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Performance Assessment of a B-COSFIRE Algorithm Extension for Craquelure Segmentation in Artworks

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RESUMO

As obras de arte, particularmente as pinturas, representam peças culturalmente valiosas com história e domínio técnico. Com o passar do tempo, estas peças desenvolvem fissuras, que são redes finas e intrincadas nas superfícies. Estes padrões proporcionam informação relevante acerca da antiguidade, origem e estado das obras de arte, contribuindo assim para a conservação e legitimação das mesmas.

Neste contexto, este projeto aborda o complexo desafio da segmentação de padrões de fissuras na análise de obras de arte, adaptando técnicas avançadas de processamento de imagem de outros campos. Mais concretamente, é apresentada uma versão modificada do algoritmo B-COSFIRE, originalmente concebido para a deteção de vasos sanguíneos na retina, adaptado e otimizado para segmentar com precisão fissuras em obras de arte diversificadas. Esta adaptação tem como objetivo ultrapassar as limitações dos métodos existentes e disponibilizar a precisão necessária para a conservação e análise eficazes da arte.

De forma a validar o algoritmo, foram criados dois conjuntos de dados especializados, consistindo num conjunto de dados em escala de cinzentos da coleção Bucklow, representando vários períodos históricos e estilos artísticos, e um conjunto de dados RGB de pinturas de domínio público, capturando a complexidade das obras de arte coloridas. Os resultados mostraram um melhor desempenho do algoritmo B-COSFIRE modificado na segmentação de padrões de fissuras em obras de arte em escala de cinzentos, enquanto obras de arte de cores mais complexas introduzem padrões de segmentação mais desafiantes, mantendo, no entanto, um melhor desempenho em comparação com o estado da arte.

Assim, este projeto apresenta uma solução para colmatar a ausência de técnicas avançadas de processamento de imagem e conservação de arte, oferecendo uma abordagem inovadora para a análise de fissuras. Dessa forma, ao demonstrar como o algoritmo B-COSFIRE modificado pode ser eficazmente adaptado para este propósito, também se destaca a importância de integrar tecnologias de ponta na preservação do património cultural. Além disso, o trabalho futuro inclui a extensão dos conjuntos de dados, a exploração de abordagens de aprendizagem profunda, a melhoria das técnicas de pré-processamento e pós-processamento, e a conceção de um filtro independente do domínio para expandir a aplicabilidade do algoritmo para além da conservação de obras de arte.

Palavras-chave: Segmentação Supervisionada de Estruturas, B-COSFIRE, Processamento de Imagem, Estruturas Curvilíneas.

ABSTRACT

Works of art, particularly paintings, represent culturally valuable pieces with history and technical mastery. Over time, these pieces develop cracks, which are fine, intricate networks on their surfaces. These patterns provide relevant information about the antiquity, origin and condition of works of art, thus contributing to their conservation and legitimization.

In this context, this project addresses the complex challenge of segmenting crack patterns in the analysis of works of art, adapting advanced image processing techniques from other fields. More specifically, it presents a modified version of the B-COSFIRE algorithm, originally designed for the detection of blood vessels in the retina, adapted and optimized to accurately segment cracks in diverse works of art. This adaptation aims to overcome the limitations of existing methods and provide the precision required for effective art conservation and analysis.

In order to validate the algorithm, two specialized datasets were created, consisting of a greyscale dataset from the Bucklow collection, representing various historical periods and artistic styles, and an RGB dataset of public domain paintings, capturing the complexity of colored artworks. The results showed a better performance of the modified B-COSFIRE algorithm in segmenting crack patterns in greyscale artworks, while more complex colored artworks introduce more challenging segmentation patterns, while still maintaining a better performance compared to the state of the art.

Thus, this project presents a solution to address the lack of advanced image processing and art conservation techniques by offering an innovative approach to crack analysis. Thus, by demonstrating how the modified B-COSFIRE algorithm can be effectively adapted for this purpose, the importance of integrating cutting-edge technologies in the preservation of cultural heritage is also highlighted. In addition, future work includes extending the datasets, exploring deep learning approaches, improving pre-processing and post-processing techniques, and designing a domain-independent filter to expand the applicability of the algorithm beyond the conservation of works of art.

Keywords: Supervised Structure Segmentation, B-COSFIRE, Image Processing, Curvilinear Structures.

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LIST OF ACRONYMS

Acronym	Meaning
AI	Artificial Intelligence
B-COSFIRE	Bar Combination of Shifted Filter Responses
COSFIRE	Combination of Shifted Filter Responses
CTH	Top-Hat Operators
DL	Deep Learning
DoG	Difference of Gaussian
DSC	Dice Similarity Coefficient
FKM	Fuzzy k-means
FN	False Negatives
FP	False Positives
GIMP	GNU Image Manipulation Program
GNNs	Graph Neural Networks
IoU	Intersection over Union
KDE	Kernel Density Estimate
MCC	Matthews Correlation Coefficient
MCNC	Morphological Convolutional Neural Network
MFD	Multispectral Feature Descriptor
MRBF	Median Radial Basis Function
OTH	Opening Top-Hat Operators
PDP	Public Domain Paintings
PPI	Pixels per Inch
RBF	Radial Basis Functions
SIFT	Scale Invariant Feature Transform
SS	Supervised Segmentation
THBPO	Thresholding and a Path Opening
TN	True Negatives
TP	True Positives
US	Unsupervised Segmentation

LIST OF SYMBOLS

Symbol	Meaning
σ	DoG standard deviation
ρ	Radial distance
n_ρ	Number of radial positions
ρ_{step}	Step size for ρ
σ_0	Base blurring
α	Scale
n_{angles_symm}	Number of symmetric orientations
n_{angles_asymm}	Number of asymmetric orientations
$G_\sigma(x, y)$	Gaussian filter with standard deviation σ
$G_{\sigma \cdot \sigma_{ratio}}(x, y)$	Gaussian filter with standard deviation σ_{ratio}

1 INTRODUCTION

This chapter presents the context and motivation, as well as the main objectives and contributions of the project.

1.1 Context and Motivation

Curvilinear structures play a pivotal role in a myriad of fields, from medical imaging where they aid in the delineation of anatomical elements, to geographical information systems where they assist in the mapping of linear terrestrial features such as roads and waterways [2]. This interdisciplinary importance sets the stage for the principal theme of this dissertation: the segmentation of craquelure patterns in artworks, a key component in the analysis of digital images and the conservation of cultural heritage.

Craquelure, the intricate network of fine cracks that appear on the surfaces of various materials, particularly in art, offers both challenges and opportunities in the conservation of artworks. These patterns provide insights into an artwork's age, geographical origin, and condition, as well as the materials and techniques used by the artist.[3]. By integrating advanced technological methods like Machine Learning (ML) and digital image processing with art conservation, the understanding of art history and theory while promoting the preservation and restoration of artworks is deepened, bridging the gap between technology and the humanities.

The main problem addressed by this project is the gap in methodology for the segmentation of curvilinear structures within the fine arts domain, specifically in analyzing and segmenting craquelure patterns. While fields like vascular imaging and road crack detection have progressed from unsupervised to supervised learning methods, this evolution is less pronounced in art conservation. To this end, it is presented a project developed in collaboration with **JTA - The Data Scientists**. It is a Portuguese company that provides support for clients to reach their full potential with customized data solutions, committed to innovation, transparency, and a commercial approach in all its projects. The company provided a supportive environment by hosting the internship for the master's dissertation, facilitating valuable resources and guidance throughout the research process.

1.2 Main Objectives

The main objective of this work is to validate the development of an algorithm for segmenting curvilinear structures within the artwork's domain, particularly focusing on the analysis of craquelure patterns in artworks. Additionally, this work aims to enhance the methodology used in art conservation by integrating

advanced segmentation techniques from fields like medical imaging, which are more developed compared to those currently employed in art conservation.

The specific objectives to achieve this goal are:

- Conduct a thorough review of current state of the art techniques in curvilinear structure segmentation to identify their limitations, especially in the context of art conservation.
- Improve the domain agnosticism of the segmentation tool developed by the JTA company, enabling its effective application across a diverse range of artworks and contexts.
- Perform comprehensive comparative tests of various segmentation approaches, focusing on their effectiveness in detecting and analyzing craquelure patterns.
- Address the efficiency requirements of segmentation methods, aiming to find a balance between high accuracy and ensuring practical applicability in art conservation.

1.3 Main Contributions

This work aims to explore and address the limitations of current state of the art techniques in curvilinear structure segmentation. To this end, the project, drawn up in collaboration with JTA focuses on improving the internal approach to segmenting curvilinear structures, ensuring its effectiveness across a broader range of contexts and artwork types. This project not only addresses a technical challenge but also highlights the relevance of combining art conservation with advanced technological approaches, offering new perspectives for understanding and preserving artistic heritage.

The contributions of this project to the field of art conservation and the broader interdisciplinary community are significant. By focusing on the segmentation of curvilinear structures, particularly craquelure patterns in artworks, this project not only addresses a specific technical challenge but also fosters a deeper integration between technological innovation and art conservation. Based on these considerations, the main contributions of this project include:

- **Methodological gap bridge**

This work specifically addresses the existing gap in the application of supervised learning methods for the analysis of craquelure patterns, a domain that has lagged others such as vascular imaging and road crack detection, contributing to making more accessible the study of craquelures across various fields.

