ACTA IMEKO
ISSN: 2221-870X
September 2026, Volume 15, Number 3, 1 - 7

Dust detector for museum environment based on Raspberry Pi: A first improvement

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ABSTRACT
This work shows the development of a low-cost, easy-to-install, scalable, and highly integrable system, suitable for real and extensive applications for dust detection in museum environments. To detect particles, the Raspberry Pi uses a high-definition camera module on which dust naturally settles. After the acquisition of the image, the platform elaborates directly the images, recognizing and clustering the particles using a self-made recognition software.

Section: RESEARCH PAPER

Keywords: LED; dust; museum; cultural heritage; measurement

Citation: M. Leccisi, G. Schirripa Spagnolo, F. Leccese, Dust detector for museum environment based on Raspberry Pi: A first improvement, Acta IMEKO, vol. 15 (2026) no. 3, pp. 1-7. DOI: 10.21014/actaimeko.v15i3.2312

Section Editor: Francesco Lamonaca, University of Calabria, Italy

Received January 29, 2026; **In final form** April 21, 2026; **Published** September 2026

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1. INTRODUCTION

The conservation of cultural heritage in museum environments is a highly critical issue that depends on factors such as the presence of various pollutants, exposure to light, humidity, temperature variations, and biological agents, which contribute to the progressive deterioration of artworks and materials, with effects that are often cumulative and difficult to manage.

All the substances that can be detected within museums come from external and internal sources, and are present in the form of particulate matter or gaseous compounds, including volatile organic compounds (VOCs), alkaline particles released by materials, or other chemicals associated with furnishings or plastics. They are introduced primarily through ventilation systems, but also by visitors passing through the rooms, inadvertently carrying and releasing fibres and particles from clothing, hair, or even fragments of skin [1]. Particulate matter deposited on objects is therefore made up of a heterogeneous mixture of materials, including textile fibres, common dust, hair fragments, plant and animal debris, but also spores and insects, with dimensions ranging from a few micrometers to several hundred micrometers [2]. Particles act according to their physical characteristics: coarser and heavier particles tend to settle on exposed surfaces under the action of gravity, while smaller and lighter particles can attach to surfaces electrostatically.

The presence of particulate matter on cultural and artistic heritage is of great interest, and is well documented in the literature. The presence of soot, for example, can darken the works and alter the visual appearance of their surfaces, while the accumulation of dust combined with the presence of humidity accelerates the degradation of materials and increases microbial growth. A further problem that interferes with the condition of the works is the formation of biofilms that ’trap’ particles dispersed in the environment, creating environments sensitive to chemical or biological reactions [3]–[6]. Furthermore, the presence of dust increases the possibility that, during normal mechanical cleaning or material handling operations, damage or abrasion may occur, representing a significant risk, especially for the most delicate materials [7]. Similarly, gaseous pollutants can also be responsible for various degradation phenomena, including the dissolution of carbonates, the damage to fabrics and leather, or the corrosion of metal artifacts.

In this context, it is essential to support strategies for preventive conservation, through the development of continuous monitoring systems that are non-invasive and, above all, cost-effective. Such systems should allow the identification, quantification, and spatial mapping of atmospheric contaminants, minimizing interference with artifacts and daily museum activities.

This study proposes the implementation of a non-invasive, low-cost system for the collection and analysis of dust in indoor environments, particularly in museums, or any location where monitoring airborne particulate matter is required. It utilises a passive deposition system, inclined at 45°, and a high-resolution camera to capture images at defined intervals, whilst a process based on image processing techniques classifies dust, fibres, and other particles for subsequent analysis. Section 2 describes the background and approaches currently available in the literature; Section 3 describes the proposed system, including its hardware architecture, configuration, and workflow; Section 4 presents the experimental setup and dataset, and discusses the results obtained, and finally, the conclusions outline further developments for the proposed system.

2. BACKGROUND AND RELATED MONITORING APPROACHES

Air quality monitoring in museums has historically been conducted using methodologies aimed at identifying the main sources of contamination, particularly focusing on ventilation systems that allow the dispersion of air pollutants, and on the presence of visitors from outside who bring material into exhibition spaces. This context has led to the development of monitoring protocols based primarily on indirect collection techniques, followed by physical-chemical laboratory analyses [8]–[10].

