

ASSESSING SMOKE PARTICLE CONTAMINATION ON FIREFIGHTER PERSONAL PROTECTIVE EQUIPMENT USING GENERATIVE AI AND EDGE DETECTION MODELS

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ABSTRACT

Firefighters at a wildland-oilfield interface (WOI) encounter complex smoke particle mixtures from biomass and hydrocarbons. These particulates settle onto Personal Protective Equipment (PPE) surfaces, remaining long after fire suppression activities. These attached smoke particles create a severe occupational hazard through secondary exposure during movement and the donning/doffing of contaminated gear. Despite the occupational risk, various commercial particle detection and size distribution techniques are destructive or requires liquid extraction of smoke particles for analysis. A non-destructive technique facilitates the understanding of particle size, and distribution onto the fabric surface. This study provides a comparative analysis of particle detection methods using non-destructive, multiple imaging technique through scanning electron microscopy. Following a comparison of traditional edge detection algorithms (Canny, LoG and Otsu) with Generative AI, An optimized detection method is established across multiple PPE textile substrates, to ensure broad applicability of the optimised detection technique. The technique successfully identifies and measures respirable ($\leq 2.5 \mu\text{m}$) and ultrafine ($\leq 1 \mu\text{m}$) particles on textile surfaces. Analysis of wood and oil smoke revealed high concentrations of ultrafine particles, highlighting the invisible threat they pose. Ultimately, this research aims to establish a universally applicable detection framework for smoke particles deposited onto PPE surfaces.

KEYWORDS: Smoke analysis, Wildland-oilfield interface fire, Generative Artificial Intelligence, Image edge detection, Occupational safety, Personal Protective Equipment.

1. INTRODUCTION

Firefighters combating wildland-oilfield interface fires (WOI) are exposed to various carcinogen carrying smoke contaminants during fighting fire (Adetona et al., 2016; Horn et al., 2024; Navarro, 2020). Exposure to these carcinogens over a period of time may lead to various health hazards including occupational cancer (Demers et al., 2011; LeMasters et al., 2006). When fighting WOI fires, firefighters wear personal protective equipment (PPE) designed to protect against all plausible occupational hazards during combating fire. However, multiple studies have reported the presence of carcinogenic compounds in skin swab samples collected from wildland firefighters (Baxter et al., 2014); samples like these are strong evidence that current PPE does not provide adequate protection against dermal exposure. Additionally, various meta-data, surveys and statistical analyses have shown strong correlation with this dermal exposure with occupational cancer for firefighters (Bates, 2007; Demers et al., 2011).

Smoke exposure is a challenging occupational hazard for WOI firefighters. Majority smoke exposure hazards come from inhalation risks (Wah et al., 2025) and dermal exposure (Adetona et al., 2016; Horn et al., 2024; Navarro, 2020). This exposure occurs through two distinct but related pathways. The first is primary exposure, which arises from the direct penetration of smoke particles through the layers of the PPE (Navarro, 2020). The second is secondary exposure, that originates from particles accumulating on the outer surface of the PPE. These deposited particles are not immobile. With adequate mechanical means surface attached particles may dislodge (Wang et al., 2019). With the movement of the firefighter, or with any shift in the geometry of the clothing, due to change in fabric folds, stretching, and compression these deposited particles can dislodge. This dislodging may lead to secondary exposure of these particulates to the firefighters. Secondary exposure can also occur during doffing, where handling of contaminated gear where there is a chance of contaminated PPE-skin contact.

WOI fire smoke particles follow a polydispersed distribution with its particles size varying from nano meters to coagulated particles ranging into micrometres (Dilger et al., 2016, 2023; Hurley et al., 2016). The major mode particle size reported for freshly emitted particles from wildfire fuel in laboratory scenario range from 29 nm to 52 nm (Hosseini et al., 2010).

However, in wildfire these particles coagulate and generally the particle size range nanometres to micrometres depending on ageing and amount of coagulation (Laing et al., 2016; Lu et al., 2025; Zheng et al., 2020). The ultrafine smoke particles (<100 nm) and fine particles (<2.5 µm) pose a major hazard for the smoke exposure of WOI firefighters through their PPE. These smoke particles can easily enter through the pores of the wildfire PPE fabrics and lead to dermal exposure. These ultrafine and fine particles pose significant hazard with their secondary exposure as well since smaller particles with lower inertia makes them easy to dislodge (Wang et al., 2019) and size make them easy to penetrate the PPE fabric.

Smoke particles deposited onto fabric surface thus pose a significant occupational hazard. One of the most common methods of characterization its geometry and particle size is through imaging of contaminated surfaces using a Scanning Electron Microscopy (SEM) (Sun et al., 2024), or a Transmission Electron Microscopy (TEM) or Atomic Force Microscopy (AFM). Imaging techniques offer fast, non-destructive solution to surface data, whereas various commercially available techniques require extraction in liquid media for analysis. SEM, TEM and AFM provide surface morphological images of smoke particles and agglomerates deposited onto the surface. Although TEM has been used in multiple literature for smoke particle imaging, however for TEM, it requires thin substrate for electron transmission (Omidi et al., 2017). Hence, in multiple cases particles from the fabric surface are extracted to obtain information regarding smoke particles. However, such extraction fails to provide any understanding of particle distribution on the fabric surface. Hence, among these techniques SEM and AFM offers the only solution to this approach.

Many commercial SEM, AFM systems are equipped with general purpose automated imaging softwares, which are often designed for fast, general imaging purposes and in various instances require human intervention for analysis. The presence of smoke particles on textile media imaging and optimization presents an additional challenge, as textiles are non-uniform and hollow media. This structural complexity introduces significant contrast variations since fabric's non-uniform surface structure allows deposition of smoke particles on different fabric plane and region. Which necessitates optimization of imaging techniques based on its end-use or application. Hence, the scope of the study is focused on the effectiveness of different advanced image processing techniques and is extended to analyse how different smoke generation and deposition techniques onto the textile surface affect detection.

Advanced imaging techniques like edge detection techniques (i.e., Canny, Laplacian of Gaussian (LoG) (Sun et al., 2024), Otsu (Otsu, 1979)) and well known Generative AI (Du et al., 2026) (e.g., ChatGPT) currently has been used extensively for acquiring information from SEM images in various applications. However, in general all image analysis techniques possess challenges when applied to SEM images, where challenges such as specimen charging, secondary electron noise, uneven particle aggregation, and poor foreground–background contrast separation exists. Despite such challenges these computational techniques offers edge over manual processing as it requires less computational time to acquire and analyse meaningful data from image (Rühle et al., 2021).

Each particle detection technique follows a distinct logic and algorithm for edge detection and noise removal to identify objects, thereby offering varying advantages and disadvantages for specific applications. In this paper, different edge detection techniques (i.e., Canny, Laplacian of Gaussian (LoG), and Otsu) and Generative AI model (i.e., ChatGPT) have been compared to detect particles on diverse textile surfaces under varying magnification and contrast conditions. Hence this study optimises each particle detection technique and aims to provide a comprehensive understanding of effectiveness of different image processing techniques for detecting smoke particles and smoke particle agglomerates on various textile surfaces. Ultimately, a comprehensive study of these techniques is necessary as it offers a non-destructive morphological measurement of these deposited particles. A morphological analysis will help assess the occupational hazards they pose to WOI firefighters through contaminated wildland PPE surfaces.

2. METHODOLOGY

2.1 SMOKE DEPOSITION ONTO FABRIC SURFACES

Smoke particles from crude oil and wood combustion were deposited onto fabric surfaces under controlled laboratory conditions^{1*}. Commercially available single-layered flame-retardant fabrics of different FR polymers and geometry (areal density), construction (woven and knitted) and flow parameters (air permeability) is chosen for this study as shown in Table 1. This broad selection of fabric construction and geometry is done since these parameters are known to govern flow parameters and thus influence smoke deposition behaviour. Incorporating fabrics across a wide range of these parameters ensures that the study reflects a wide spectrum of commercial textile substrates encountered in practice, rather than being optimised for any single fabric type.

^{1*} Details of the deposition apparatus and protocol are proprietary and constitute part of a parallel study currently under preparation

Table 1: Fabric construction and paramaters

Fabric Code	Construction	Composition	Yarn density	Areal Density (oz/yard2) ⁱ	Air permeability (cm ³ /cm ² /s) ⁱⁱ
S ₁	Twill, Woven	FR cotton	EPI-85, PPI-50	6.16	69.6
S ₂	Single Jersey Knitted	FR cotton	CPI-70, WPI-40	7.5	33.2
S ₃	Twill, Woven	Kevlar/Nomex	EPI-30, PPI-25	6.25	105
ⁱ Average value measured in accordance with ASTM D3776					
ⁱⁱ Average value measured in accordance with ASTM D737					

2.2 SCANNING ELECTRON MICROSCOPY

Scanning electron microscopy (SEM) was used to analyse smoke contained textile substrates. A low accelerating voltage ($\leq 5\text{KV}$), with zero tilt was used to analyse surface bound particles. A lower accelerating voltage corresponds to lower sample beam penetration and improve imaging of surface bound smoke particles. A wide magnification range of 500x to 50,000x was utilized to acquire high-resolution images of coagulated fine and ultrafine smoke particles with distinct image boundaries. A SEM database of 28 images is created with of particle deposited onto fabric surfaces using SEM imaging ^{2**}. This database is used in this study to obtain Feret diameter (μm) and area of smoke particles (μm^2) of the smoke particles based on different particle detection techniques, including edge detection algorithms and generative-AI tools.