- **Creation of art-specific dataset**

Development of a specialized dataset for the segmentation of craquelure patterns in artworks. This dataset not only facilitates the current research but

also serves as a valuable resource for future studies in art analysis and conservation.

- **Advancement in segmentation techniques**

The adaptation and development of advanced segmentation methods for the analysis of craquelure patterns represents a significant leap forward. This project moves beyond traditional approaches by integrating ML and digital image processing techniques, tailoring them to the unique challenges presented by artworks.

- **Comprehensive evaluation and documentation**

Presentation of a detailed evaluation of various segmentation techniques, providing a critical analysis of their effectiveness in the context of art conservation. The detailed documentation of the research process, findings, and recommendations offers a roadmap for future advancements in the field.

- **Interdisciplinary impact**

While the primary focus is on art conservation, the methodologies and findings of this research have potential implications for other domains. The techniques developed can be adapted for use in medical imaging, environmental science, and materials science, where accurate segmentation of curvilinear structures is crucial.

As part of this project, the following scientific contributions were produced:

- Oral presentation at the Twentieth International Conference on Condition Monitoring and Asset Management (CM2024) in Oxford, United Kingdom (**Extending B-COSFIRE for Automatic Extraction of Craquelure**), available on Appendix A.
- Publication submitted to the RECPAD 2024 - 30th Portuguese Conference on Pattern Recognition (**Extending the B-COSFIRE Algorithm for Craquelure Segmentation**), available on Appendix B.
- Third publication is being prepared to be submitted to an international conference to be defined.

By addressing these key areas, this project makes a meaningful contribution to the understanding and preservation of cultural heritage, demonstrating the important role that technology can play in the conservation of art.

1.4 Project Planning

This sub-chapter outlines the strategic approach to managing the tasks involved in this project. The management plan is designed to ensure the systematic and timely achievement of the objectives outlined earlier. The key components of the task management strategy include:

Task 1 (T1) – Literature review - comprehensive examination of existing literature in the areas of computer vision and different segmentation techniques, with a particular focus on algorithms applicable to the segmentation of curvilinear structures.

Task 2 (T2) – Labelling of datasets - manually label datasets of images of paintings for algorithm training and testing, ensuring a reasonable amount of data samples with annotations essential for effective segmentation.

Task 3 (T3) – Evaluative analysis of the B-COSFIRE algorithm - analyze the B-COSFIRE algorithm’s performance on segmentation tasks, identifying strengths, limitations, and potential improvements.

Task 4 (T4) – Experimental execution and parameter optimization - conduct several experiments focusing on optimizing parameters for improved performance and efficiency.

Task 5 (T5) – Examination of existing segmentation techniques - review existing and available segmentation techniques and approaches to evaluate their applicability and performance.

Task 6 (T6) – Development of a comparative framework with selection/collection of appropriate metrics - design and implement a framework for comparing segmentation effectiveness, selecting metrics that effectively measure performance.

Task 7 (T7) – Scientific papers writing – writing of scientific papers for submission to international conferences, aiming to contribute to the academic community.

Task 8 (T8) – Final report writing – dissertation writing for public exams.

Table 1.1 shows the tasks implemented during the development of the project over time.

Table 1.1. Project schedule.

Tasks	Sept	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul
T1											
T2											
T3											
T4											
T5											
T6											
T7											
T8											

1.5 Document Structure

This document is structured in 7 chapters:

Chapter 2 addresses the main concepts in a theoretical review for a better understanding of the scope of the dissertation and the project.

Chapter 3 details the research methodology for literature review, as well as the main approaches implemented by relevant studies that have influenced this research, highlighting the advancements and gaps in the current state of the art.

Chapter 4 describes the B-COSFIRE algorithm, its original application, as well as the adaptation made by JTA to be used with craquelure segmentation in art conservation.

Chapter 5 introduces the project implementation methodology, including the development of the art-specific dataset, the segmentation techniques employed, and the experimental methodology.

Chapter 6 presents the results of the segmentation validation and a detailed analysis of the performance of different methods, as well as the interpretation of the results, analyzing the limitations of the study and the practical applications and potential future research.

Finally, Chapter 7 discusses the conclusions of the project, emphasizing its contributions to the accurate segmentation of curvilinear structures in works of art and the proposal for future work.

2 BACKGROUND KNOWLEDGE

This chapter describes the fundamental concepts in artwork, curvilinear structures, the methods for segmentation of these types of structures and the importance of segmentation in artworks, as well as its main challenges.

2.1 Artworks Analysis

A brief overview of the principal aspects associated with artworks can be found below, providing some insights about the description, characteristics, importance and main challenges of the analysis of artworks.

2.1.1 Overview

Artwork analysis and conservation encompass the study, preservation, and restoration of artistic creations. This field plays a crucial role in maintaining the author's cultural heritage, deepening the understanding of artistic techniques, and ensuring the longevity of valuable artworks. Conservation science is a multidisciplinary field that combines knowledge from art history, chemistry, physics, and increasingly, computer science to develop effective methods for analyzing and preserving art.

Artwork analysis can be defined as the systematic study of the physical, chemical, and aesthetic properties of art objects. It involves the examination of the materials used, the techniques employed, and the condition of the artwork. The importance of artwork analysis lies in its ability to provide valuable information about the creation, history, and conservation needs of art objects. By understanding the composition and structure of an artwork, conservators can make informed decisions regarding its preservation and restoration [4]-[6].

2.1.2 Main Characteristics

Artwork analysis and conservation are characterized by several key features. Non-destructive examination techniques are crucial, allowing conservators to study artworks without causing damage. Material analysis is essential for understanding the composition of artwork and informing preservation strategies. Thorough documentation of an artwork's condition provides a baseline for future reference and helps track changes over time. Preventive conservation measures are implemented to slow deterioration and protect artworks from potential harm. When necessary, restoration work is carried out to address damage or degradation, always with the goal of preserving the artwork's integrity and original intent (Figure 1).

The main characteristics of artwork analysis include the use of non-invasive and micro-invasive techniques, the integration of scientific methods with art historical research, and the collaboration among professionals from various

disciplines. Non-invasive techniques, such as imaging and spectroscopy, allow for the examination of artworks without causing damage [7].

Micro-invasive techniques, such as sampling and analysis of small fragments, provide detailed information about the materials used. The integration of scientific methods with art historical research helps to contextualize the findings and interpret their significance and the collaboration among conservators, scientists, art historians, and other experts is essential for a comprehensive understanding of the different types of artworks [8].



Figure 1. Artwork restoration example. Source: [9].

2.1.3 Art Conservation

The applications of artwork analysis in conservation are diverse and impactful. By identifying original materials and techniques, conservators gain relevant information into an artist's process and the historical context of the artwork. These methods also play a crucial role in detecting forgeries, helping to maintain the integrity of art collections and the art market. Assessing damage and degradation allows conservators to prioritize treatment needs and develop targeted conservation strategies. Analysis techniques guide restoration efforts, ensuring that any interventions are appropriate and minimally invasive. Furthermore, the knowledge gained through analysis informs the development of long-term preservation strategies, helping to protect artworks for future generations.

Artwork analysis has numerous applications in the field of art conservation. It aids in the documentation and condition assessment of artworks, helping conservators to identify and prioritize conservation needs. By understanding the materials and techniques used, conservators can develop appropriate treatment strategies and preventive measures. Artwork analysis also contributes to the authentication and attribution of artworks, assisting in the detection of forgeries and the identification of artists' techniques. Furthermore, it provides insights into the degradation processes affecting artworks, enabling the development of targeted conservation interventions [10].

2.1.4 Main Challenges

Artwork analysis faces several significant challenges. The inherent fragility of many artworks limits the types of analysis that can be safely performed. The complexity of artistic materials and techniques, often unique to each artwork, requires a nuanced and adaptable approach. Conservators must constantly balance the need for preservation with the desire for public accessibility, finding ways to protect artworks while still allowing them to be studied and enjoyed. Ethical considerations in restoration work are paramount, with ongoing debates about the extent to which artworks should be altered or restored. Finally, the field has been continually adapted to keep pace with technological advancements, integrating new tools and methods while maintaining respect for traditional techniques.

Despite its many benefits, artwork analysis also faces several challenges. One of the main challenges is the need for non-invasive and non-destructive techniques that can provide meaningful information without compromising the integrity of the artwork. The complexity and heterogeneity of art materials pose additional challenges, requiring the development of specialized analytical methods. The interpretation of analytical data also requires expertise and interdisciplinary collaboration to ensure accurate and meaningful conclusions. Additionally, the cost and accessibility of advanced analytical equipment can be a barrier for many institutions, highlighting the need for collaborative research and resource sharing.

To address these challenges, the project intends to cope with the gap between advanced image processing techniques and artworks conservation, by providing an approach to craquelure analysis, demonstrating the effectiveness of the algorithm for this purpose.

2.2 Image Segmentation

This sub-chapter presents the definition and significance of image segmentation, explores the main types of image segmentation, and describes the main challenges associated with this process.

2.2.1 Definition and Importance

Image segmentation is a fundamental task in image processing that involves dividing an image into different, non-overlapping regions or segments based on specific criteria [11]-[15]. The main goal of image segmentation is to simplify the image and extract meaningful information from it, serving as the basis for image analysis, feature extraction, and recognition [16]-[17]. In an image classification task, the model assigns a label (or class) to each input image (Figure 2). However, if the main objective is to know the shape of that object or which pixel belongs to which object, there is a need to assign a class to each pixel of the image this task is known as segmentation [18]-[19]. Therefore, a segmentation model returns much more detailed information about the image compared to classification [20]-[23].

