resolutions, as well as multiple different droplet size distributions.

The background of a WSP was generated with a radial gradient and random imperfections to mimic real-world scenarios. Droplet sizes were determined using the Rosin-Rammler distribution. Both colors for the background and the droplets were sourced directly from real datasets. The algorithm generates the placement of each droplet randomly. Then, it identified the overlaps between the droplets and applied a "shape burst" coloring technique for realism. Droplets were positioned using a sliding window technique to manage the computational load. Once positioned, droplets were colored based on the distance to the nearest edge, ensuring smooth color transitions.

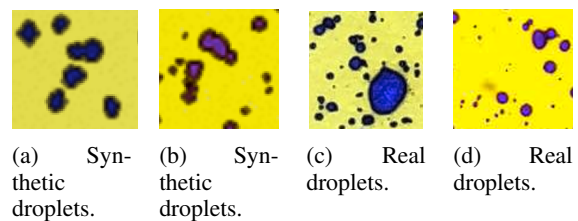
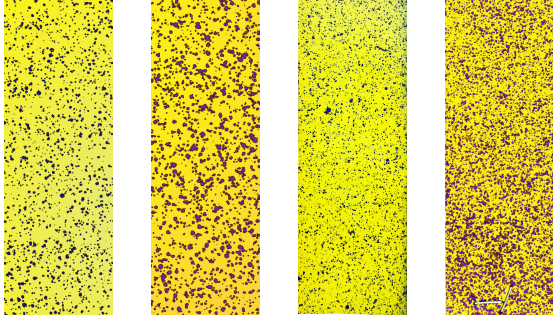


Figure 1: Comparison between droplets from the synthetic dataset (image (a) and (b)) and the real dataset (image (c) and (d)).

In the end, for testing purposes, background compositing was applied to seamlessly integrate synthetic droplets with realistic backgrounds, using the base images from real datasets. This process involved scaling and layering synthetic elements to maintain authenticity, ensuring the resulting composite image looked natural.



(a) Syn- (b) Syn- (c) Real (d) Real
thetic WSP. thetic WSP. WSP. WSP.

Figure 2: Comparison between droplets from the synthetic dataset (image (a) and (b)) and the real dataset (image (c) and (d)).

3.2 Water-Sensitive Paper Statistics

To accurately assess the quality of a spray in a water-sensitive paper (WSP) analysis, several statistical measures must be considered. The most representative and widely used statistical measurements are the Volume Median Diameter (VMD) and Relative Span Factor (RSF), which both require the diameter of each droplet.

Since the measurements are conducted using the pixels of a digital image, droplets are initially measured in pixels. The software detects the area of each droplet rather than the diameter. Therefore, to calculate the real-world measurements of each droplet, the server-side application must obtain the size of the paper to be analyzed in real-world units, specifically in centimeters. This value is then used to establish the true ratio between the measurements in pixels and centimeters. With the area of each droplet measured in pixels, the diameter can be calculated by approximating the droplet shape to a perfect circle and using the relation between area and diameter. The following equation is used throughout the algorithms developed to calculate the statistics of a WSP:

$$d_{\mu m} = 2 \times \sqrt{\frac{A_{px}}{\pi}} \times \frac{width_{\mu m}}{width_{px}} \quad (1)$$

$d_{\mu m}$ is the diameter in micrometers, A_{px} is the area of the droplet in pixels, $width_{px}$ is the measurement

of the width of the paper in pixels and $width_{\mu m}$ is the measurement of the width of the paper in micrometers.

When calculating real-world statistics such as VMD or RSF, the measurements of the droplets, which are all in pixels, are converted to real-world measurements in centimeters using a pre-defined scale. This scale factor accounts for the resolution of the image and the physical dimensions of the WSP. Additionally, a spread factor is applied, assuming that all droplets have the same physical properties and impact on the WSP under similar conditions. This ensures consistency in the interpretation of droplet measurements.

The values of VMD and RSF are calculated using the representative diameters of the droplets. Therefore, for an accurate analysis of a WSP, it is crucial to know the correct measurement of the diameter of each droplet. If droplets overlap, it is important to separate them, as the calculation of the diameter based on the area assumes a perfect circle. Additionally, if a droplet is considered an ellipse, it introduces further errors in the calculation.

Moreover, the coverage percentage, which indicates the proportion of the WSP covered by droplets, along with the quantity of droplets, is computed. This information is used to assess the precision of the algorithms developed and is displayed as a statistical result in the Android application to offer additional details about the paper.