2.3 PARTICLE DETECTION TECHNIQUES

To ensure broad applicability of the optimised detection technique, the study was conducted across multiple PPE textile substrates with different geometrical and construction parameters. Rather than optimising detection parameters for individual fabrics, the study aimed to establish a universally applicable detection technique. This ensures that the technique is robust and does not require re-optimisation when applied to different textile substrates.

2.3.1 EDGE DETECTION ALGORITHMS

Canny, Laplace of Gaussian (LoG), Otsu algorithms were used for the initial study for detection of smoke particles from SEM images. Python 3.14.4 along with PyCharm 2026.1 IDE (Integrated Development Environment) is used for coding the individual edge detection algorithms. Multistep edge detection technique was for each algorithm. Initially prior to use of edge detection algorithm all images were optimised for their brightness using Contrast Limited Adaptive Histogram Equalization (CLAHE). For the current methodology CLAHE is optimised to 0.005 and this value is used for all further processing. A low CLAHE value is used to improve contrast for better particle detection. Using a higher value causes closely situated smoke particles to merge, making it difficult to identify them individually. Following brightness optimization Canny, LoG and Otsu algorithm were used and optimised as described below.

The Canny edge detection algorithm was applied using its standard methodology. First a gaussian blur is used to minimize the localized errors caused by the electron beam which was followed by optimization of threshold and sensitivity range represented as (threshold value, sensitivity value). Following this to ensure each particle was identified as a solid object rather than just hollow particle edges a hole-filling algorithm is used to ensure the particle inside the detected boundary is detected. The pictorial steps of the algorithm are shown in Fig. 1a.

The Laplacian of Gaussian (LoG) edge detection algorithm was applied using its standard technique. Where following contrast enhancement with CLAHE a gaussian blur is used to minimize the localized errors. After the gaussian blue standard deviation (σ) was optimised to identify zero-crossings in the second-order derivative. This σ optimization is essential for tuning the sensitivity of the algorithm to the edges of the smoke particles. Standard deviation (σ) defines the spatial scale of the gaussian bell curve (Marr & Hildreth, 1980). It is a general standard practice for selection of σ is its value to be spaced by a factor of $\sqrt{2}$ (Lindeberg, 1994). However, due to significant localised contrast variations in SEM images, a factor of $\sqrt{2}$ shift leads to massive shift of zero crossing pixels. Hence during optimization, a factor of 0.1 is used. This was followed by a hole-filling algorithm for detecting particle inside the detected boundary. The pictorial steps of the algorithm are shown in Fig. 1b.

Otsu global-thresholding optimization depends on the particle size within the image. For this algorithm, it requires a prior knowledge of particle size distribution. Otsu global-thresholding algorithm uses a top-hat filter which is optimized to remove the background noise from the images. A circular probe top-hat filter is used which scans across the image for particles lower than or equal to its radius value. Hence, depending on the particle size in the given image the highest radius value for all the given images is chosen as the optimised value. Following the filter, the image was binarized (black and white) where the binarization level was optimised by maximizing pixel intensity variance. The thresholding of otsu operates to

^{2 **} The full SEM database is available to researchers on request

automatically separate the image into foreground and background based on global image intensity. Hence, otsu inherently dependent on the degree of intensity separation between particles and background. As a result, contrast variation occurring due to SEM voltage change, current intensity change poses a significant challenge for global thresholding as otsu doesn't tackle these localised changes. Hence otsu uses an auto thresholding as compared to a fixed optimised thresholding in comparison to Canny or LoG as shown in Fig. 1c. Following the auto thresholding a hole-filling algorithm is used for detecting particle inside the detected boundary.

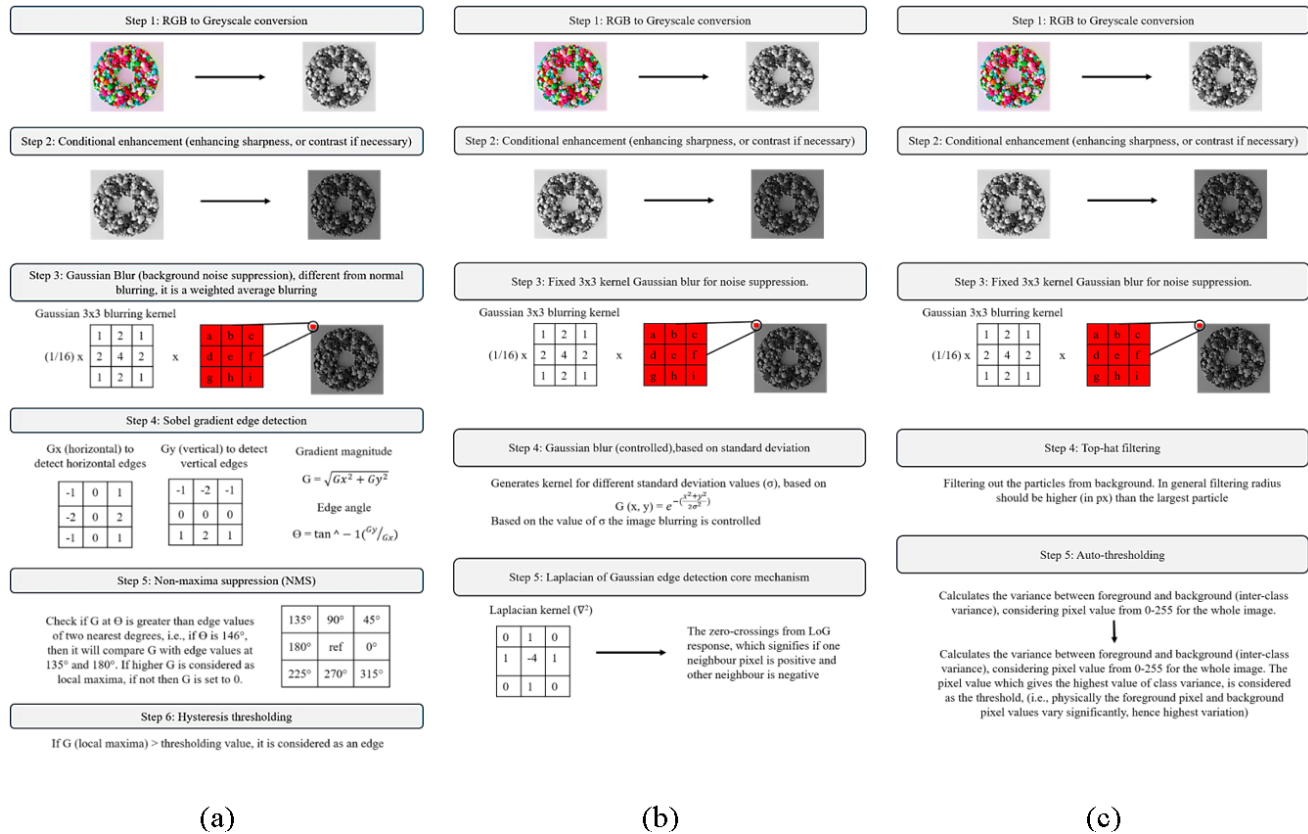


Figure 1: Pictorial steps for different algorithm for (a) Canny edge detector, (b) LoG edge detector, (c) Otsu-thresholding edge detector

2.3.2 GENERATIVE AI

Open version of Large Language model (LLM) ChatGPT GPT-5.3 with AIPRM 1.4.3.19 is used for this analysis. LLM models provide a stochastic output depending on computer system as well as user. Hence prompt design and selection was carried out in two steps to obtain a zero-shot prompt. A zero-shot prompt is chosen as the final prompt since few-shot prompts often lead to overfitting of data, adding to the stochasticity of LLM outputs across different images.

In the first stage, prompt refinement was performed within ChatGPT using a scaffolded few-shot prompting approach. Where the task was broken down into simple one line sequence of small prompts. Initial prompts were used to detect the smoke particles with particles described as describing particles as circular, near circular, or aggregated circular objects. This was followed by closed boundary detection. This ensured all smoke particles detected are closed structures. Following these prompts to determine the scale bar and extract subsequent information for pixel-to-physical distance scale (i.e., number of pixels in a given physical distance based on scale provided in the image). Followed by prompts for maximum Feret diameter and projected area measurement.

The complete few-shot prompt conversation from ChatGPT was then exported to Claude AI (Sonnet 4.6) to consolidate the staged sequence into 4 zero-shot prompts following meta-prompting approach. Among the 4 zero-shot prompts, the one with the most direct, unambiguous description of the task in natural language, with very well-defined section and task direction is chosen as the optimised final prompt.

Following the first stage of prompt optimization, the selected prompt was deployed using a different computer system and a different ChatGPT account than the one that was used during the few-shot prompt stage. This was done to avoid influence from prior conversation memory and ensure un-biased and un-trained zero-shot prompting.

In general, LLM models may give extrapolated results based on amount of training. Hence a section is included in the prompt to prevent the AI from extrapolating the data. Based on literature prior instances of data extrapolation have been noted during image analysis using generative AI tools (Davydiuk et al., 2025). Prompt is provided in Appendix I.