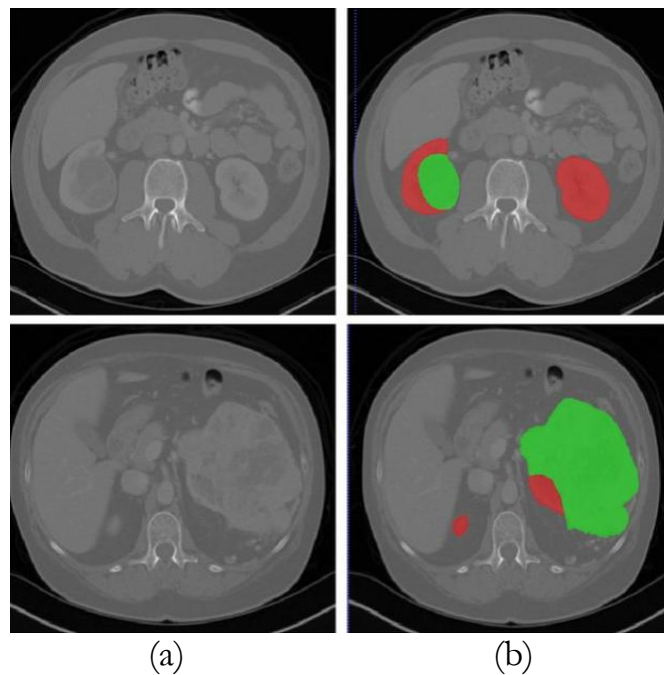


Figure 2. Example of image segmentation of an abdominal computed tomography scan. Red indicates kidneys, green color indicates tumor region. (a) Original image. (b) Segmentation/mask generated.

It is possible to use image segmentation in various fields, such as medical imaging, autonomous vehicles, video surveillance, augmented reality, robotics, scene understanding and others. By accurately segmenting images, researchers and practitioners can develop more advanced and efficient systems in these domains, making it an important task to be implemented. A key objective of image processing is to extract necessary information without disrupting other features, and image segmentation divides an image into segments that convey information in terms of different image properties, such as color, intensity, or texture. Consequently, isolating image boundaries by assigning a unique value to each pixel assists in distinguishing regions according to these properties, with the chosen technique depending on the problem domain [24].

2.2.2 Types of Image Segmentation

The evolution of image processing technologies has given rise to a group of segmentation types, ranging from simple techniques like thresholding and region growing to more advanced methods such as active contours, graph cuts, and sparsity-based approaches. Inspired by existing segmentation techniques, these methods can be systematically classified. However, in recent years, Deep Learning (DL) models have revolutionized the field of image segmentation, achieved remarkable performance improvements and become the dominant approach [23][24].

It is observed that there is not a perfect method for all fields related to image segmentation, since each image has its own different type. It is also a very difficult task to find a segmentation technique for a particular type of image. An example of the behavior of two of the different types of image segmentation is presented in Figure 3.

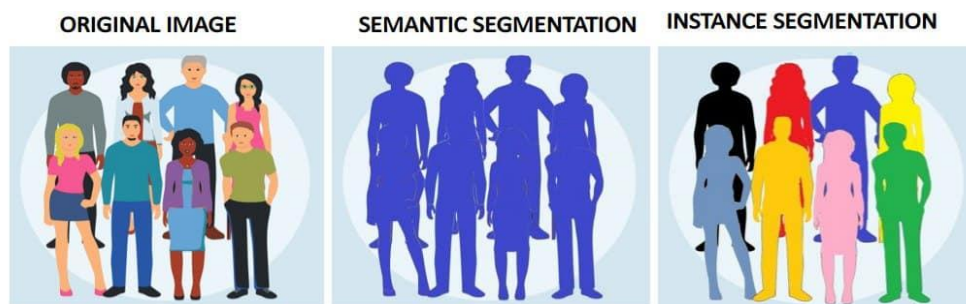


Figure 3. Illustration of a comparison between two types of image segmentation. Source: [25].

Below is presented a brief description of each segmentation type, highlighting their main advantages and disadvantages [16][24].

- **Cluster segmentation**

Identifies segments based on similar data patterns or clusters, offering efficient grouping and identification of similar data patterns. It is sensitive to initialization and noise and is limited to specific data distributions. This method is useful for identifying patterns and groups within the data but may struggle with irregular shapes.

- **Edge segmentation**

Relies on intensity transitions between regions, providing accurate delineation of organ boundaries and structures. It is sensitive to noise and may have difficulties capturing complex structures. This technique is suitable for images with clear organ boundaries and well-defined edges but may struggle in low-contrast areas.

- **Neural Network segmentation**

Neural Network (NN) segmentation involves learning models to segment images based on learned features, achieving high accuracy and efficient learning from data. However, it requires large training datasets and is computationally intensive. It is suitable for various types of data due to its flexibility and adaptability.

- **Region segmentation**

Divides images based on homogeneous regions, offering simple implementation and intuitive methodology. It is sensitive to initialization and may struggle with fine details. This method is often used where interpretability is a concern.

- **Semantic segmentation**

Based on the semantic meaning of pixels, providing pixel-level segmentation and fine-grained structural detail. It is complex to implement, resource-intensive, and computationally demanding. This technique is suitable for segmenting anatomical structures with distinct features.

- **Instance segmentation**

Instance segmentation takes semantic segmentation a step further by identifying and segmenting individual objects within the image, making it an object partitioning problem.

- **Threshold segmentation**

Uses intensity thresholds to segment images, which is simple, fast, and easy to implement. However, it is sensitive to threshold selection and suffers from noise and artifacts. It is commonly used where there are clear intensity differences between the region of interest and other regions.

2.2.3 Main Challenges

Image segmentation faces several significant challenges that continue to drive research in the field:

- Managing the complexity and variability of image content, as real-world images often encompass a wide range of objects, textures, and lighting conditions.
- Achieving precise boundary delineation, particularly for objects with indistinct or complex edges.
- Mitigating the impact of noise and artifacts on segmentation performance, requiring the development of robust algorithms capable of distinguishing between genuine image features and defects.

- Balancing computational efficiency with good performance, a critical consideration for applications that require real-time processing.
- Developing segmentation algorithms with strong generalization capabilities across diverse image types and domains, which frequently requires the incorporation of domain-specific adaptations.

Given these challenges, this project introduces several improvements to image segmentation specifically for craquelure analysis. By adapting and optimizing algorithms that deal with the complexity and variability of image data, it presents the validation of a strategy for segmentation despite diverse textures and lighting conditions, using improved boundary delineation techniques to accurately capture the intricate edges of craquelure patterns. Robust algorithms stand to mitigate the impact of noise and artifacts by distinguishing genuine features from defects. This project also emphasizes computational efficiency, enabling real-time processing without compromising performance. The segmentation approach incorporates domain-specific adaptations, improving generalization capabilities across image types and domains, effectively bridging the gap between advanced image processing techniques and the conservation of artworks.

2.3 Curvilinear Structures Segmentation

This sub-chapter introduces the definition of curvilinear structures segmentation, its main applications and challenges.

2.3.1 Definition

Curvilinear structures segmentation is a specialized area of image analysis focused on identifying and extracting curved linear structures within images. These structures are characterized by their elongated shape, which can vary in thickness along their length [27]-[32]. Curvilinear structures often have the potential for branching or intersecting, forming complex networks or patterns. Examples include blood vessels in medical images, road networks in satellite imagery, and, pertinent to this thesis, craquelure patterns in paintings. The unique properties of curvilinear structures necessitate specialized segmentation approaches that can handle their specific geometrical and topological characteristics [33]-[36].

2.3.2 Main Applications

The segmentation of curvilinear structures finds applications in various fields (Figure 4).

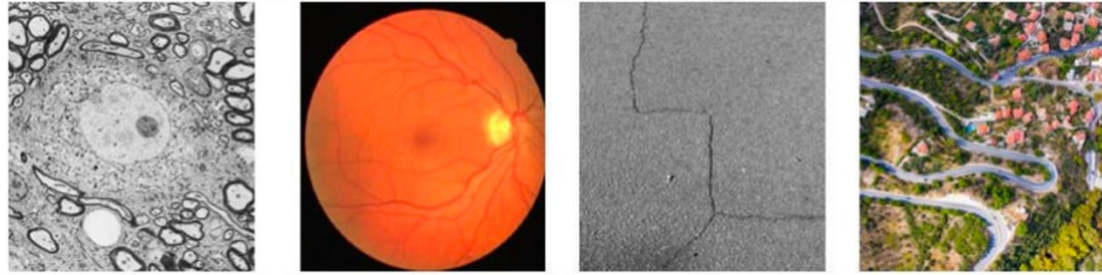


Figure 4. Difference in scales in multiple curvilinear structures.

The analysis of curvilinear structures is crucial in many fields, including but not limited to:

- **Medical imaging**

Segmentation of blood vessels, airway trees, and neuronal structures is essential for diagnosis, surgical planning, and understanding disease progression.

- **Environmental science**

Detecting and mapping road networks, rivers, and geological faults from aerial or satellite imagery is vital for urban planning, resource management, and disaster response.

- **Materials science**

Identifying and characterizing cracks, defects, and fiber structures in materials is crucial for quality control, structural integrity assessment, and understanding material behavior.

The principles and methods developed for these applications can often be adapted and applied to the analysis of craquelure in paintings, demonstrating the cross-disciplinary nature of this field.