3.3 Water-Sensitive Paper and Droplet Segmentation

The server-side application focuses on the instance segmentation of droplets on WSP, meaning that the algorithm must identify and delineate the individual each individual droplet within the image, including the overlapped droplets. This is crucial for accurately measuring and assessing droplet size and distribution. These measurements are used to calculate the statistical values mentioned before like average droplet size, distribution uniformity, and coverage percentage. Two segmentation types are required: segmentation of the WSP and segmentation of the droplets on the WSP.

3.3.1 Segmentation of the Water-Sensitive Paper

The classical computer vision method for segmentation of the WSP involves a multi-step process to accurately delineate the paper from its background. Initially, the image is processed with a Gaussian blur to minimize noise and a 3D color histogram is em-

ployed to identify and isolate the predominant color, masked to generate a binary image. This binary image is produced by converting the original image to grayscale and applying a binary threshold to accentuate the edges. OpenCV’s `findContours` function is used to detect contours, with the largest contour presumed to outline the paper’s boundary. The convex hull of this contour is computed to establish a more precise boundary. Finally, the corner points of the detected shape are identified, and a perspective transformation matrix is applied to correct any distortion, resulting in a properly aligned image of the WSP.

For the machine learning approach, a pre-trained model from YOLOv8 is utilized due to its efficiency and rapid performance in object detection tasks. The model, specifically a small-sized version optimized for segmentation, was retrained using a dataset comprising 591 images for training, 54 images for validation, and 27 images for testing. The model was trained with 50 epochs and AdamW optimizer for 30 minutes. This dataset originally included 278 annotated real images of WSP with diverse backgrounds. The annotations were done manually using Roboflow’s smart polygon tool. The augmentation techniques were applied on Roboflow as well, expanding the dataset to a total of 672 images.

3.3.2 Droplet Segmentation on Water-Sensitive Paper

The developed algorithm utilizes classical computer vision techniques to segment and classify WSP droplets, thereby providing meaningful distribution statistics. The process begins with Otsu thresholding (Mugele and Evans, 1951) from the OpenCV library, which effectively distinguishes droplets from the background and outperforms adaptive thresholding that often results in fragmented and inconsistent segmentations. As cited by various researchers (Lipiński and Lipiński, 2020; Wen et al., 2022), this thresholding method stands out as particularly effective in the domain of this research

To minimize noise and enhance droplet separation, the image is first blurred before applying thresholding. The thresholding mask is inverted, and the `findContours` function in OpenCV is employed to identify contours. Contours are classified into single circles, single ellipses, and overlapped shapes, with additional notation for edge shapes. Circularity and ellipse fitting are determined using OpenCV functions, while convexity analysis helps identify potential individual droplets within complex shapes.

For complex shapes, the Hough Circle Transform combined with KMeans clustering is used to detect circles. A mask isolates the region of interest, and

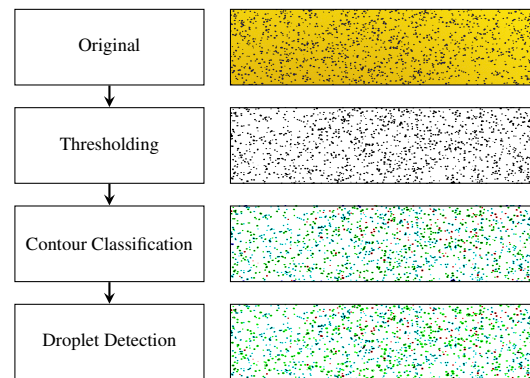


Figure 3: Image processing algorithm using classical computer vision methods.

parameters are finely tuned to maximize circle detection. Circles are then refined through clustering and Intersection over Union (IoU) score improvements, ensuring accurate droplet identification and analysis. Figure 4 illustrates the steps taken for individual droplet segmentation.

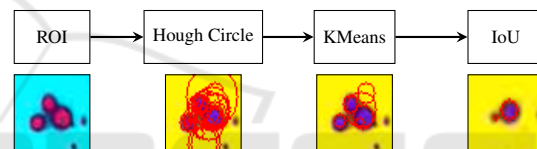


Figure 4: Separation of individual droplets process given a non-circular shape.

The machine learning approach uses a pre-trained medium segmentation model from YOLOv8. The model is trained with 5 000 images of the synthetic dataset. Given the small size of the droplets to be detected, the images are cut into squares of 320 by 320 pixels to minimize the number of droplets per image and maximize the visibility of each droplet for the model. The model was trained with 300 epochs and SGD optimizer for 7 hours and 30 minutes.