2.3.3 GROUND TRUTH ANALYSIS EVALUATION OF PARTICLE DETECTION TECHNIQUE

Benchmarking and verification of any edge detection technique requires a reliable reference standard. Human annotation is one of the widely used technique for determining the ground truth (Jerez et al., 2021; Meester & Baslamisli, 2022; Rettenberger et al., 2025; Xie & Tu, 2015). This technique has been widely used in multiple image processing applications for comparison. In the current study human annotated ground truth is generated using SketchAndCalc application software (SketchAndCalc, 2024). This software has been widely used in prior literature for determining different parameters of irregular shapes (Datta et al., 2022; Kamano et al., 2022). Ground truth annotation was performed by a single expert annotator who has prior experience in working on fabric-smoke deposition, SEM imaging and characterization. Given the specialist nature of SEM image analysis, an expert is necessary who has prior experience in working on smoke deposited particulates. A single expert human annotator in a specialised field is consistent with established methodology (Jerez et al., 2021; Rettenberger et al., 2025).

A systematic comparative analysis based on image overlay technique was conducted to evaluate the performance of various edge detection techniques against the established ground truth. Precision, Recall, and F1-Score were employed as performance metrics to assess the effectiveness of each edge detection technique in this specific application (Li et al., 2025; Muntarina et al., 2023). Precision is the ratio of correctly classified edges to everything classified as edges, Recall is the ratio of correctly classified as edges to all actual edges based on ground truth detection (*Classification*, 2026). F1-score is the harmonic mean of Precision and Recall. These techniques evaluate the effectiveness of the edge detection technique using values ranging from 1.0 to 0.0, with 1.0 representing a perfect score. These techniques overlay images with ground truth, and checking is done using pixel matching.

Among the following evaluation matrix to quantitatively compare technique performance, F1-score was adopted as the primary evaluation metric. Since F1-score is harmonic mean of precision and recall, it depicts the overall performance of the image processing tool more effectively. The F1-scores are statistically analysed through paired t-tests to determine whether significant differences existed between different particle detection techniques as well as across the two magnification conditions.

2.4 EVALUATION OF SMOKE PARTICLE PARAMETERS

Each particle detection technique was analysed for different images from the database to obtain average precision, recall and F1 scores. Following the image analysis, the particle detection technique which performed best in these parameters is used over all images from the database to obtain various smoke particle parameters including number of particles detected, particle size (Feret diameter) distribution in micrometres.

3. RESULTS AND DISCUSSION

3.1 SCANNING ELECTRON MICROSCOPY IMAGES

Scanning electron microscopic images for fine and ultrafine smoke and soot particles deposited onto the fabric surface was obtained as shown in Fig. 2. Fig. 2 shows 12 image samples from the SEM database used for this study. Distinct differences in particle morphology and spatial distribution were observed in the SEM images between smoke particles generated from wood combustion and those derived from hydrocarbon burning as seen in Figure 2.

Smoke particles originating from hydrocarbon (OP) combustion exhibited a finer particle size Fig. 2 (g-i), with different degree of agglomerated particles composed of discrete, circular ultrafine particles that were more even distributed across the fabric surface as seen in Fig. 2 (a-c). In contrast, smoke particles produced from wood (WP) Fig. 2 (j-l) combustion displayed a comparatively coarser morphology with lower particle density as seen in Fig. 2 (d-f). The agglomerated structures observed in wood-derived smoke particles appeared to have undergone partial fusion, resulting in less defined particle boundaries compared to hydrocarbon.

SEM images obtained due to exposure from crude oil showed higher contrast among the deposited smoke particles as observed in Fig. 2 (a-c) compared to that of wood Fig. 2 (d-f). This is due to fineness of crude oil smoke particles (OP). Higher fineness leads to deeper penetration of the particles into the fabric resulting in varying contrast in the image.

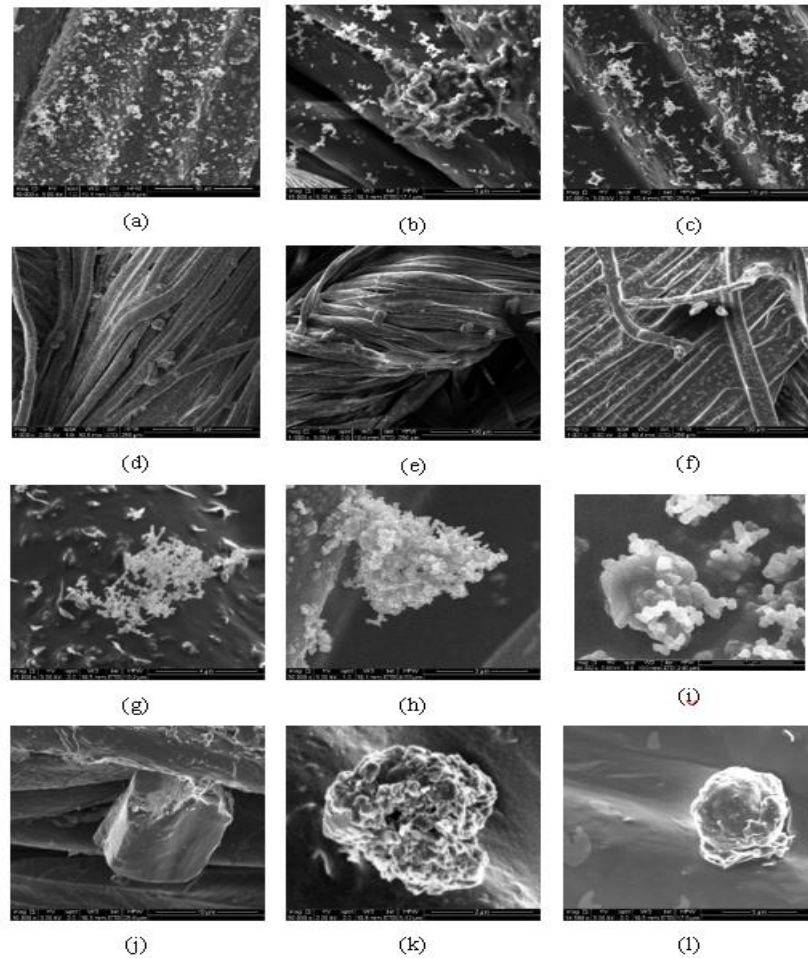


Figure 2: Scanning electron microscopic images of soot particles on fabric surfaces (a) OP on S₁, (b) OP on S₂ samples, (c) OP on S₃ (d) WP on S₁, (e) WP on S₂ samples, (f) WP on S₃ (g-i) OP single particle samples, (j-l) WP single particle samples

3.2 EDGE DETECTION TECHNIQUES

3.2.1 OPTIMIZATION OF CANNY EDGE DETECTOR ALGORITHM

Using the images obtained from scanning electron microscopy, Canny algorithm thresholding and sigma was optimised for several sample images and for various values combinations of thresholding as shown in Fig. 3. The threshold controls the minimum gradient pixel intensity a pixel must have to even be considered as a potential edge. The sensitivity defines the minimum strength for a pixel to be confidently accepted as a definite edge.

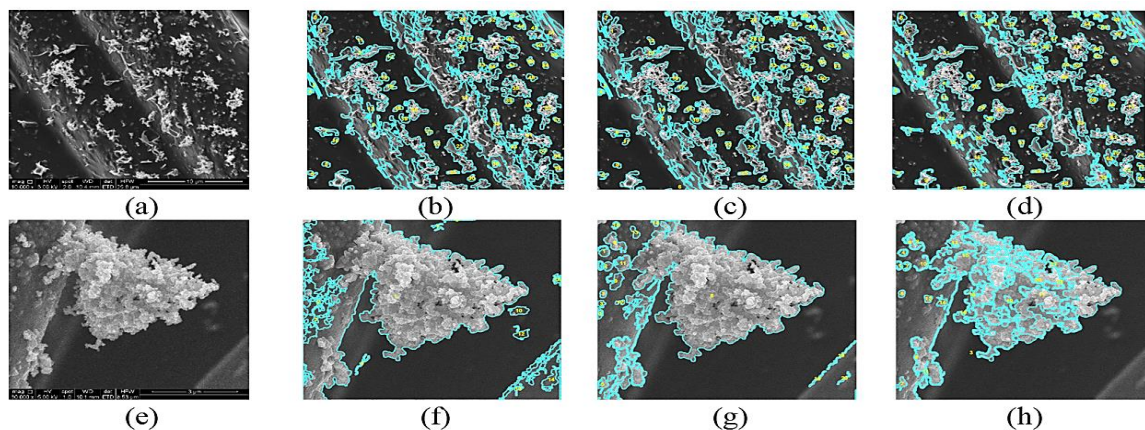


Figure 3: Canny Edge detection based on different thresholding values (a)OP sample, (b) OP sample (0.1, 0.2) thresholding, (c) OP samples (0.2, 0.3) thresholding, (d) OP sample (0.2, 0.3) thresholding, (e) single OP sample, (f) single OP sample default thresholding, (g) single OP sample (0.1, 0.2) thresholding, (h) single OP sample (0.2, 0.3) thresholding

The Canny algorithm at its default threshold and sensitivity value was not suitable for smoke particle detection at either lower or higher magnifications as observed in Fig. 3b, Fig. 3f respectively. Default values were unable to detect particle edges and localised contrast variations resulting in merging of multiple closely situated particles as observed in Fig. 3b, Fig. 3f. For the OP sample at lower magnification, the detection showed better results at a thresholding value of (0.2, 0.3), however, due to local changes in contrast, false edges were still detected in various instances (as seen in Fig. 3(d)). In contrast, for a single OP sample, a thresholding value of (0.1, 0.2) showed good edge detection. At higher magnifications, localized contrast variations occur within the particle itself, therefore, any higher thresholding value (as seen in Fig. 3(h)) may result in false edges within the particle boundary.