2.3.3 Main Challenges

Segmenting curvilinear structures presents unique challenges that set it apart from general image segmentation tasks, such as [37]-[39]:

- Segmenting curvilinear structures with varying widths, as these features can range from very fine lines to broader bands within the same image.
- Accurately detecting junctions and intersections where multiple curvilinear structures converge, necessitating algorithms that maintain structural continuity while correctly identifying branching points.
- Addressing discontinuities and gaps within curvilinear structures, which may result from image quality issues or actual breaks in the features, requiring algorithms capable of inferring continuity without erroneously connecting unrelated structures.

- Distinguishing between authentic curvilinear structures and noise or similar-looking artifacts within the image, necessitating advanced filtering and validation techniques.

To address these challenges, this project provides an approach to craquelure analysis, demonstrating the effectiveness of the algorithm for this purpose, by introducing two specialized datasets created within the scope of the project, as well as the potential for integrating advanced segmentation techniques in the conservation of artworks.

2.4 Craquelure in Artworks

This sub-chapter outlines the definition of craquelure formation in artwork, its significance in art conservation, and the main challenges associated with its analysis.

2.4.1 Definition and Cause

Artworks are characterized by several unique visual and material properties, as presented below in Table 2.1 [5]-[7].

Table 2.1. Description of the main aspects related to artwork.

Medium	Technique	Condition	Aesthetic elements
Materials used in creating artwork, such as oil paint, watercolor, marble, bronze, or digital media, significantly influence its appearance and durability.	Methods like brush strokes, sculpting techniques, digital manipulation	The current state of preservation, including any visible signs of deterioration or damage, is crucial for conservation efforts. Factors such as craquelure, discoloration, and structural integrity are assessed.	Composition, color, form, and style are fundamental aspects that define an artwork's visual impact and artistic value

Craquelure refers to the network of fine cracks that develop on the surface of paintings over time (Figure 5). This phenomenon is a natural part of the aging process for many artworks.

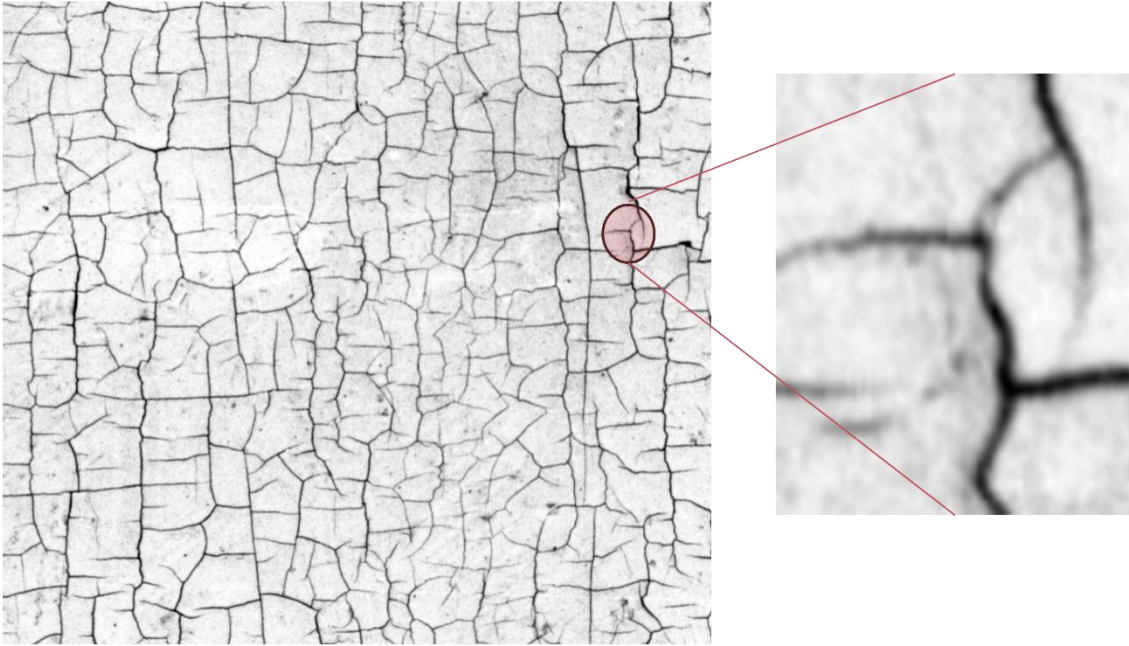


Figure 5. Craquelure present in an artwork.

2.4.2 Difference Between Scratches and Craquelures

In the context of artwork damage, **scratches** and **craquelure** refer to two distinct types of surface irregularities, each with different causes, characteristics, and implications for art conservation [40]- [43].

2.4.2.1 Scratch

A scratch is a superficial, often linear mark or groove that has been physically inscribed onto the surface of an artwork. It typically results from an external force or sharp object coming into direct contact with the artwork's surface, scraping away or displacing the material.

Scratches occur due to accidental or intentional actions, such as improper handling, transportation, cleaning, or vandalism. They can be caused by tools, sharp objects, or even abrasive materials encountering the artwork.

The main characteristics of a scratch are related to:

- **Appearance**

Scratches are usually straight or slightly curved lines that vary in depth and length, depending on the force applied and the object causing the damage.

- **Surface Impact**

Scratches often remove or displace the material on the surface, potentially exposing underlying layers. In paintings, this might mean the removal of paint, varnish, or even the ground layer, leading to visible damage that disrupts the artwork's appearance.

- **Restoration**

Restoring scratches can involve filling, inpainting, or reapplying the surface coating. The process often requires careful matching of the original materials and colors to minimize the visibility of the repair.

2.4.2.2 Craquelure

Craquelure refers to a network of fine cracks that naturally develop in the surface layers of a painting or other artworks over time. It is typically considered a normal aspect of the aging process in many artworks, particularly those made with materials like oil paint.

Craquelure is primarily caused by the natural aging of materials. Factors such as the drying and shrinking of paint layers, temperature and humidity fluctuations, and the expansion and contraction of the underlying support (e.g., canvas, wood) contribute to the formation of these cracks. Craquelure can also result from the differential aging rates of different layers within the artwork.

The main characteristics of a craquelure are related to:

- **Appearance**

Craquelure forms a pattern of interconnected cracks that can vary in size, shape, and density. These cracks can appear as fine, spiderweb-like networks or as more pronounced and irregular fractures.

- **Surface Impact**

While craquelure does not typically involve material loss, it can affect the structural integrity of the paint layer. The cracks can sometimes lead to paint flaking or lifting, especially if environmental conditions change or if the artwork is not properly conserved.

- **Restoration**

Craquelure is often left untreated unless it poses a threat to the stability of the artwork. Conservation efforts might focus on stabilizing the paint layer to prevent further deterioration rather than attempting to eliminate the craquelure itself, as it is often considered part of the artwork's history and character.

2.4.3 Impact in Artwork Conservation

Understanding craquelure is of vital importance in art conservation for several reasons. The patterns and characteristics of craquelure can provide valuable insights into a painting's age and history, helping to authenticate works and place them in their historical context. In some cases, the specific patterns of craquelure can be indicative of a particular artist's technique, or the materials used, potentially aiding in attribution. Craquelure also serves as an important indicator of an artwork's overall condition, helping conservators assess the

stability of the paint layers and identify areas that may require attention. This information is crucial in guiding conservation and restoration efforts, ensuring that interventions are targeted and appropriate [40].

2.4.4 Main Challenges

Segmenting features within artworks, particularly craquelure patterns, presents several challenges [41]-[46]:

- **Variability**

Crack patterns vary significantly across different artworks due to the artist's technique, materials used, and the artworks' history, making it difficult to develop generalized segmentation methods.

- **Craquelure intentionality**

Distinguishing between intentional craquelure, which may be part of the artist's technique, and unintentional damage or age-related cracking is challenging.

- **Non-invasive analysis**

Developing non-invasive analysis techniques that accurately assess craquelure without risking damage to the artwork is an ongoing challenge.

- **Noise and artifacts**

Digital images of artworks often contain noise and artifacts due to factors such as lighting conditions, camera quality, and image compression.

- **Complexity**

Artworks often feature intricate and fine details that require precise and accurate segmentation to avoid loss of important information.

- **Limited data**

The scarcity of labeled data for training supervised models poses a significant challenge, as creating annotated datasets for artworks is labor-intensive and requires expertise.

The challenges associated with craquelure segmentation underscore the complexity and interdisciplinary nature of artwork conservation. These challenges are not only technical but also contextual, requiring a nuanced understanding of both the artistic and material aspects of artworks. The variability in crack patterns, the need for non-invasive analysis, and the presence of noise and artifacts all highlight the necessity for advanced image processing techniques tailored to the unique characteristics of each artwork. This work aims to address these challenges by developing a robust segmentation approach that leverages recent advancements in image processing and ML.

2.5 Artificial Intelligence Application in Image Segmentation

This sub-chapter provides an overview of the application of Artificial Intelligence (AI) in image segmentation, covering concepts such as Unsupervised Segmentation (US) and Supervised Segmentation (SS). It also discusses the transition from US to SS, presenting some of the advantages and limitations of each approach.

2.5.1 Overview

AI and ML have revolutionized the field of image analysis, bringing about significant advancements in segmentation techniques. These technologies have enabled the automation of complex segmentation tasks that were previously time-consuming or infeasible to perform manually. AI and ML algorithms have dramatically improved the performance and efficiency of image segmentation, allowing for the processing of large datasets that would be impractical to analyze using traditional methods. Moreover, these approaches have demonstrated an impressive ability to adapt to varied image types and conditions, making them valuable tools across a wide range of applications [44].