A typical practice involves the use of adhesive surfaces made of inert materials (e.g., Teflon or vinyl), placed in selected locations and left exposed for defined periods of time. These supports allow the collection of dust, textile fibres, and suspended particulate matter, which is then examined using optical microscopy, scanning electron microscopy (SEM), or ion chromatography techniques to characterize their morphology, composition, and possible origin [10]–[14].

Alongside these approaches, optical instruments capable of providing a direct measurement of airborne particulate matter concentrations are widely used. Nephelometers, for example, are based on the evaluation of light scattered by particles illuminated inside a laser camera, allowing an indirect estimate of their size and density [15]–[16]. Aethalometers, on the other hand, are specifically designed for the analysis of black carbon, and measure the attenuation of light through quartz fibre filters on which the carbonaceous material is progressively deposited [17].

More advanced systems involve the use of wireless sensor networks, capable of continuously acquiring environmental parameters thanks to sensors distributed throughout the environment, which communicate with each other via wireless sessions, exchanging data and sending it to a processing unit [18]–[20]. Despite their potential, the use of such solutions in museums is often limited by practical constraints, such as battery life, data storage capacity, and restrictions related to wireless transmission, which make their large-scale implementation complex.

Although these techniques guarantee high reliability of the results, their diffusion is frequently discouraged by the high costs and complexity of the analytical procedures. In this scenario, image processing represents a more accessible alternative for the evaluation of particles dispersed in the environment. The analysis of morphological characteristics, such as geometry, size, and orientation, allows for effective distinction between compact particles and fibrous structures [21]–[23]. In general, elements with an approximately circular shape are attributable to particulate matter of mineral or organic origin, while elongated and thin elements indicate the presence of textile fibres. Further discriminating criteria can be derived from the length and diameter of the fibres: those deriving from clothing are, on average, thinner than those deriving from textile coverings, such as carpets (with indicative dimensions of about 30 μm), while longer fibres, such as hair or animal hair, can be differentiated by their diameter, which is normally smaller in animal hair than in human hair [24]–[25].

The entire system is designed to operate autonomously and continuously, requiring a limited human intervention. The compact structure and the automation of the entire acquisition and analysis flow make the system particularly suitable for use in contexts where space is limited or the environment is sensitive, such as museums, exhibition spaces, and areas intended for the conservation and storage of materials.

3. PROPOSED MONITORING SYSTEM

The developed solution is designed to monitor and analyse dust particles and fibres settling on an inclined surface, through an image processing approach. The system allows for identification and classification of these elements, enabling morphological characterization using artificial intelligence techniques. The implementation is based on a combination of low-cost hardware components and open-source software, integrated on a Raspberry Pi platform.

3.1. Hardware configuration

A Raspberry Pi 4 serves as the central processing unit of the system, operating under the lightweight Raspberry Pi OS Lite and executing Python-based scripts for image acquisition and processing. The imaging subsystem is based on an Arducam camera module equipped with the Sony IMX477 sensor, a 12.3-megapixel back-illuminated CMOS sensor featuring a native resolution of 4056 × 3040 pixels.

The sensor is characterised by a pixel size of 1.55 μm × 1.55 μm, offering a compromise between spatial resolution and sensitivity. This configuration enables the imaging of particles and fibres with characteristic dimensions from approximately 5 μm to several hundred micrometres. The camera interfaces with the Raspberry Pi through a four-lane MIPI CSI-2 connection, and supports interchangeable C/CS-mount lenses, allowing the adjustment of the field of view and magnification.

All components are positioned in a custom-designed enclosure developed through a 3D printer. The enclosure integrates a dedicated support for a standard microscope glass slide, which is the surface for the deposition of the particles. The slide is mounted on an inclined holder fixed at an angle of 45°, a configuration adopted to promote the gravitational settling of airborne particulate on the glass surface (Figure 1.(a)). This passive deposition allows the natural accumulation of the particles without the need for active sampling or pumps.

The camera is positioned on a support, facing the glass slide at a controlled distance to ensure stable focus and repeatable imaging conditions (Figure 1.(b)). This arrangement enables in situ observation of deposited particles, maintaining at the same time a compact and stable configuration.

Illumination is provided by a white-spectrum surface-mounted LED positioned tangentially to the glass slide, generating a grazing-angle (raking) light incidence. This geometry allows the edges of particles and fibres to be highlighted, increasing the visual contrast between the deposited dust and the background.