Lower magnification aims to capture particle mapping in the image. Here, higher thresholding works effectively for oil smoke particles because there is a significant contrast difference between the particles and the background fibers, while the internal contrast of the particles is negligible. This higher threshold helps the algorithm minimize the detection of false edges. However, at higher magnification, morphology of single particle is evaluated. At this scale, the contrast within the particle itself becomes significant. Therefore, a thresholding value must be chosen that allows the algorithm to recognize the particle-background boundary while successfully ignoring the internal contrast variations.

Additionally, Canny algorithm with worked well for hydrocarbon exposed samples where there is a high contrast of the particles with the background. However, for wood exposed samples there is very limited contrast variation between the fibre and background, hence for wood samples the thresholding and sensitivity optimization pose a significant challenge as shown in Fig. 4. As a result, the algorithm showed very poor edge detection accuracy even with very low threshold and sensitivity as shown in Fig. 4 (d).

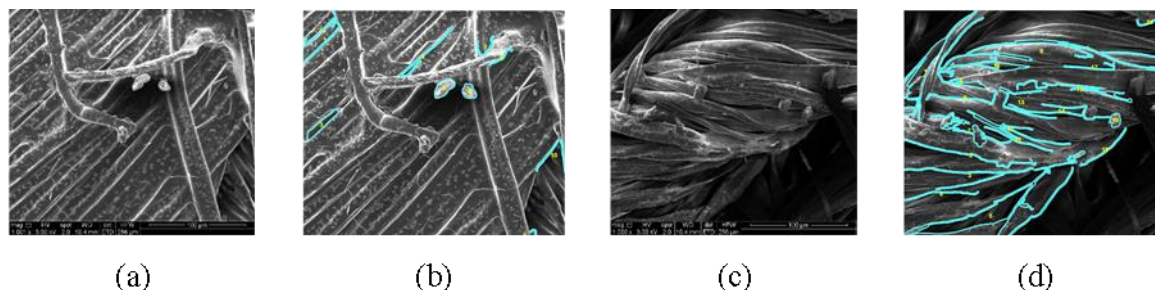


Figure 4: Canny Edge detection based on different thresholding values for WP samples (a) WP sample, (b) Best fit detection with (0.3, 0.9) thresholding, (c) WP sample, (d) Best fit detection with (0.1, 0.6) thresholding.

3.2.2 OPTIMIZATION OF LAPLACE OF GAUSSIAN (LOG) EDGE DETECTOR ALGORITHM

Laplace of Gaussian (LoG) standard deviation was optimised based on various value combinations for lower magnification and higher magnification images as shown in Fig. 5.

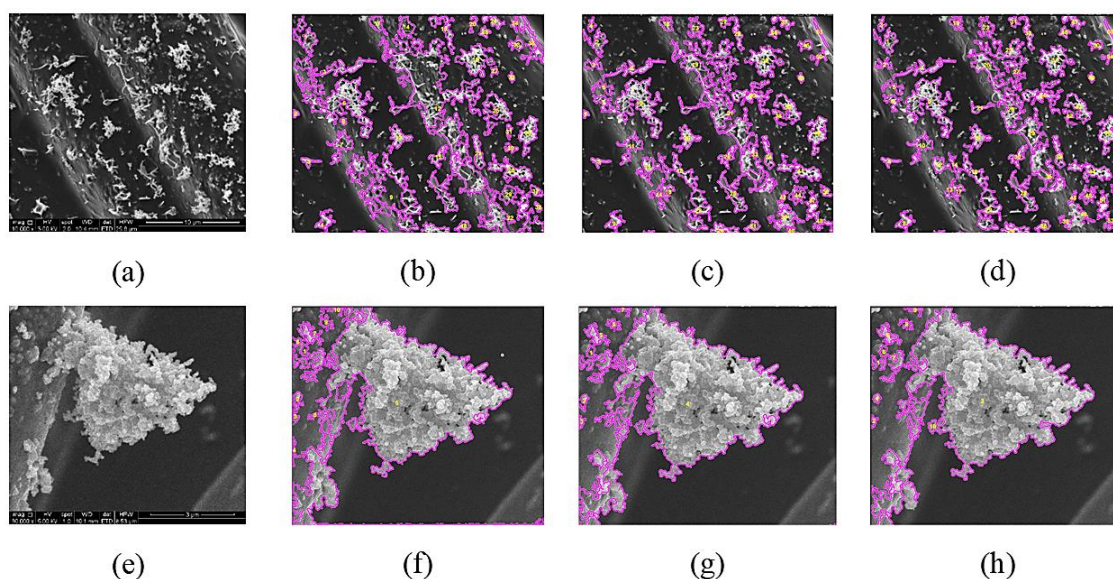


Figure 5: LoG Edge detection based on different standard deviation (σ) values (a) OP sample, (b) OP sample $\sigma = 1.7$, (c) OP samples $\sigma = 1.9$, (d) OP sample $\sigma = 2.1$, (e) single OP sample, (f) single OP sample $\sigma = 1.3$, (g) single OP sample $\sigma = 1.5$, (h) single OP sample $\sigma = 1.7$

For lower magnification, the optimized value obtained for σ is 1.9. Lower σ values showed fewer improper identifications of zero-crossing edges; however, a lower value of σ leads to higher sensitivity in edges, and as a result, it detects sharp drops in contrast values. This causes the algorithm to detect several closely distributed particles as a single particle, as seen in Fig. 5(b). At higher values of σ , many smaller particles are ignored since σ averages out more noise in the Gaussian spatial scale as shown in Fig. 5(d). Consequently, smaller particles get filtered out when the average is calculated over a large area. Similarly, at higher magnification, the optimized value of σ was found to be 1.5, based on achieving proper edge detection for closely situated particles (Fig. 5(f)) and avoiding the detection of the inner contours of individual particles Fig. 5(h).

The LoG algorithm also fails to detect WP samples where there is very little variation between the background and the particles, as seen in samples S_2 and S_1 . Although LoG algorithm showed very good edge detection results for single WP samples, it inadequately detected the WP particles present in the fabric samples at lower magnification, as shown in Fig. 6(d). Additionally, unlike Canny, LoG fails to detect the particles for the S_3 sample as well; this occurs because LoG averages out the spatial contours based on the σ value. Since the S_3 fabric shows the presence of inherent stripes due to the blending of different polymers, the spatial averaging concept in LoG is not suitable for particle detection in such cases, as shown in Fig. 6(b).

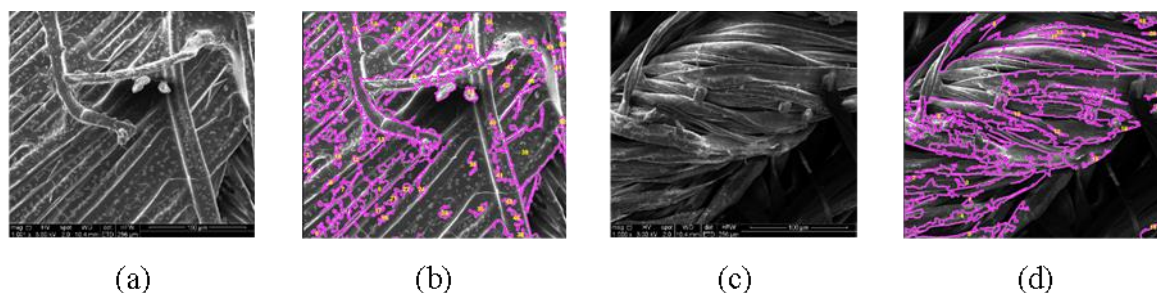


Figure 6: LoG Edge detection based on different σ values for WP samples (a) WP sample, (b) Best fit detection with $\sigma = 1.3$, (c) WP sample, (d) Best fit detection with $\sigma = 2.3$.

3.2.3 OPTIMIZATION OF OTSU THRESHOLDING-EDGE DETECTOR ALGORITHM

Otsu thresholding algorithm was optimised for radius of top-hat filter lower and higher magnification images as shown in Fig. 7.