2.5.2 Unsupervised Segmentation

US refers to methods that do not require labeled training data, instead relying on algorithms that can identify patterns and structures within the image data itself. These approaches typically work by grouping similar pixels or regions together based on various criteria such as color, intensity, or texture. Common techniques in this category include clustering algorithms and adaptive thresholding methods.

One of the main advantages of US is that it does not require the time-consuming and often expensive process of creating labeled datasets. Additionally, these methods have the potential to discover unexpected patterns or structures in the data that might be overlooked in a supervised approach. However, US methods also have limitations. They may not always align with human perception of meaningful segments, as they are based purely on statistical properties of the image. Furthermore, they can be less accurate than supervised methods for specific, well-defined segmentation tasks, and can be challenging to fine-tune for applications without introducing some level of supervision.

2.5.3 Supervised Segmentation

SS utilizes ML models that are trained on labeled data, where the correct segmentation is provided for a set of training images. These methods learn to recognize patterns and features associated with different segments or objects, and then apply this learned knowledge to new, unseen images. Many modern

SS approaches use DL techniques, particularly Convolutional Neural Networks (CNNs), which have shown remarkable performance on a wide range of segmentation tasks.

The main advantage of SS is its potential for high performance, especially on complex images where traditional methods might struggle. These approaches can be tailored to specific segmentation tasks, learning to identify objects or structures of interest. However, SS methods also have their challenges. They typically require large amounts of labeled training data, which can be time-consuming and expensive to produce. They can also be computationally intensive, both during training and inference. Additionally, there is always the risk of overfitting the training data, potentially leading to poor performance on images that differ significantly from the training dataset.

2.5.4 Transition from Unsupervised to Supervised Segmentation

The field of image segmentation has seen a gradual shift from unsupervised to supervised approaches, driven by several factors. The increased availability of large, labeled datasets has made SS more feasible for a wide range of applications. Advancements in DL architectures have dramatically improved the performance of supervised methods, often surpassing traditional unsupervised techniques. Additionally, the need for higher accuracy in critical applications has pushed the field towards supervised approaches that can be fine-tuned for specific tasks.

Despite these challenges, the transition also presents numerous opportunities. There is growing interest in combining US and SS approaches, leveraging the strengths of both methods. Semi-supervised segmentation techniques are being developed to reduce the reliance on fully labeled datasets, potentially making supervised approaches more accessible. Transfer learning is another promising area, allowing models trained on one type of image to be adapted for use on different, but related, segmentation tasks. These developments suggest a future where image segmentation methods become increasingly sophisticated, accurate, and adaptable to a wide range of applications.

The project leverages these advancements by integrating both unsupervised and supervised segmentation techniques to optimize craquelure analysis. By presenting two labeled datasets, the project focuses on the improved accuracy of DL architectures.

2.6 Performance Evaluation Metrics

In the context of craquelure segmentation, evaluating the performance of the segmentation models involves comparing the predicted segmentation masks to the ground truth masks. These masks are binary, indicating whether each pixel

is part of the craquelure (the object of interest) or not. This sub-chapter presents the metrics used to quantify the similarity between the predicted segmentation and the ground truth [18].

2.6.1 Matthews Correlation Coefficient

MCC is a measure of the quality of binary classifications. It considers true and false positives and negatives and is generally regarded as a balanced measure which can be used even if the classes are of very different sizes. MCC can be defined as presented below in equation (1):

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (1)$$

where:

TP = True Positives

TN = True Negatives

FP = False Positives

FN = False Negatives

MCC ranges from -1 to 1, where 1 indicates a perfect prediction, 0 indicates a random prediction, and -1 indicates total disagreement.

2.6.2 Precision

Precision is the ratio of correctly predicted positive observations to the total predicted positives, measuring the accuracy of the positive predictions. It is calculated using the formula (2):

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

High precision indicates that most of the pixels identified as craquelure are indeed correct, but it does not account for any missed craquelure pixels.

2.6.3 Recall

Recall, also known as sensitivity or the true positive rate, is the ratio of correctly predicted positive observations to all observations in the actual class. It is defined in equation (3):

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

High recall suggests that the model captures most of the craquelure, but it does not penalize for including many non-craquelure pixels.

2.6.4 Accuracy

Accuracy is the ratio of correctly predicted observations to the total number of observations, providing a measure of overall correctness. It is defined by the equation (4):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

While accuracy is straightforward, it can be misleading in imbalanced datasets. For instance, if craquelure occupies only a small fraction of the image, a model predicting mostly background might still achieve high accuracy.

2.6.5 F1 Score

F1 score is the harmonic meaning of precision and recall, making it a more useful metric than accuracy, particularly in cases of uneven class distribution. It is calculated in equation (5):

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

F1 score considers both false positives and false negatives, making it valuable for evaluating performance on imbalanced datasets.

2.6.6 Intersection over Union

IoU, also known as the Jaccard index, is used to measure the accuracy of an object detector on a dataset by evaluating how well the predicted bounding box overlaps with the ground truth. It is defined in equation (6):

$$IoU = \frac{|A \cap B|}{|A \cup B|} = \frac{TP}{TP + FP + FN} \quad (6)$$

Where:

- **Area of overlap:** area where the predicted bounding box and the ground truth bounding box overlap.
- **Area of union:** total area covered by both the predicted and ground truth bounding boxes.

IoU is a robust metric for segmentation tasks, providing a clear indication of overlap quality.

2.6.7 Dice Similarity Coefficient

DSC, also known as the Sørensen-Dice coefficient or Dice index, measures the similarity between two sets and is often used to assess the performance of image segmentation algorithms. It is calculated in equation (7):

$$DSC = \frac{2|A \cap B|}{|A| + |B|} = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (7)$$

Where:

- **|A∩B|**: cardinality of the intersection of sets A and B.
- **|A| and |B|**: cardinalities of sets A and B, respectively.

DSC is particularly useful for comparing the spatial overlap between the predicted segmentation and the ground truth.

2.6.8 Summary

In the context of craquelure segmentation, various performance evaluation metrics were employed to provide a comprehensive overview of the segmentation algorithms' behavior.

The selected metrics - (MCC), Precision, Recall, Accuracy, F1 Score, IoU, and DSC - are widely recognized in the literature for assessing segmentation tasks, particularly for curvilinear structures. Each metric offers unique insights into the model's performance: MCC provides a balanced measure of classification quality, while Precision and Recall highlight the model's ability to identify true positives amidst potential false positives and negatives. Accuracy offers a general measure of correctness, though it can be misleading in imbalanced datasets. The F1 Score serves as a harmonic mean of Precision and Recall, making it particularly valuable in scenarios with uneven class distributions. IoU and DSC are robust metrics that quantify the overlap between predicted and ground truth masks, essential for evaluating segmentation quality.

By utilizing this array of metrics, the main goal was to capture a holistic view of the algorithms' performance, acknowledging that different studies may prioritize different metrics based on their specific objectives. This approach not only aligns with common practices in the field but also facilitates a comparative analysis of the segmentation models, ensuring a thorough evaluation of their effectiveness in detecting craquelure.

3 STATE OF THE ART

This chapter provides an analysis of the state of the art techniques, from traditional methods to more advanced and recent for craquelure segmentation in artworks, highlighting the main findings of this review.

3.1 Research Methodology

Google Scholar was used for document retrieval, and the most representative document from each year was selected, which involved synthesizing existing knowledge, critically assessing methodologies, and analyzing results to compare the performance of each segmentation method.

A search performed in December 2023, with the keyword “automatic craquelure segmentation in artwork” returned approximately 205 papers, filtering the years to the period 2000 - 2023.

The most relevant studies have been included in this literature overview. In the context of **Google Scholar**, relevance refers to the degree to which the search results match the criteria or context of the keyword. The sorting algorithm considers several factors to determine the order of the results, including the presence of search terms and citation counts.

The exclusion criteria set to exclude studies that did not meet the criteria defined above. Studies written in languages other than English and Portuguese were also not included. As a final exclusion criterion, the studies of which the full document was not available to the public were excluded, considering that, despite the restricted number of papers in the area, many of the papers are not publicly available through public access journals and conferences, therefore many of the papers found were either not directly related to the aim of the project or were not publicly available.

Once inclusion and exclusion criteria had been applied to the data source tool, it was ensured that the studies selected were relevant to the research questions and met the needs of the project. The objective of this rigorous selection process was to include studies that contributed valuable information on the specific topic of interest and to exclude those that did not meet the predefined selection criteria.

The earliest papers searched dates from 2000, as shown in Figure 6, with at least one paper being published until 2023. Nonetheless, after analyzing the papers retrieved through the keyword used, it became noticeable that many of them did not meet the inclusion criterion, with some that could not be accessed (private papers), as well as many papers referring only to artworks, whether or not the impact of craquelures on artworks is explicit, but not presenting a methodology for their segmentation, just a brief context of their cause and

importance. Considering the purpose of the literature review is to study related work that has been carried out up to 2023 in the field of automatic or semi-automatic segmentation of craquelures in artworks, it was decided to discard papers that were not within this scope, or whose results were not sufficiently explicit and clear to bring value to this analysis of the gaps in the literature. As such, a total of 17 papers were selected.