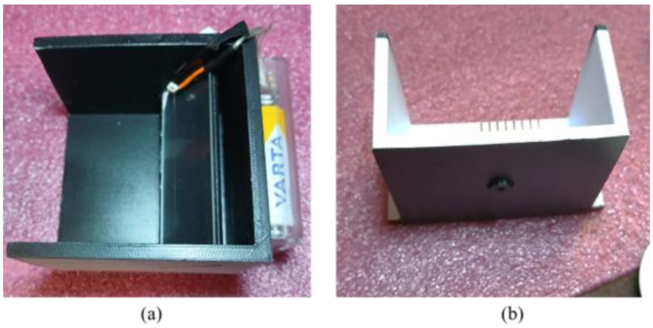

Figure 1. Schematic representation of the custom 3D-printed enclosure. (a) Inclined support for a standard microscope glass slide, mounted at 45° to promote the passive gravitational deposition of airborne particulate matter onto the collection surface. (b) Fixed camera mount positioned in front of the glass slide at a controlled distance, ensuring stable focus and repeatable imaging conditions during acquisition.

The use of grazing illumination allows the finest particles arranged on transparent substrates to be specifically highlighted, facilitating image segmentation and morphological analysis of the material (Figure 2).

3.2. Operating flow

The operating flow of the system is based on the periodic acquisition of images, through an automated scheduling mechanism. The image capture is performed using the libcamera framework, while image processing is handled by a Python application using the OpenCV library.

The pre-processing stage is designed to enhance image quality by reducing optical, environmental, and digital noise that could affect the accuracy of segmentation and classification negatively. This is particularly important in applications where the preservation of particle shape and geometric proportions is essential to perform a reliable morphological analysis.

Initially, the RGB images acquired by the camera are converted to grayscale through a weighted combination of color channels. This operation helps remove information irrelevant to the analysis, and simultaneously normalizes images acquired under different lighting conditions. Pixel intensity redistribution techniques are then applied to achieve contrast enhancement, resulting in an image that highlights local intensity differences between the deposited particles and the background.

Figure 2. The custom 3D-printed enclosure integrating the imaging and deposition system.

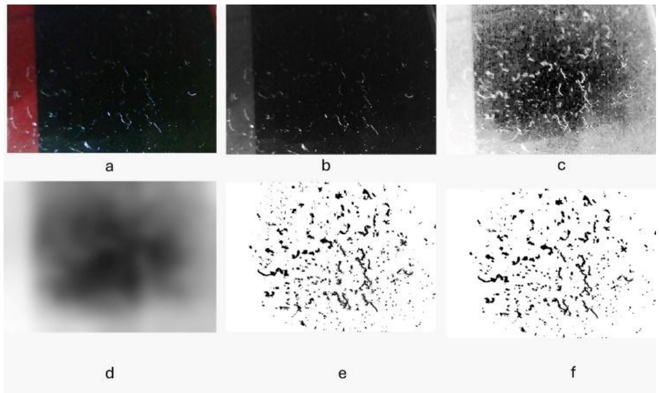

Figure 3. Sequence of the pre-processing steps, from the original input to the final binary image used for block-based segmentation and feature extraction. (a) the original picture, (b) grayscale conversion, (c) increase of contrast (d) background estimation and subtraction (e) binary image obtained through Otsu thresholding; (f) final result.

The 45° tilt of the camera and the inherently non-uniform illumination geometry compromise segmentation effectiveness, resulting in acquired images often displaying variations in background intensity. To compensate for this effect, background estimation is performed by applying a Gaussian low-pass filter with standard deviation σ to the contrast-enhanced image. The estimated background component is then subtracted from the original image, according to the formula:

$$I_{\mathrm{corr}}\,(x,y) = I_{\mathrm{eq}}\,(x,y) - G_{\sigma} * I_{\mathrm{eq}}\,(x,y). \tag{1}$$

This effectively reduces intensity variations while preserving particle-associated information.

Image segmentation is achieved through an automatic thresholding method based on the Otsu method, which determines the optimal threshold by minimizing the intra-class variance between foreground and background regions. The resulting binary image is composed of white pixels representing the background and black pixels corresponding to particles. Finally, average filtering is applied to further reduce the remaining noise while preserving particle edges (Figure 3).