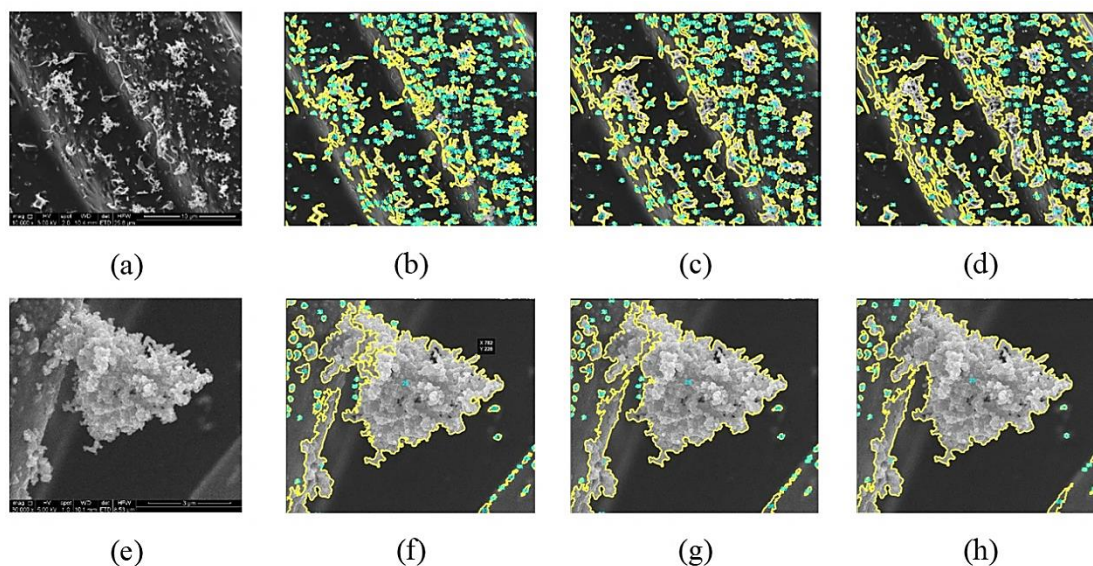


Figure 7: Otsu Thresholding-Edge detection based on different top-hat filter radius (r) values (a) OP sample, (b) OP sample $r = 10$, (c) OP samples $r = 20$, (d) OP sample $r = 30$, (e) single OP sample, (f) single OP sample $r = 50$, (g) single OP sample $r = 70$, (h) single OP sample $r = 90$

Otsu thresholding posed a significant challenge for generalized optimization, as it is a particle-size-dependent filter. For Otsu the filter radius should be higher than the largest particle (in pixel) in the image. Consequently, an optimization approach based on magnification levels was adopted. A range of 5,000x to 10,000x, with multiple particles distributed throughout the image, is considered lower magnification image. At this scale, a top-hat filter radius higher than 20 offered the best-fit solution, as shown in Fig. 7(c). Based on optimization from multiple images top hat filter of 30 offered best fit solution with magnification <14,000. A lower radius value leads to the over-segmentation of various particles, as shown in Fig. 7(a), while a higher radius value results in the detection of closely distributed particles as a single entity. At higher

magnifications ($>14,000\times$), a top-hat filter radius of 90 offered the best-fit solution across multiple single-particle images (Fig. 7(h)). A radius value higher than 90 showed negligible differences in results compared to 90. However, with a higher radius value, the computational time increased significantly.

Similar to LoG and Canny algorithm Otsu thresholding also fails to detect the characteristics of WP samples for limited particle-background contrast variation. Otsu algorithm relies on clear distinction of particle and background based on pixel intensity. This aspect is very well visible in Fig. 8b, where although Otsu thresholding has been optimised, due to charging and non-uniformity of the textile substrate, there are various region with similar pixel intensity as the particles. Hence, Otsu fails to distinguish between the particle and background. Additionally, in Fig. 8d, the particle intensity is very similar to background intensity, hence Otsu fails here as well.

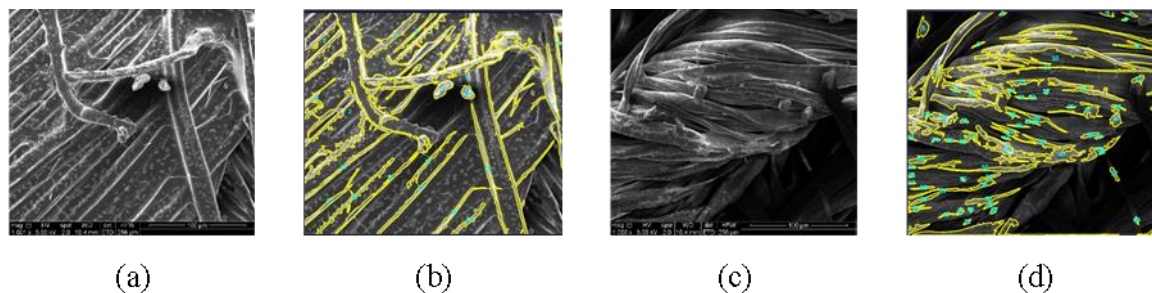


Figure 8: Otsu thresholding-Edge detection based on different top-hat filter radius (r) for WP samples (a) WP sample, (b) Best fit $r = 26$, (c) WP sample, (d) Best fit detection with $r = 35$.

3.3 GENERATIVE AI

ChatGPT is used for detection of smoke particles based on prompt are shown in Fig. 9.

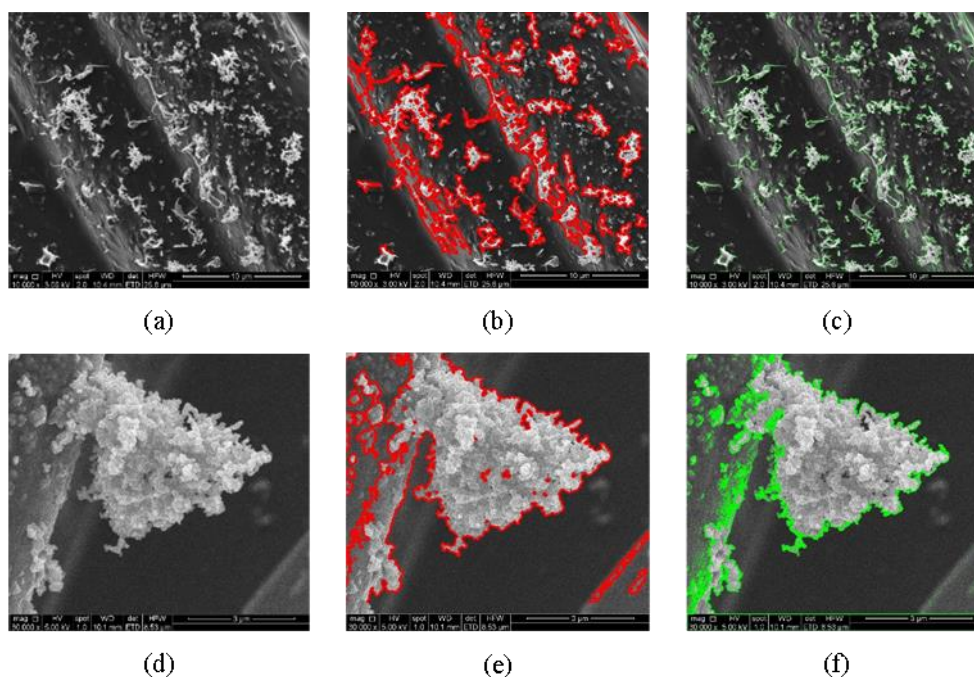


Figure 9: Image generation from ChatGPT (a)OP sample, (b) ChatGPT generated image of OP sample based on zero-shot prompt, (c) OP sample After multiple ChatGPT prompts (d) single OP sample, (e) ChatGPT generated image of single OP sample based on zero-shot prompt, (f) single OP sample After multiple ChatGPT prompts

ChatGPT was unable to detect the particles using the zero-shot prompt, as shown in Figs. 9b and 9e. In several instances, zero-shot prompt fails to provide a downloadable image, hence another probing prompt is used to generate the images “Provide downloadable JPEG images for the image provided. Include visible regular or irregular enclosed boundary/edges detected of all the particles for the input image. Make sure the border of the particles are clearly visible”.

However, when ChatGPT was trained with edge detected images and multiple prompts, it demonstrated excellent detection of agglomerated smoke particles, as shown in Figs. 9c and 9f, respectively. However, because ChatGPT is trained on edge detected images, as are edge detection techniques, it fails to detect several small particles at low magnification when compared to Otsu thresholding (Fig. 7c). Although ChatGPT shows promising results as an edge detection tool when trained,

replicability of such aspects necessitates a large amount of image data with edge detection or human annotation for model training. As a result, for this study, images generated from the zero-shot prompt were used.

3.4 COMPARATIVE ANALYSIS

3.4.1 EFFECTIVENESS OF EDGE DETECTION TECHNIQUE

Precision, recall, and F1-score evaluate the image overlay of the edge detection image in comparison to the ground truth image. Figure 10 depicts a comparison of a sample image to ground truth using image overlay.

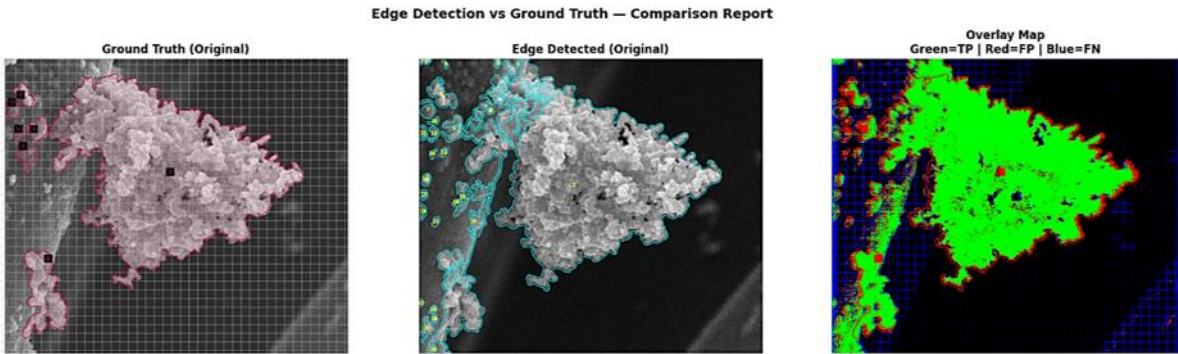


Figure 10: Sample image comparison with ground truth using image overlay method, for the image Fig. 3g is used as Edge Detection (Original)

A comparative analysis is carried out for all the images of the database to obtain average Precision, Recall, and F1-score for each technique is discussed as shown in Table 2.