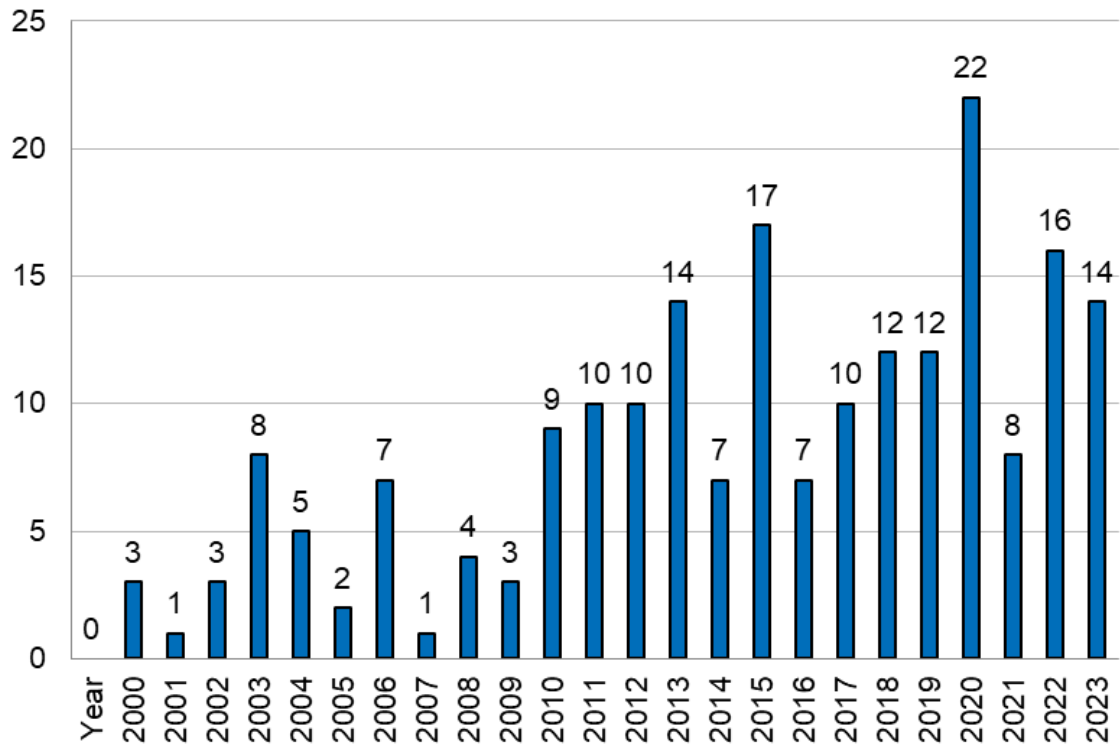


Figure 6. Distribution of the studies found over the years.

3.2 Craquelures Segmentation Approaches for Artworks

Based on the selected studies, this literature review provides an overview of different methods and approaches for craquelures segmentation in artworks. It covers different segmentation methods, comparing the results and discussing the potential applications and strengths of each method.

As mentioned in sub-chapter 3.1, studies between the years 2000 and 2023 were selected, summing to a total of 17 documents. Unfortunately, the full text of some works was not available or applicable for the scope of the project. A comparative table of the remaining 17 papers can be found in Appendix C.

The field of craquelure segmentation in artworks has seen an evolution from traditional image processing techniques to more complex AI-based approaches. In early work by Abas and Martinez [46], eight differently oriented Gabor filters, combined with a morphological thinning algorithm were used to detect crack patterns in X-radiographs of paintings. Although their results were not

quantitatively evaluated, they demonstrated the potential of multi-oriented filters for capturing craquelure structures. In their subsequent study [48], the same authors explored a morphological top-hat operator with grid-based thresholding and fuzzy k-means clustering, emphasizing the difficulties posed by the absence of standardized datasets and ground truths for method validation. Building on morphological techniques, Giakoumis et al. [49] proposed two segmentation approaches using top-hat transformations and median radial basis function (MRBF) NNs, achieving qualitative success evaluated by field experts. However, this approach struggled with detecting craquelures in dark areas, a common limitation in many methods, due to the complexity of the task. Spagnolo and Somma [50] similarly used top-hat operators in conjunction with grayscale morphological dilation and erosion. Their results, while showing improved crack filling methods, lacked quantitative validation and relied on visual assessments.

The methodological trend continued with work by Sangeetha and Saradha [50], who employed morphological top-hat operators and grid-based thresholding to analyze and classify crack patterns in a private dataset. Despite a lack of quantitative results, their method contributed to a structured approach to crack detection that has practical applications in art preservation. Gancarczyk [52] introduced a semi-automatic technique based on region growing and decision trees to enhance crack pattern identification, highlighting the challenges in feature selection. The following year, Gancarczyk and Sobczyk [53] applied top-hat transformation and k-means clustering combined with Bayesian learning models, facilitating targeted restoration by minimizing misclassified pixels in private heritage datasets.

Gillooly et al. introduced different segmentation post-processing methods like spectral top-hat and path opening operators on manually labeled patches from a single artwork [54], with this work providing one of the first quantitative evaluations, using Intersection over Union (IoU) metrics to assess segmentation accuracy, marking a step towards standardized evaluation. Dulecha et al. [55] introduced a CNN-based labeling approach on edge-detected image patches, achieving 76.83% average classification accuracy on multi-light images, which improved accuracy compared to single-image methods. This shift towards NNs demonstrated the potential of DL for complex craquelure patterns. Sidorov and Hardeberg [56] further extended this trend with Graph Neural Networks (GNNs) combined with statistical feature extraction, achieving enhanced accuracy in artwork origin classification and robustness to geometric distortions in a high-resolution, private dataset. The study by Sparavigna, while exploratory, applied a GIMP Retinex filter to isolated artworks, offering a preprocessing alternative that could facilitate subsequent segmentation efforts [57]. Sizyakin et al. [58] used a Morphological Convolutional Neural Network (MCNC) to segment the Ghent Altarpiece, comparing it against traditional classifiers like SVM and AdaBoost and their results underscored the superior performance of

CNNs in crack detection tasks, with recall and precision scores of over 81%. Angheluta and Chiroasca [59] applied a VGG-16 CNN model, achieving high precision 87% and recall 83% on a private dataset of 2148 images, noting that further refinements in model architecture could improve accuracy, allowing the detection of different types of physical damages in artwork images.

Sindel et al. [60] introduced CraquelureNet, a ResNet-based approach for multimodal image registration and segmentation, showcasing the efficacy of DL in managing complex datasets using different image modalities. Their method demonstrated superior registration performance, especially in handling historical artworks with multimodal annotations, a significant advancement in addressing segmentation challenges in heterogeneous datasets. In another recent development, Toorn and Wiersma [61] employed multimodal feature descriptors like SIFT and SuperPoint to achieve high matching accuracy in segmentation tasks, underscoring the importance of modality-specific feature extraction. Jamalabadi used an AI-based framework to analyze crack patterns by transforming them into simplified lines, providing insights into their distribution and evolution. Although lacking quantitative results, this approach offered an innovative visualization tool for restoration [62] while Yuan et al. [63] demonstrated the power of ResUNet in achieving quantitative segmentation accuracy on a dataset of 600 images, yielding a high F1-score 93.42% and 98.19% accuracy, positioning their model as a reliable tool for craquelure recognition.

Through this chronological review, it is evident that craquelure segmentation has progressed from morphological methods to sophisticated NNs and multimodal techniques, addressing issues of dataset availability, quantitative evaluation, and robustness to image variability. This work builds upon these advancements, refining segmentation approaches to offer both qualitative and quantitative evaluations of craquelure patterns in artworks. Further details on these studies are available in Appendix C - Table 1 systematically organizes the principal contributions in this field.

3.3 Findings

The structure of many earlier papers often lacked the rigorous structure necessary for clear scientific communication, particularly those published before 2015. This inconsistency led to disjointed presentations of introductions, methodologies, results, and conclusions. Many studies prioritized novelty over clarity, offering innovative methods without sufficient background or detailed introductions, making it difficult for readers to contextualize the research. Methodology sections frequently lacked the detail needed for reproducibility, a cornerstone of scientific research. Additionally, results and conclusions were often underdeveloped, lacking quantitative evidence and comprehensive discussions, complicating the comparison of techniques across studies. This

trend highlights the importance of a clear and structured format in scientific writing, with well-defined introductions, detailed methodologies, robust results, and thoughtful conclusions, essential for advancing the field and applying new techniques in real-world scenarios.

In the field of craquelures segmentation, various techniques have been explored, each with its own strengths and limitations. While some methods have shown potential as previously presented, there are still several challenges that need to be addressed, along with opportunities for future research.

3.3.1 Evolution of the Segmentation Techniques

The progression from simple filtering and morphological operations to more complex region-growing techniques, and eventually to ML-based approaches, reflects the field's natural evolution. Initially, methods like those proposed by Abas [47] were groundbreaking but limited by the available computational power and data. By contrast, more recent approaches leveraging NNs, as seen in the works of Sparavigna [56] and Yuan & He [62], have demonstrated superior performance, albeit with the caveat of requiring large, well-labeled datasets.

3.3.2 Adoption of Artificial Neural Network-based Methods

Early methods, primarily from 2002 to 2012, focused on filters, morphological operations, and thresholding techniques. For instance, Abas & Martinez [45] and subsequent studies employed Gabor filters and morphological transformations, which, while innovative at the time, lacked quantitative validation. These methods relied heavily on handcrafted features and were often limited by the dataset's size and quality, leading to a reliance on qualitative rather than quantitative evaluations.