3.3. Segmentation and feature extraction

Following the pre-processing stage, which produces an optimised binary representation of the scene, the image is structured to support efficient classification. To this end, a block-based segmentation strategy is adopted, whereby the binary image is partitioned into non-overlapping square blocks arranged in a regular grid.

This approach offers several advantages: it reduces computational complexity, enables independent analysis of local regions, improves robustness against spatial variability, and ensures invariance with respect to the position of particles within the image. Each block can therefore be analysed as an individual observation, simplifying subsequent processing steps.

The choice of block size represents a critical design parameter. Smaller blocks (below approximately 30 pixels) provide higher spatial resolution, but may not contain sufficient information for reliable classification. Conversely, larger blocks (above approximately 80 pixels) increase the likelihood of including multiple particle types within the same block, leading to class mixing and reduced classification accuracy. For these reasons, intermediate block sizes were selected and systematically evaluated.

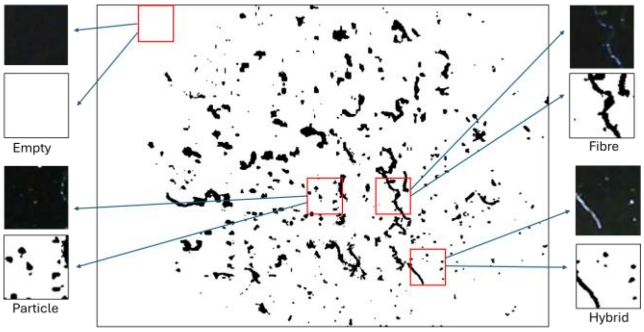

Figure 4. Comparison between the original image and the corresponding binary representation, with selected blocks highlighting the four classification categories adopted in this study (Empty, Particle, Hybrid, and Fibre). The figure provides a visual reference for the block-level annotation process and the morphological criteria used during labelling.

3.4. Classification strategy

After the segmentation of the image, data classification can be performed. To this aim, a supervised, non-parametric algorithm is used, based on the k-Nearest Neighbours (k-NN) method.

For each block of image, a feature vector is computed, containing statistical and morphological descriptors capable of distinguishing between circular and filamentous shapes. These features include the total number of black pixels (indicating the density of the deposit), the number of identified elements, their average area, the average area-to-perimeter ratio, the length, width, and average orientation of the elements.

All feature values are normalized between 0 and 1 to avoid scale-related biases.

The k-NN classifier assigns a class to each test block by comparing it to the k most similar blocks in the labelled dataset, based on a distance metric. Various distance metrics were tested in this study, such as the Euclidean distance, the Manhattan distance, the Chebyshev distance, and the Hamming distance. Among these, the Hamming distance provided the best performance results, probably due to the binary or discretized nature of the extracted features.

4. EXPERIMENTAL SETUP AND RESULTS

4.1. Experimental setup

The experimental phase was designed to evaluate the effectiveness and robustness of the proposed image-based monitoring system in the automatic classification of deposited dust and fibre particles. All experiments were conducted under controlled laboratory conditions to minimise external variability and ensure repeatability of the results.

Dust and fibrous particulate matter were allowed to naturally deposit on the inclined collection surface over predefined exposure intervals. Images were acquired periodically using the proposed hardware configuration, maintaining fixed acquisition parameters, including camera position, optical settings, illumination geometry, and exposure time. This approach ensured consistency across the dataset and prevented bias related to varying imaging conditions.

Following acquisition, each image underwent the complete pre-processing pipeline described in Section 3, resulting in a binary representation in which particles were clearly separated from the background. The binary images were subsequently segmented into non-overlapping square blocks, which constituted the basic units for feature extraction and classification.

To assess the influence of system parameters on classification performance, three key variables were systematically varied during the experiments:

- the block size used for image segmentation, ranging from 30 to 80 pixels;
- the number of neighbours k in the k-Nearest Neighbours (k-NN) classifier, with values of 1, 3, 5, 7, and 9;
- the distance metric employed to compute similarity between feature vectors, including Euclidean, Manhattan, Chebyshev, and Hamming distances.