Table 2: Comparative analysis of different particle detection technique (Raw data provided in Appendix II)

Particle detection technique	Magnification	Optimised values	Precision	Recall	F1-score
Canny	(lower than 14,000 x)	(Threshold, sensitivity) = (0.2, 0.3)	0.63 (25.4)	0.49 (49.41)	0.54 (37.65)
	(higher than 14,000 x)	(Threshold, sensitivity) = (0.1, 0.2)	0.78 (8.82)	0.54 (32.80)	0.63 (23.09)
LoG	(lower than 14,000 x)	$\sigma = 1.9$	0.65 (28.67)	0.48 (42.11)	0.54 (37.84)
	(higher than 14,000 x)	$\sigma = 1.5$	0.82 (10.12)	0.54 (27.49)	0.64 (18.89)
Otsu	(lower than 14,000 x)	Top-hat filter radius = 30	0.69 (19.57)	0.54 (34.35)	0.60 (25.78)
	(higher than 14,000 x)	Top-hat filter radius = 90	0.82 (8.76)	0.49 (37.25)	0.60 (26.31)
Untrained ChatGPT	(lower than 14,000 x)	-	0.51 (35.66)	0.38 (38.7)	0.42 (35.03)
	(higher than 14,000 x)	-	0.71 (9.78)	0.36 (43.41)	0.46 (31.52)
* Value indicated for Precision, Recall, and F1-score are average values with values within the parenthesis representing the coefficient of variation of the parameter.					

A consistent trend was observed for all the techniques based on image magnification. At higher magnification (>14,000 x) all the particle detection models performed significantly better compared to that in lower magnification (< 14,000 x). This is due to better contrast variation was observed between the particle and background at higher magnification compared to that of lower magnification. Additionally, the coefficient of variation for all the edge detection models were lower at higher magnification, showing less variation and better detection performance of all models at higher magnification. The statistical analysis is shown in Table 3.

Table 3: Statistical analysis for F1-score (Raw data provided in Appendix III)

Technique	Canny High Mag.	Canny Low Mag.	LoG High Mag.	LoG Low Mag.	Otsu High Mag.	Otsu Low Mag.	ChatGPT High Mag.	ChatGPT Low Mag.
Shapiro-Wilk's Normality test for F1-score								
W-statistics	0.93	0.89	0.90	0.93	0.92	0.92	0.97	0.95
p-value	0.52	0.18	0.25	0.44	0.36	0.37	0.88	0.68
Test of significance (paired t-test) for different techniques p-values for F1-score of the respective horizontal row and vertical column								
Canny High Mag.	—	0.42	0.45	0.40	0.01	0.87	2.64E-06	0.03
Canny Low Mag.	0.42	—	0.35	0.96	0.59	0.02	0.39	0.03
LoG High Mag.	0.45	0.35	—	0.34	0.09	0.74	1.94E-06	0.01
LoG Low Mag.	0.40	0.96	0.34	—	0.57	0.04	0.38	0.07
Otsu High Mag.	0.01	0.59	0.09	0.57	—	0.87	1.39E-05	0.05
Otsu Low Mag.	0.87	0.02	0.74	0.04	0.87	—	0.07	0.03E-02
ChatGPT High Mag.	2.64E-06	0.39	1.94E-06	0.38	1.39E-05	0.07	—	0.63
ChatGPT Low Mag.	0.03	0.03	0.01	0.07	0.05	0.03E-02	0.63	—

The Shapiro-Wilk normality test confirmed that F1-score values for all eight technique-magnification combinations were normally distributed (all $p > 0.05$, W-statistics ranging from 0.89 to 0.97), validating the use of paired t-tests for significance testing.

The t-test results revealed several statistically significant differences between techniques. ChatGPT High Magnitude differed significantly from Canny High ($p = 2.64 \times 10^{-6}$), LoG High ($p = 1.94 \times 10^{-6}$), and Otsu High ($p = 1.39 \times 10^{-5}$), while ChatGPT Low Magnitude showed significant differences against Canny High ($p = 0.03$), Canny Low ($p = 0.03$), and LoG High ($p = 0.01$). Among the conventional methods, Otsu High differed significantly from Canny High ($p = 0.01$), and Otsu Low differed significantly from Canny Low ($p = 0.02$) and LoG Low ($p = 0.04$).

Among the individual models Canny performed moderately at lower magnification, however its detection improved significantly at higher magnification. Canny showed an average value of 0.63 F1-score at higher magnification whereas compared to lower magnification the value dropped to 0.54. Canny at higher magnification also failed to detect faint wood smoke particles, where there is very limited contrast variation between the particle and background as shown in Fig. 11c.

LoG edge detector showed a similar trend as that of Canny, where its detection performance dropped significantly from higher magnification (F1-score 0.64) to lower magnification (F1-score 0.54). LoG showed over detection at lower magnification due to presence of background noise in the SEM image. Such false positive detection significantly reduced the edge detection prediction of this detector at lower magnification. Additionally, LoG failed to detect any particles at higher magnification whenever there is very limited contrast variation between the particle and background as shown in Fig. 11d.

Among all the particle detection techniques Otsu algorithm showed a consistent detection of edges 0.6 F1-score for both higher and lower magnification. Otsu offered a higher precision and was consistent in detection of smoke particles over a wide range of image contrasts where both Canny and LoG failed to detect particles as shown in Fig. 11e. Otsu recall score dropped due to its detection of false positives as well as detection of extremely small (dot-sized particles) particles, which were not considered in the human annotations due to its size. Manual annotation of the ground-truth dataset did not include

extremely small, dot-sized particles in densely populated smoke particles of some images. This gap in ground-truth completeness is a well-documented and common limitation of manual image annotation for small, densely distributed objects. This aspect has also been observed in major benchmark datasets used in edge detections such as COCO (Bolya et al., 2020; Wu et al., 2019) and OpenImagesV4 (Wu et al., 2019). In object detection literature more broadly, a substantial proportion of apparent false positives have similarly been attributed to missing small-object annotations in the ground truth rather than genuine algorithmic error (Bolya et al., 2020; Wu et al., 2019). Overall, Otsu provided a consistent detection compared to other particle detection models.

Statistical analysis further showed Otsu as the most robust technique across magnification conditions. At high magnification, Otsu demonstrated a statistically reliable advantage over ChatGPT High Magnitude ($p = 1.39 \times 10^{-5}$), confirming that its superior F1-score is not attributable to chance. At low magnification, Otsu outperformed Canny Low ($p = 0.02$), LoG Low ($p = 0.04$), and ChatGPT Low ($p = 0.03 \times 10^{-2}$), further establishing its consistency where other methods show greater variability. Additionally, at higher magnification it showed no statistically significant value compared to LoG at higher magnification ($p = 0.09$). Although Canny showed statistically significant difference compared to Otsu at higher magnification ($p = 0.01$), the average value showed very little difference (Canny high mag. average F1-score 0.63, Otsu high mag. average F1-score 0.60) Thus, confirming it as more reliable and robust technique.

Untrained ChatGPT underperformed compared to classical edge detection models. At lower magnification it showed a F1-score of 0.42 and 0.46 at higher magnification. This value is largely attributed to untrained ML ChatGPT model. However, trained ChatGPT showed much better particle detection. ChatGPT however, was able to detect particles in various instances where both Canny and LoG models failed as shown in Fig. 11f. However, trained ChatGPT may offers a suitable alternative if it is trained with Otsu model with a large number of SEM images.