The period from 2010 to 2013 saw a shift towards more sophisticated methods like region-growing techniques and clustering approaches. For example, Ganarczyk [51] applied a semi-automatic technique based on region-growing algorithms, which represented a significant advancement in dealing with the irregularities of crack patterns. However, these methods still lacked comprehensive quantitative analysis, making it challenging to evaluate their performance against earlier techniques.

From 2018 onwards, the introduction of ML and NN-based methods marked a significant evolution in the field. Techniques like CNNs, ResNet, and U-Net architectures demonstrated considerable potential, particularly in the work of Dulcsa, Giachietti [54], and Yuan, He, [62]. These methods were better equipped to handle the complexity of crack patterns, offering higher accuracy and better generalization across different datasets. However, despite these advancements, the lack of standardized, publicly available datasets continued to

impede progress. The absence of large, labeled datasets particularly limits the effectiveness of SS models, which depend heavily on robust training data.

3.4 Challenges Highlighted by the Literature

While the literature provides valuable insights into the segmentation of craquelure patterns, several challenges and limitations persist that hinder progress in this field. Two prominent issues identified are the lack of publicly available datasets, which limits reproducibility and comparative analysis, and the scarcity of quantitative results, making it difficult to evaluate and benchmark methods effectively. These challenges are discussed in detail in the following subsections.

One of the most significant challenges highlighted in literature is the lack of large public datasets, including the ground truth. This issue is particularly acute in the field of supervised learning, where models require vast amounts of annotated data to achieve high performance. The absence of such datasets not only limits the ability to train robust models but also restricts the reproducibility of results, which is crucial for the field's advancement.

The lack of quantitative data in the literature limits the ability to conduct meta-analyses or systematic reviews, which are essential for identifying the most effective techniques. This deficiency also complicates the task of selecting the appropriate method for specific use cases, particularly in real-world applications where the consequences of failure can be significant.

A recurring theme in the reviewed literature is the lack of quantitative results, as noted in studies like Abas & Martinez [45], Spagnolo & Somma [49], and Sidorov & Hardebreg [55]. This deficiency significantly hampers the ability to make fair and accurate comparisons between different segmentation techniques. Qualitative assessments, while useful for preliminary evaluations, do not provide the rigorous statistical validation needed to advance the field effectively.

4 B-COSFIRE ALGORITHM

In this chapter, the Bar Combination of Shifted Filter Responses (B-COSFIRE) filter, an algorithm designed for the detection of curvilinear structures in images, is briefly introduced. We discuss its original formulation, its evolution over time, and present our extension to the algorithm tailored for the segmentation of craquelure patterns in paintings. The chapter includes mathematical formulations and pseudocode to illustrate the working of the algorithm and our proposed enhancements.

4.1 Introduction

The B-COSFIRE filter was introduced by Azzopardi et al. [63] for the automatic detection of curvilinear structures such as blood vessels in retinal images (see Figure 7). It is based on the Combination of Shifted Filter Responses (COSFIRE) approach and is designed to detect elongated and curvilinear patterns in images. Inspired by the mechanisms of simple cells in the visual cortex, the filter models orientation-selective responses, making it highly effective for detecting line-like structures such as vessels, cracks, or other curvilinear features [64]-[66].



Figure 7. Application of the B-COSFIRE in the automatic identification of curvilinear structures. Source [63].

The key advantages of the B-COSFIRE filter are its orientation selectivity and rotation invariance, allowing it to detect structures in various orientations. These properties make it highly adaptable for use in both medical imaging and art conservation, where segmentation and analysis of patterns, such as craquelure, are crucial. Craquelure, the fine cracking patterns that develop in painted surfaces, presents unique challenges due to its irregularity in shape, size, and texture [67]-[69].

4.2 Evolution of the B-COSFIRE algorithm

Since its inception, the B-COSFIRE filter has been extended and adapted in multiple contexts. Strisciuglio et al [69] demonstrated its robustness in delineating noisy and incomplete lines. Despite its robustness, the original filter exhibited limitations in handling varying curvilinear structures and complex image conditions. In the context of craquelure segmentation, these challenges include dealing with line thickness variations, incomplete cracks, and noise.

Recent advancements in B-COSFIRE filters, allowed for a wider utility in image analysis, particularly in detecting and delineating elongated and curvilinear structures across different fields. However, challenges in flexibility and adaptability to different scenarios, including complex artistic works persist, because determining the optimal configuration for the algorithm still relies on manual tuning and heuristic methods, which can be time-consuming and may not always yield the best results for every specific task.

The operation of B-COSFIRE filter can be systematized into five stages:

1. Filter Configuration

The B-COSFIRE filter configuration begins by selecting a prototype pattern, such as a line or bar, representing the curvilinear structures to be detected. This prototype is processed using Difference of Gaussian (DoG) filters to capture intensity gradients.

The DoG filter is mathematically defined in equation (8).

$$\text{DoG}(x, y) = G_{\sigma}(x, y) - G_{\sigma \cdot \sigma_{\text{ratio}}}(x, y) \quad (8)$$

where $G_{\sigma}(x, y)$ and $G_{\sigma \cdot \sigma_{\text{ratio}}}(x, y)$ are Gaussian filters with standard deviations σ and σ_{ratio} , respectively. The parameter σ_{ratio} controls the ratio between the two Gaussian standard deviations, influencing the scale and width of the detected structures.

2. DoG Responses

The DoG response is computed by convolving the input image $I(x, y)$ with the DoG filter presented in equation (9).

$$\text{Response}_{\text{DoG}}(x, y) = I(x, y) * \text{DoG}(x, y) \quad (9)$$

where $*$ denotes convolution. Negative values in the DoG response are set to zero to focus on the significant gradients corresponding to curvilinear structures (equation (10)).

$$\text{Response}_{\text{DoG}}(x, y) = \max(\text{Response}_{\text{DoG}}(x, y), 0) \quad (10)$$

3. Blurred DoG Responses

The DoG responses are then blurred using Gaussian filters of increasing standard deviation to achieve scale invariance, defined in equation (11).

$$\text{Blurred DoG}_{\sigma_i}(x, y) = \text{Response}_{\text{DoG}}(x, y) * G_{\sigma_i}(x, y) \quad (11)$$

where $\sigma_i = \sigma_0 + i \cdot \sigma_{\text{const}}$ and i ranges from 0 to n_ρ . The parameters σ_0 and σ_{const} define the initial scale and the increment between scales, respectively.

4. Symmetric and Asymmetric Responses

Once the blurred DoG responses are computed, the filter calculates both symmetric and asymmetric responses at multiple orientations.

- **Symmetric Responses**

For symmetric responses, the filter positions are defined along a line centered at the origin, with positions defined in equation (12).

$$\rho_k = k \cdot \rho_{\text{step}} \quad (12)$$

Where $k = -n_\rho, \dots, n_\rho$.

At each orientation θ , the positions are rotated in equation (13).

$$\begin{pmatrix} \Delta x_k \\ \Delta y_k \end{pmatrix} = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} \rho_k \\ 0 \end{pmatrix} \quad (13)$$

The symmetric response is then computed as presented in equation (14).

$$R_{\text{symm}}(x, y, \theta) = \prod_{k=-n_\rho}^{n_\rho} \text{Blurred DoG}_{\sigma_{|k|}}(x + \Delta x_k, y + \Delta y_k) \quad (14)$$

- **Asymmetric Responses**

For asymmetric responses, the positions are defined for $k = 0$ to n_ρ , as shown in equation (12), where $k = 0, \dots, n_\rho$.

Similarly, the positions are rotated, and the asymmetric response is computed as presented in equation (15).

$$R_{\text{asymm}}(x, y, \theta) = \prod_{k=0}^{n_\rho} \text{Blurred DoG}_{\sigma_k}(x + \Delta x_k, y + \Delta y_k) \quad (15)$$

5. Final Response Calculation

The combined response of the filter is given by equation (16).

$$R_{\text{BCOSFIRE}}(x, y) = \max_{\theta} [R_{\text{symm}}(x, y, \theta)] + \max_{\theta} [R_{\text{asymm}}(x, y, \theta)] \quad (16)$$

This results in a response map indicating the locations of detected curvilinear structures in the input image. This response represents the original B-COSFIRE method.

4.3 Extension of the B-COSFIRE Algorithm for Craquelure Segmentation

To adapt the B-COSFIRE filter for craquelure segmentation in art conservation, we introduced several enhancements. Craquelure patterns, characterized by irregular cracks in paintings, require a filter that can handle variations in line thickness, incomplete lines, and noise. Our extended version of B-COSFIRE addresses these challenges by introducing new response mechanisms focused on homogeneity.

The homogeneity response enhances the filter's ability to detect uniform patterns while remaining robust to incomplete or irregular structures. It introduces intra-bar and inter-bar homogeneity measures.

4.3.1 Intra-Bar Homogeneity

Intra-bar homogeneity measures consistency within the left or right side of the bar structure.

For symmetric responses, equations (17) and (18).

$$H_{\text{intra}}^{L, \text{symm}}(x, y) = |L1_{\text{symm}}(x, y) - L2_{\text{symm}}(x, y)| \quad (17)$$

$$H_{\text{intra}}^{R, \text{symm}}(x, y) = |R1_{\text{symm}}(x, y) - R2_{\text{symm}}(x, y)| \quad (18)$$

Where $L1_{\text{symm}}(x, y)$ and $L2_{\text{symm}}(x, y)$ are the responses at left bar positions offset by a new parameter introduced, h_{off} and $2 * h_{\text{off}}$, respectively. Similarly, for $R1_{\text{symm}}(x, y)$ and $R2_{\text{symm}}(x, y)$.