YOLOv8 was trained using images of 320 by 320 pixels, which was chosen to balance the need for detail and the computational efficiency required for real-time processing. This resolution provides enough detail for identifying and segmenting droplets while ensuring the processing time remains practical for applications that demand quick responses.

3.4 Android Application

The client-side is an Android application designed to meet the system’s real-time requirements and was primarily developed using the programming languages Kotlin and Java in the Android Studio IDE. The application GUI is illustrated in Figure 5

When using the app, the user can select to take a

picture of the WSP using the smartphone-integrated camera or choose an image from the gallery. After that, they need to choose the segmentation algorithm they intend to use and will be able to view the statistics obtained through the computer vision analysis of the server-side application. The communication between the two sides is done by sending a file in JSON format.

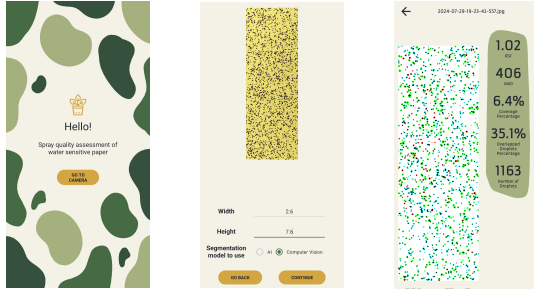


Figure 5: Preview of the Android application.

Given the computationally intensive nature of the image segmentation algorithms, processing on the smartphone’s processor was deemed impractical. To address this, a web service server was developed to handle the image-processing tasks. This server receives requests to process images, performs the necessary computations, and returns the processed image along with relevant statistics.

The web service was developed using Python and Flask, a lightweight web framework. The service features a single REST API endpoint designed to receive and process images and send back the evaluation of the WSP.

4 EXPERIMENTAL RESULTS

4.1 Segmentation of Water Sensitive Paper Results

The validation of the segmentation of the water-sensitive paper is done by calculating the IoU metric using both methods on a collection of 20 images, which were put aside when the training of YOLOv8 took place. These images include a multitude of backgrounds with the WSP being not always centered or the main focus of the image, assuming the worst type of user for the images.

Table 1: Results of the two algorithms developed for detecting water-sensitive paper.

Method	IoU	Time (ms)
YOLOv8	0.9776	0.2801
CCV	0.3664	0.0357

The results presented in Table 6 indicate that the YOLOv8 method significantly outperforms the CCV approach in terms of IoU. This outcome aligns with expectations, as CCV techniques rely on predefined fixed values and are often less adaptable to image variations. The CCV method struggles with generalization, particularly when the dataset exhibits diversity in the shapes, colors, and orientations of the WSP.

The detection of the WSP using the CCV method implements a histogram of the colors in the image. Therefore, when the main focus of the WSP image is not the paper itself, this method is not the most effective. The algorithm performs with much more precision when the WSP is centered and occupies most of the pixels in the image.

Figure 6 depicts two examples of the images used to validate the algorithms. The image on the left achieved an IoU value of 97.34%, whereas the image on the right attained a value of 8.59%. This illustrates that while segmentation with classical computer vision can be effective in certain cases, it has notable failure points. On the other hand, the YOLOv8 model obtained values of 97.03% and 93.78% respectively.



Figure 6: Two examples of images used for validating the algorithms of WSP segmentation.

4.2 Segmentation of Droplets

For the evaluation of the segmentation of droplets, the metrics presented in Table 2 were chosen for the task of validating the different algorithms across various datasets. The primary goal was to assess the performance of each algorithm in terms of precision (P), recall (R), F1-score (F1), mean average precision at 50% intersection over union (mAP50), and processing time (Time).

Three different datasets were used. The synthetic dataset (SD) comprises 30 images, which were put aside during the training of YOLOv8, representing a comprehensive sample of the synthetic dataset created, including multiple image resolutions, colors, and droplet distributions available. From the real dataset, two images were annotated and verified, RD1 and RD2. Although this task was performed meticulously, it is still susceptible to human error.

From the results, it can be inferred that YOLOv8

Table 2: Results of algorithms for calculating statistics for water-sensitive paper.