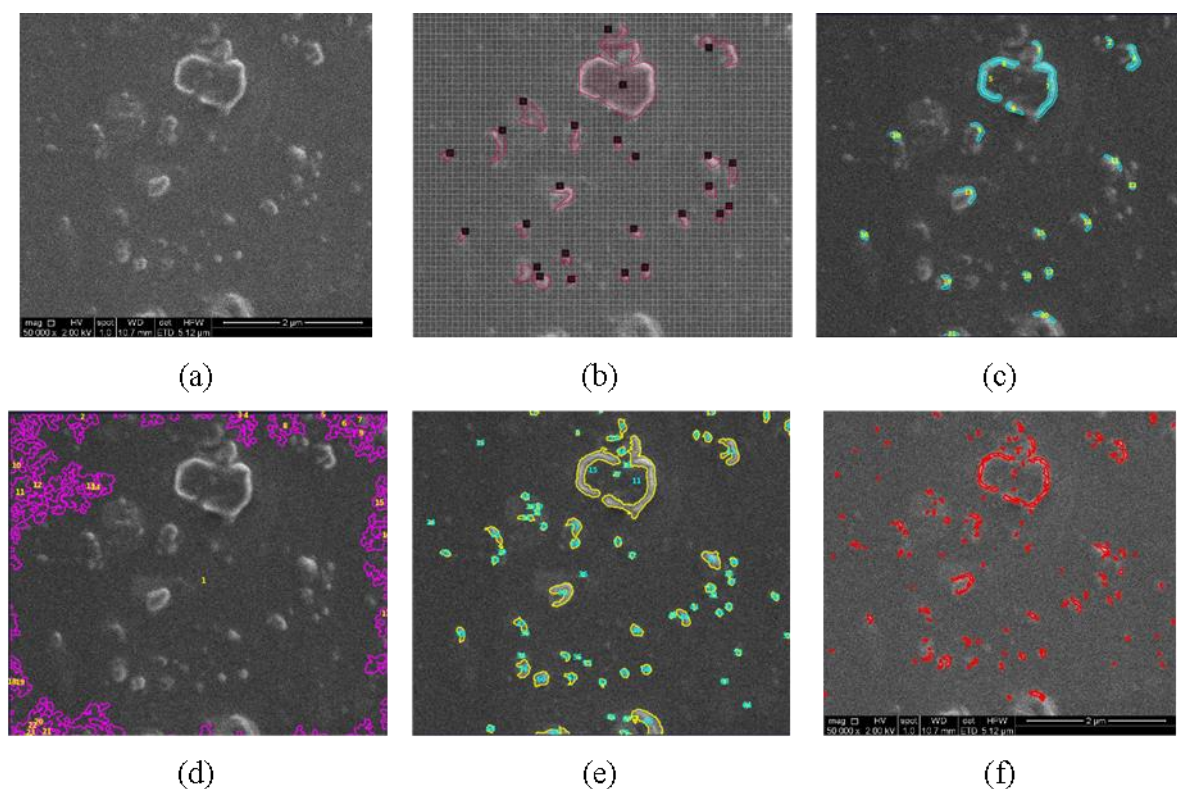


Figure 11: Wood particle image at higher magnification and performance of each particle detection technique at optimised values (a) Original image, (b) Ground Truth (c) Canny edge detector, (d) LoG edge detector, (e) Otsu edge detector, (f) Untrained ChatGPT

3.5 SMOKE PARTICLE PARAMETERS

Optimised Otsu algorithm was used to obtain smoke particle parameters from SEM images. Particle size distribution for wood and oil smoke particles based on the various obtained SEM images used in this paper are shown in Fig. 12.

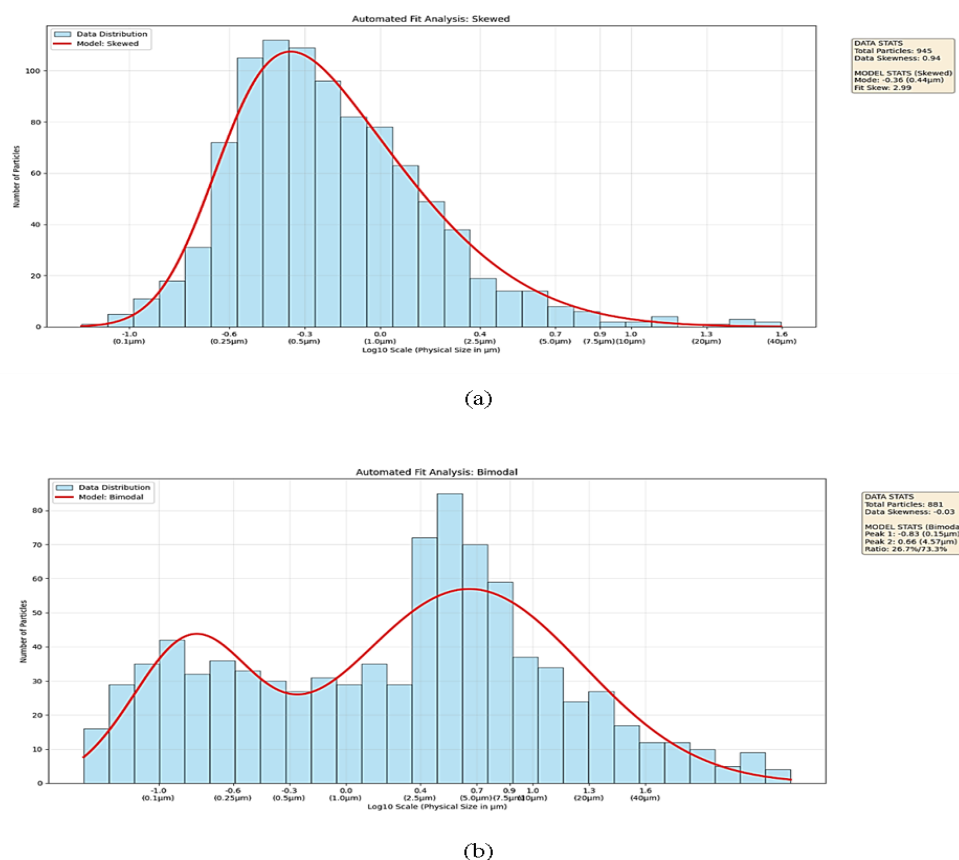


Figure 12: Particle size distribution (Feret diameter) of SEM image detected particles using OTSU algorithm for (a) Oil particles, (b) Wood particles

Oil particle distribution (Fig. 12a) showed a skewed normal distribution with particle modal diameter of 0.44 μm . This data was based on over 900 oil particles and agglomerates detected from oil particle samples from the database. The oil particle distribution is skewed due to presence of high number of finer oil particles deposited onto the fabric surfaces. Wood particles (Fig. 12b) however followed a bi-modal distribution with 0.15 μm and 4.57 μm peaks. Where 4.57 μm is the modal Feret diameter for agglomerated particles. This data was based on close to 900 wood particles and wood particle agglomerates detected from wood smoke deposited textile samples. With higher modal wood particles in 4.57 μm range. This is apparent from the particle size agglomerates as seen in earlier SEM images.

Based on the particle size detected, it is evident a significant number of fine ($\leq 2.5 \mu\text{m}$) and ultrafine ($\leq 1 \mu\text{m}$) particles are generated during wood and oil burning smoke and present on top of PPE surface when exposed to it. This signifies, a serious occupational safety these particles may pose and may lead to secondary exposure.

4. CONCLUSION

In this study, we developed a way to measure exactly for determining smoke particle characteristics deposited onto the surface of PPE fabrics Using a comparison of edge detection techniques as well as generative AI, we were able to obtain a best-fit particle detection technique using Otsu algorithm. During the comparison it was observed untrained generative AI underperformed compared to other techniques for detection of smoke particles onto PPE surface. However, aspects of training generative AI through Otsu may offer an intriguing avenue for smoke particle detection onto PPE surfaces. Our approach successfully mapped out the particle distribution for both oil and wood smoke. Most importantly, it was able to detect fine ($\leq 2.5 \mu\text{m}$) and ultrafine ($\leq 1 \mu\text{m}$) onto the textile surface. These findings elucidate a significant occupational health risk, since fine and ultra fine particles may stay stuck in the textile surface long after the wildfire suppression activity. These particles may offer significant risk through secondary exposure during doffing and donning of contaminated PPE as well as through particle movement within the fabric that may occur due to firefighter movement. This research opens the door to understanding how fine and ultrafine particles deposited onto protective clothing. The presence of high number of ultrafine particles onto PPE surface highlights the occupational hazard these particles may pose. This technique may further

serve as a milestone for characterizing fine and ultrafine smoke particles on different textile substrate, highlighting the effectiveness of a PPE fabric when dealing with secondary smoke exposure.

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APPENDIX I: OPTIMISED ZERO-SHOT PROMPT FOR CHATGPT

“You are an expert in electron microscopy image analysis and materials characterisation. You are provided with an SEM image of smoke/soot particles. These are carbonaceous particles typically appearing as dark or bright circular to near-circular blobs or chain-like aggregates against the image background.

IMPORTANT CONTEXT:

- SEM images have variable contrast and may contain noise (including small dots in the background) from the electron detector
- The image contains a scale bar; identify and use it to calibrate all measurements in physical units (nm or μm)
- Smoke particles may appear as isolated primary particles or aggregated structures

YOUR TASK:

For each clearly identifiable smoke particle or particle aggregate visible in the image, these particles appear as circular or nearly circular or aggregated circular structures. Following this perform the following measurements:

1. **MAXIMUM DIAMETER:** Measure the longest straight-line distance across the particle (maximum Feret diameter), from one edge to the opposite edge at its widest point. Express in nm or μm according to scale bar.
2. **PROJECTED AREA:** Estimate the 2D projected area of the particle boundary. If the particle is roughly circular, use $\text{Area} = \pi \times (d/2)^2$. For irregular particles, estimate from the visible boundary extent. Express in nm^2 or μm^2 .

OUTPUT FORMAT (downloadable JPEG): Include visible regular or irregular enclosed boundary/edges detected of all the particles for input image

Additionally include based on the particles detected:

```
{
  "scale_bar_detected": "<value and unit>",
  "particles": [
    {
      "particle_id": 1,
      "max_diameter_nm": <number>,
      "projected_area_nm2": <number>,
      "shape_description": "<circular/elongated/aggregate/irregular/spherical/blocks>",
      "confidence": "<high/medium/low>"
    }
  ],
  "notes": "<any relevant observations about image quality or measurement limitations>"
}
```

Be precise. Flag any caveats about overlapping or aggregated particles. Be rigorous and do not extrapolate beyond what is visible. Low confidence measurements must be flagged.”