4.2. Dataset description

To determine the optimal spatial resolution for classification purposes, tests were carried out which showed that 50 px blocks offer the best resolution in our context. Consequently, a dataset comprising 1,215 50-px blocks was created, obtained from image segmentation. The blocks do not overlap with one another and represent the individual unit of analysis. To carry out the classification, labelling was performed by manually annotating the blocks using RoboFlow, according to the predominant particle morphology observed within each block.

Blocks were classified into four main categories:

- ‘Empty’ for empty blocks; indicating absence of particles and fibres, corresponding to blocks with fewer pixels than a minimum threshold or with very low density (< 20 px), such that they are considered acquisition noise or insignificant particles.
- ‘Particle’ for blocks containing predominantly circular and compact structures, including individual particles or aggregates, but without any dominant filamentous structures. The circularity is defined as the ratio of the area of the polygon to the area of a circle with the same perimeter, thus, a circularity of 1 indicates a perfect circle, while a lower circularity indicates elongated or irregular shapes. In our dataset, a circularity of 0.7 has been considered.
- ‘Fibre’ for blocks dominated by filamentous, elongated and thin structures with a distinct primary axis often curved, but still longer in length than in width, with a high aspect ratio (the ratio between the major and minor dimensions of the bounding box enclosing the object); a value 1 indicates compact shapes, while higher values indicate elongated structures.
- ‘Hybrid’ for blocks with no predominance of either circular particulate matter or filamentous structures; characterized by mixed morphologies, irregular structures, or the presence of multiple heterogeneous components that represent intermediate or complex conditions that cannot be attributed to a single category. (Figure 4).

The resulting dataset includes 509 Particle (41.9 %), 186 Fibre (15.3 %), 296 Hybrid (24.4 %) and 224 Empty (18.4 %) samples. The approach, using classification at block level rather than at object level, reduces the computational complexity, providing at the same time a coarse but efficient representation of the distributed particulate.

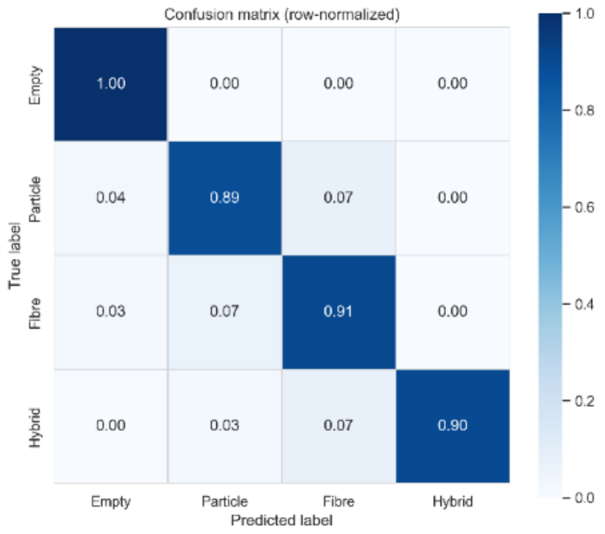

Figure 5. Normalized confusion matrix expressed as percentages. Each row is normalized by the total number of samples in the corresponding true class. The results show high recognition rates for all classes.

4.3. Classification results and performance analysis

Classification performance was evaluated in terms of overall accuracy, defined as the ratio between correctly classified blocks and the total number of analysed blocks. The results clearly indicated that classification accuracy strongly depends on both the block size and the classifier configuration.

Among the tested distance metrics, the Hamming distance consistently yielded the highest accuracy across all experimental conditions. The best overall performance was achieved using a block size of 50 pixels combined with $k = 1$, reaching accuracy values exceeding 90 %. Accuracy was observed to increase progressively with block size up to this optimal value, followed by a decline for larger block sizes.

This trend can be explained by the trade-off inherent in block-based segmentation. Smaller blocks, although offering higher spatial resolution, often lack sufficient morphological information to reliably distinguish between particle classes. Conversely, larger blocks tend to include multiple particle types or mixed morphologies, which reduces classification reliability due to class ambiguity.

The choice of k also had a significant impact on classification outcomes. While $k = 1$ provided the most accurate results, increasing k beyond 3 led to a gradual decrease in performance. Values of k greater than or equal to 5 introduced overgeneralisation effects, limiting the classifier's ability to capture subtle morphological differences between circular particles and fibrous structures.