Method	Dataset	P	R	F1	mAP50	Time (ms)
YOLOv8	RD	0.1516	0.0859	0.1096	0.01378	10.6307
YOLOv8	SD	0.6077	0.5725	0.5896	0.3796	8.2397
CCV	RD	0.6551	0.8485	0.7393	0.5545	5.3724
CCV	SD	0.9085	0.6304	0.7443	0.6010	5.3204

does not outperform CCV in segmentation. The segmentation by YOLOv8 is imperfect, with many rough edges due to the low resolution of images and the small size of objects. Nevertheless, YOLOv8 exhibits acceptable metrics, especially given the constraints of the task. The performance metrics highlight specific strengths and weaknesses of each method. For example, while CCV shows higher precision on RD, its recall is considerably lower, indicating that it misses more droplets than YOLOv8.

The confidence threshold for the prediction of YOLOv8 was set to 0.1 and 0.5, respectively. During the segmentation task, the YOLOv8 solution was found to be conservative. It often failed to detect droplets even when there was a clear distinction between the background and the droplet. Upon evaluating the results, it was apparent that assigning the lowest confidence score during the prediction generated much better results for the task at hand. To assess the precision and recall of the predictions, the IoU threshold was set to 0.5 (or 50%). This means that a prediction was considered accurate when the IoU relationship between the predicted mask and the ground-truth mask of the object was over 0.5.

Another important aspect to consider to validate the algorithms developed is to evaluate the values obtained for the most relevant statistics for spray quality assessment. For this, it was used an external software developed by Machado et al. (2018), DropLeaf. Multiple applications are available on the Google Play Store, but only DropLeaf allows image uploads from the gallery. This process was done manually for both the datasets and the results were annotated for later evaluation and metric calculation. The datasets used are the same datasets used for the before table. To utilize DropLeaf, a virtual machine for Android 7.3.1 was utilized since the software stopped being compatible with newer Android versions.

DropLeaf consistently evaluates the coverage percentage as high, approximately 90%. However, according to Machado et al. (2018), the density should be lower and more accurate. When recalibrating the value to 100% minus the Coverage Percentage, the accuracy of DropLeaf improved significantly. This suggests a potential error in the application rather than the calculation of the coverage percentage in the algorithm, as no other cause was identified.

The ground truth statistics of the datasets were cal-

culated using the same algorithm as the segmentation algorithm developed. Therefore, it is crucial to consider that significant discrepancies in DropLeaf values might stem from differences in the calculation module, as it is the only varying factor.

5 CONCLUSIONS

This study analyzes WSP methodologies, identifies limitations, and proposes innovative solutions. A synthetic dataset is generated to improve model training and generalizability. The development of a partial annotation algorithm for real datasets reduces manual effort while maintaining accuracy. However, further improvements to the synthetic dataset are needed to enhance both human perception and transfer learning results.

The methodology compares classical computer vision techniques with advanced machine learning for WSP and droplet segmentation. An Android app and web service are also developed for real-time data collection, demonstrating practical applications.

The evaluation of droplet segmentation algorithms on both synthetic and real datasets revealed distinct performance differences between the methods. While YOLOv8 demonstrated reasonable results, it was outperformed by CCV in terms of segmentation accuracy, particularly with real-world data. CCV achieved superior precision and recall, making it more effective at detecting droplets in diverse conditions. Nevertheless, YOLOv8 showed promising results in synthetic datasets, especially when dealing with reasonably sized objects and higher-resolution images.

Further analysis using metrics such as droplet count, VMD, RSF, and coverage percentage highlighted additional performance disparities between the algorithms. These findings emphasize the critical need to select algorithms tailored to the specific characteristics of a dataset and segmentation task, and they underline the importance of thorough validation to ensure precise droplet segmentation and accurate statistical assessment.

In summary, this research contributes to the field by addressing current limitations in WSP analysis by providing a smartphone application and instance segmentation methodology for future studies. The

Table 3: Percentage error of each one of the metrics used to evaluate the spray quality of a water-sensitive paper.

Method	Dataset	No Droplets	VMD	RSF	Coverage Percentage
YOLOv8	RD	0.5561	0.2233	2.7338	0.6095
YOLOv8	SD	0.2621	0.1423	0.2729	0.4593
CCV	RD	0.4189	0.1952	1.9945	0.1533
CCV	SD	0.3144	2.5103	0.5108	0.0842
DropLeaf	RD	0.6096	0.7362	0.0916	0.5223
DropLeaf	SD	0.9667	0.3738	8.5897	0.2639

findings emphasize the potential of using synthetic datasets to train machine learning models to enhance accuracy and efficiency. Future research could focus on refining the process of generating synthetic datasets of WSP and developing more advanced machine-learning models to further advance its analysis.

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