APPENDIX II: (RAW DATA FOR TABLE 2)

Edge Detection Results — Raw Per-Image Data							
Pair #	Image	Canny High Magnification			Canny Low Magnification		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score
1	1.png	0.8320	0.7970	0.8141	0.7825	0.8310	0.8060
2	3.png	0.7136	0.5234	0.6039	0.8495	0.8427	0.8461
3	4.png	0.7066	0.2793	0.4004	0.7154	0.8133	0.7612
4	6.png	0.8643	0.6839	0.7635	0.3300	0.3427	0.3362
5	8.png	0.7769	0.4217	0.5467	0.7014	0.4079	0.5158
6	10.png	0.7647	0.3650	0.4942	0.4992	0.2381	0.3224
7	11.png	0.6974	0.4986	0.5814	0.6930	0.4743	0.5631
8	12.png	0.7868	0.5169	0.6239	0.5497	0.3650	0.4388
9	13.png	0.8860	0.7578	0.8169	0.4733	0.2255	0.3055
10					0.6841	0.3870	0.4943
Average		0.78	0.54	0.63	0.63	0.49	0.54
Std Dev		0.07	0.18	0.14	0.16	0.24	0.20
CV (%)		8.82	32.80	23.09	25.40	49.41	37.66
		LoG High Magnification			LoG Low Magnification		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score
1	1.png	0.8282	0.7904	0.8088	0.8939	0.7511	0.8163
2	3.png	0.8768	0.4366	0.5829	0.8632	0.7346	0.7938
3	4.png	0.7383	0.3193	0.4458	0.8123	0.6895	0.7459
4	6.png	0.9413	0.6342	0.7578	0.3335	0.3442	0.3387
5	8.png	0.7585	0.4557	0.5694	0.7474	0.4470	0.5594
6	10.png	0.7825	0.5118	0.6189	0.5209	0.1282	0.2058
7	11.png	0.7009	0.5269	0.6015	0.6502	0.4649	0.5422
8	12.png	0.8593	0.4480	0.5890	0.6372	0.5230	0.5745
9	13.png	0.9197	0.7025	0.7965	0.4346	0.2748	0.3367
10					0.5761	0.4585	0.5106
Average		0.82	0.54	0.64	0.65	0.48	0.54
Std Dev		0.08	0.15	0.12	0.19	0.20	0.21
CV (%)		10.12	27.49	18.89	28.67	42.11	37.84
		Otsu High Magnification			Otsu Low Magnification		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score
1	1.png	0.8410	0.7589	0.7979	0.8052	0.8275	0.8162
2	3.png	0.7388	0.4618	0.5684	0.8659	0.8209	0.8428
3	4.png	0.7165	0.2490	0.3696	0.7388	0.7636	0.7510
4	6.png	0.9261	0.6523	0.7654	0.4335	0.4066	0.4200
5	8.png	0.8034	0.3306	0.4685	0.7974	0.4503	0.5755
6	10.png	0.8230	0.3106	0.4510	0.5862	0.3186	0.4150
7	11.png	0.7625	0.4616	0.5750	0.7789	0.5188	0.6241
8	12.png	0.8714	0.4786	0.6179	0.7056	0.4362	0.5391
9	13.png	0.8980	0.7176	0.7977	0.5897	0.4899	0.5350
10					0.5870	0.4163	0.4911
Average		0.82	0.49	0.60	0.69	0.54	0.60

Std Dev		0.07	0.18	0.16	0.13	0.19	0.15
CV (%)		8.76	37.25	26.30	19.57	34.35	25.78
		ChatGPT High Magnification			ChatGPT Low Magnification		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score
1	1.png	0.8109	0.6312	0.7098	0.7196	0.5963	0.6522
2	3.png	0.6893	0.2702	0.3882	0.7159	0.5958	0.6503
3	4.png	0.6626	0.1580	0.2552	0.5832	0.4378	0.5002
4	6.png	0.7286	0.4584	0.5627	0.3367	0.1395	0.1973
5	8.png	0.6822	0.2185	0.3310	0.7137	0.2654	0.3869
6	10.png	0.8034	0.2541	0.3861	0.4465	0.4416	0.4441
7	11.png	0.6276	0.3235	0.4269	0.6406	0.2288	0.3371
8	12.png	0.6256	0.3870	0.4782	0.2448	0.3363	0.2833
9	13.png	0.7533	0.5299	0.6221	0.3862	0.4175	0.4013
10					0.3354	0.3701	0.3519
Average		0.71	0.36	0.46	0.51	0.38	0.42
Std Dev		0.07	0.16	0.15	0.18	0.15	0.15
CV (%)		9.78	43.41	31.52	35.66	38.70	35.03

APPENDIX III: RAW DATA FOR TABLE 3

Shapiro-Wilk Normality Test — per technique per metric					
<i>H₀: data is normally distributed. $p > 0.05 \rightarrow$ fail to reject normality (treat as normal). $p \leq 0.05 \rightarrow$ reject normality.</i>					

Technique	Metric	W statistic	p-value	Normal?	Interpretation
Canny High Magnification	F1-Score	0.9344	0.5242	Yes	Normal ($p > 0.05$)
Canny Low Magnification	F1-Score	0.8851	0.1776	Yes	Normal ($p > 0.05$)
LoG High Magnification	F1-Score	0.8992	0.2475	Yes	Normal ($p > 0.05$)
LoG Low Magnification	F1-Score	0.9253	0.4383	Yes	Normal ($p > 0.05$)
Otsu High Magnification	F1-Score	0.9157	0.3582	Yes	Normal ($p > 0.05$)
Otsu Low Magnification	F1-Score	0.9174	0.3712	Yes	Normal ($p > 0.05$)
ChatGPT High Magnification	F1-Score	0.9686	0.8827	Yes	Normal ($p > 0.05$)
ChatGPT Low Magnification	F1-Score	0.9487	0.6759	Yes	Normal ($p > 0.05$)

						T-test	
Technique A	Technique B	Mean A	Mean B	Diff (A-B)	Higher mean	t-statistic	p value
LoG High Magnification	ChatGPT High Magnification	0.6412	0.4622	+0.1789	LoG High Magnification	+12.1593	0.0000019387936718713
Canny High Magnification	ChatGPT High Magnification	0.6272	0.4622	+0.1650	Canny High Magnification	+11.6745	2.64298345908656E-06
Otsu High Magnification	ChatGPT High Magnification	0.6013	0.4622	+0.1390	Otsu High Magnification	+9.3590	0.0000138877415697048
Otsu Low Magnification	ChatGPT Low Magnification	0.6132	0.4281	+0.1851	Otsu Low Magnification	+6.0540	0.0003
Canny High Magnification	Otsu High Magnification	0.6272	0.6013	+0.0260	Canny High Magnification	+3.3435	0.0102
LoG High Magnification	ChatGPT Low Magnification	0.6412	0.4281	+0.2131	LoG High Magnification	+3.1778	0.0130
Canny Low Magnification	Otsu Low Magnification	0.5439	0.6132	-0.0693	Otsu Low Magnification	-2.8388	0.0219
Canny High Magnification	ChatGPT Low Magnification	0.6272	0.4281	+0.1991	Canny High Magnification	+2.7470	0.0252
Canny Low Magnification	ChatGPT Low Magnification	0.5439	0.4281	+0.1158	Canny Low Magnification	+2.6481	0.0293
Canny High Magnification	Canny Low Magnification	0.6272	0.5439	+0.0833	Canny High Magnification	+0.8446	0.4229
Canny High Magnification	LoG High Magnification	0.6272	0.6412	-0.0140	LoG High Magnification	-0.7962	0.4489
Canny High Magnification	LoG Low Magnification	0.6272	0.5459	+0.0813	Canny High Magnification	+0.8906	0.3991

Canny High Magnification	Otsu Low Magnification	0.6272	0.6132	+0.0140	Canny High Magnification	+0.1698	0.8694
Canny Low Magnification	LoG High Magnification	0.5439	0.6412	-0.0973	LoG High Magnification	-0.9940	0.3493
Canny Low Magnification	LoG Low Magnification	0.5439	0.5459	-0.0020	LoG Low Magnification	+0.0485	0.9625
Canny Low Magnification	Otsu High Magnification	0.5439	0.6013	-0.0574	Otsu High Magnification	-0.5555	0.5937
Canny Low Magnification	ChatGPT High Magnification	0.5439	0.4622	+0.0817	Canny Low Magnification	+0.9162	0.3863
LoG High Magnification	LoG Low Magnification	0.6412	0.5459	+0.0953	LoG High Magnification	+1.0143	0.3401
LoG High Magnification	Otsu High Magnification	0.6412	0.6013	+0.0399	LoG High Magnification	+1.9070	0.0930
LoG High Magnification	Otsu Low Magnification	0.6412	0.6132	+0.0280	LoG High Magnification	+0.3438	0.7399
LoG Low Magnification	Otsu High Magnification	0.5459	0.6013	-0.0553	Otsu High Magnification	-0.5912	0.5707
LoG Low Magnification	Otsu Low Magnification	0.5459	0.6132	-0.0673	Otsu Low Magnification	-2.3763	0.0448
LoG Low Magnification	ChatGPT High Magnification	0.5459	0.4622	+0.0837	LoG Low Magnification	+0.9328	0.3782
LoG Low Magnification	ChatGPT Low Magnification	0.5459	0.4281	+0.1178	LoG Low Magnification	+2.1273	0.0661
Otsu High Magnification	Otsu Low Magnification	0.6013	0.6132	-0.0119	Otsu Low Magnification	-0.1689	0.8700
Otsu High Magnification	ChatGPT Low Magnification	0.6013	0.4281	+0.1732	Otsu High Magnification	+2.2520	0.0544
Otsu Low Magnification	ChatGPT High Magnification	0.6132	0.4622	+0.1509	Otsu Low Magnification	+2.0744	0.0717
ChatGPT High Magnification	ChatGPT Low Magnification	0.4622	0.4281	+0.0342	ChatGPT High Magnification	+0.5001	0.6305