From a qualitative perspective, blocks containing elongated and thin elements, typically associated with textile fibres, were classified with high precision. This result is primarily attributed to their distinctive orientation and high length-to-width ratios, which are effectively captured by the extracted morphological features. Blocks dominated by circular particles were also reliably identified, despite variability in particle size and density, as their compact shapes produced consistent feature patterns.

The Hybrid label was introduced to classify clusters in which no single shape was dominant, i.e., clusters containing various types of elements such as elongated and round structures, or other structures that cannot be classified as particles or fibres, of various and ambiguous shapes.

Empty blocks were correctly classified in most cases, contributing to the overall robustness of the system.

Only a limited number of misclassifications were observed. These were mainly attributable to residual noise, partial particle fragments at block boundaries, or optical artefacts introduced during image acquisition. However, such errors did not significantly affect the overall performance and were found to be sporadic.

Figure 5 shows the classifier's normalized 4 x 4 confusion matrix, represented as a heatmap. Each row corresponds to the actual class of each block, while each column indicates the predicted class. The values are normalized and expressed as a percentage, highlighting the distribution of predictions for each class.

The strong concentration of values along the main diagonal indicates that most blocks are correctly classified. The cells off the diagonal represent error cases, which are limited and concentrated primarily among the Particle and Fibre classes, which have some similar morphologies.

4.4. Discussion of results

Experimental results show that the proposed system can classify deposited particles based on their morphology and position with good accuracy, despite relying on a compact device and a relatively simple classification method. In particular, the positive performance achieved using Hamming distance suggests that basic morphological features are sufficient for image-based analysis, especially when the data are binary or quasi-binary.

The analysis also shows that system performance strongly depends on how the image is segmented. A block size of 50 pixels proved to be a reasonable compromise between preserving spatial detail and the reliability and stability of particle features, supporting the design choices adopted.

5. CONCLUSIONS AND FUTURE WORK

This work presents a compact, low-cost and automated system designed to monitor and classify dust and fibre particles in indoor environments. By combining image acquisition with morphological analysis and simple machine learning techniques, the proposed solution allows to classify fibres and dust particles contaminating the environment, without the need for complex instrumentation or invasive sampling methods.

Experimental results show a very high classification accuracy, exceeding 90 % under optimal conditions, keeping computational requirements low. The use of block-based image segmentation and of a limited but meaningful set of morphological features seemed to be effective in distinguishing between circular particles, fibrous elements, and empty areas. In particular, the use of the Hamming distance within a k-Nearest Neighbours classifier consistently led to better results, suggesting that discretised feature representations are well suited to this type of analysis.

Moreover, the integration of a Raspberry Pi platform with a high-resolution camera module resulted in a scalable and easy-to-deploy solution. The simple mechanical design, which includes a deposition surface inclined at 45°, supports natural gravitational settling of airborne particles and enables in situ observations without active collection mechanisms. These features make the system suitable for sensitive contexts, such as museums, galleries, and archive spaces, where continuous monitoring is required, but without interfering with the conservation of the objects.

The autonomous operation and simplicity of the system contribute to its robustness, and make it suitable for long-term use and possible integration into distributed monitoring infrastructures or wireless sensor networks.

Compared to the traditional air quality monitoring approaches, the proposed system offers a balance between cost, scalability, and information provided, making it a practical tool for safeguarding the preservation of objects.

Future developments will focus on adding functionality to the system, such as integrating additional environmental sensors for temperature, humidity, and airflow, to more accurately correlate particle deposition and quantity to surrounding conditions. The adoption of more advanced data processing methods, including deep learning approaches, will also be explored to improve classification robustness and enable a more detailed categorization of particles and fibres. Finally, tools and applications for real-time data visualization and long-term trend analysis will be developed, with the aim of supporting decision-making and the continuous assessment of environmental quality in cultural heritage contexts.

AUTHORS' CONTRIBUTION

Conceptualization, Fabio Leccese (F.L.); methodology, F.L. and Mariagrazia Leccisi (M.L.); validation, Giuseppe Schirripa Spagnolo (G.S.S.); formal analysis, M.L.; investigation, F.L. and M.L.; resources, F.L.; data curation, G.S.S.; writing—original draft preparation, M.L.; writing—review and editing, G.S.S. and F.L.; supervision, F.L. and G.S.S. All authors have read and agreed to the published version of the manuscript.

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