4.3.2 Inter-Bar Homogeneity

Inter-bar homogeneity measures the consistency between the left and right sides of the bar structure.

For symmetric responses, equation (19):

$$= \left| \frac{L1_{symm}(x, y) + L2_{symm}(x, y)}{2} - \frac{R1_{symm}(x, y) + R2_{symm}(x, y)}{2} \right| \quad (19)$$

Similar calculations are performed for asymmetric responses.

4.3.3 Final Response Calculation with Homogeneity Measures

The final response combines the original B-COSFIRE response with the homogeneity responses, incorporating sensitivity parameters α_{intra} and α_{inter} , as shown in equations (22) and (21), resulting in equation (22).

$$R_{sym,h}(x, y) = R_{sym}^{max}(x, y) \times (1 - H_{l,intra}^{sym})^{c_{intra}} \times (1 - H_{r,intra}^{sym})^{c_{intra}} \times (1 - H_{inter}^{sym})^{c_{inter}} \quad (20)$$

$$R_{asym,h}(x, y) = R_{asym}^{max}(x, y) \times (1 - H_{l,intra}^{asym})^{c_{intra}} \times (1 - H_{r,intra}^{asym})^{c_{intra}} \times (1 - H_{inter}^{asym})^{c_{inter}} \quad (21)$$

$$R_h(x, y) = R_{sym,h}(x, y) + R_{asym,h}(x, y) \quad (22)$$

Where:

- $R_{sym}^{max}(x, y)$ and $R_{asym}^{max}(x, y)$ are the maximum symmetric and asymmetric responses across all orientations, respectively.
- $H_{l,intra}(x, y)$ and $H_{r,intra}(x, y)$ are the intra-bar homogeneity measures for the symmetric filter, corresponding to the left and right sides of the bar, respectively.
- $H_{inter}(x, y)$ is the inter-bar homogeneity measure for the symmetric and asymmetric filters.

This enhanced response calculation represents the developed extension.

4.3.4 Performance Evaluation and Challenges

The extended B-COSFIRE filter demonstrates improved performance in segmenting complex craquelure patterns in paintings. The homogeneity response mechanism, combined with tunable sensitivity parameters, enhances the filter's ability to handle variations in line thickness, noise, and incomplete structures.

However, challenges remain, particularly in dealing with scale and orientation variations in highly textured or noisy images. Future work may focus on

addressing these limitations to further improve the filter's performance in art conservation applications.

This sub-chapter provides a comprehensive overview of the B-COSFIRE filter, its adaptation for craquelure segmentation, and the mathematical foundations underlying its operation. The integration of homogeneity responses and sensitivity parameters represents a significant advancement in the filter's capability to handle the complex patterns encountered in art conservation.

5 METHODOLOGY

This chapter outlines the methodology used to test the efficacy of the B-COSFIRE algorithm modified. It details all the processes from data collection and labelling to model evaluation and performance. The motivations for all decisions and design choices are also described below.

5.1 Overview

Figure 8 illustrates the workflow for the methodology of the implementation of the project.

The project workflow is composed of the following elements:

- Dataset preparation
- Data loading and pre-processing
- Model configuration and initialization
- Hyperparameter tuning and grid search execution
- Model evaluation
- Logging to MLflow
- Results and visualization

The results, including hyperparameters and performance metrics, were logged to MLflow for tracking and analysis. This allowed for easy comparison and selection of the best hyperparameters.

5.2 Project Setup

The implementation of the experimental procedure was developed using an Intel® Core™ i7-9750HF CPU @ 2.60GHz with 6 cores and 12 logical processors on a local Windows machine. The workflow pipeline was implemented in Python, using jupyter notebooks for testing and prototyping with Anaconda managing the environments.

The main dependencies of the pipeline include NumPy and Numba for calculations, Pandas for data manipulation, and scikit-learn for ML algorithms.

Additionally, Matplotlib was used for data visualization, MLflow was employed for tracking and managing experiments, and Adobe Photoshop was used for data labelling.

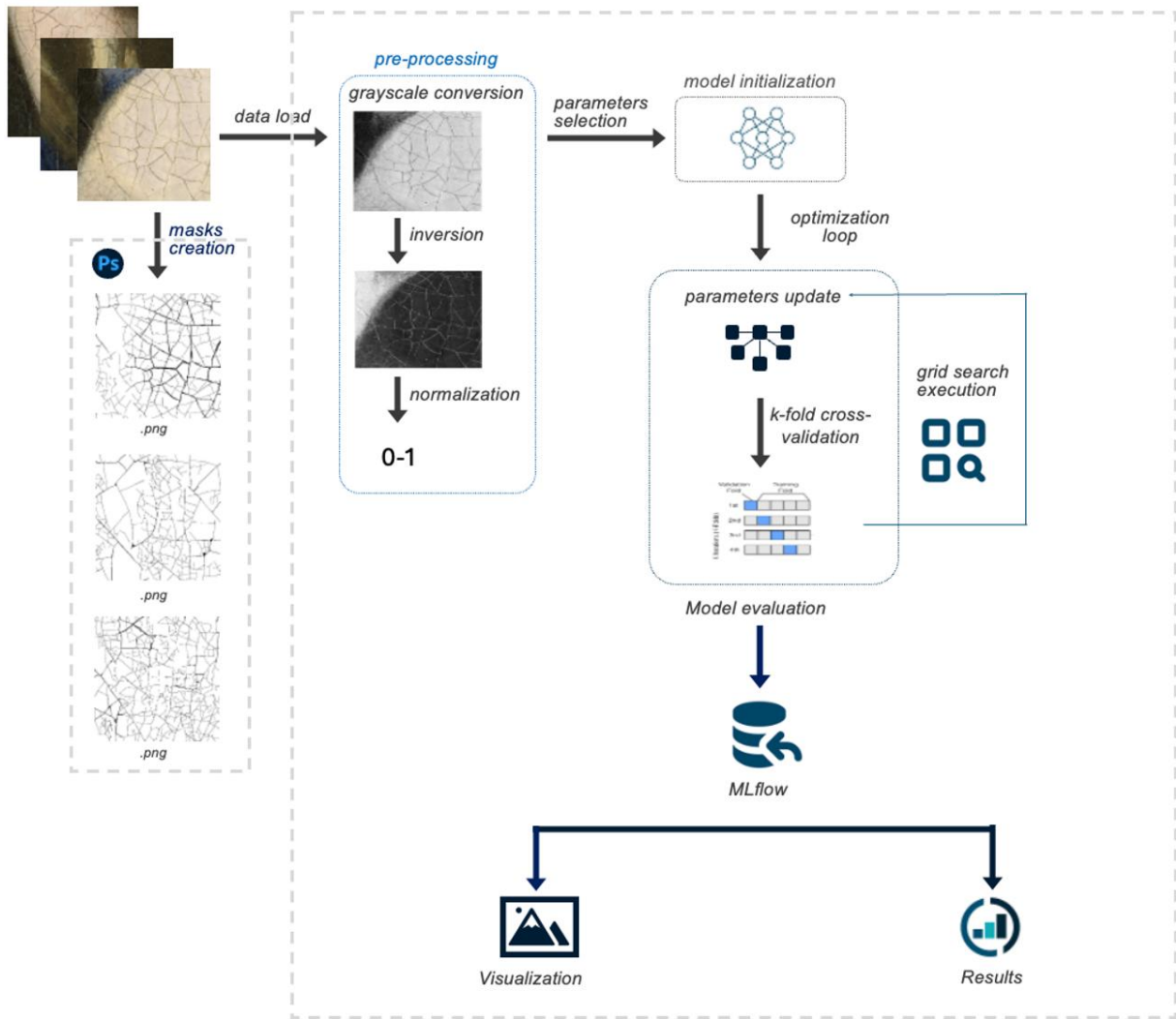


Figure 8. Methodology for the proposed solution.

5.3 Data Preparation

This sub-chapter describes the process of creating a dataset and ground truth for the scope of this project, along with the data labelling process, as well as some statistics, characteristics, and additional information regarding their provenance.

The materials (hardware and software) used to carry out the data labelling, as well as the selection criteria, are described below.

Initially, the open-source tool Label Studio was considered for data annotation, but it proved unsuitable due to a significant degradation in image quality and the inability to distinguish cracks effectively.

Furthermore, the available tools within Label Studio lacked the precision necessary for accurate pixel-wise segmentation since the pencil tool was often too large to accurately outline the intricate crack patterns, and at the optimal zoom level, the pen movement was restricted to 45-degree angles, making it

impossible to trace the cracks with the required level of detail (Appendix D - Figure 1).

Consequently, Adobe Photoshop was chosen as the software for the annotation process, offering a wider range of tools and techniques, albeit with a steeper learning curve. To facilitate pixel-wise segmentation across the images, a pen and a Wacom tablet were applied (Appendix D - Figure 2).

The labelling process followed a standardized protocol to ensure as much consistency as possible, which selection criteria for data labelling tool are presented in Appendix D.

Since the definition of craquelure is subjective, an empirical criterion outlined in the literature for segmentation of curvilinear structures was followed. These criteria included geometric constraints, such as the necessity for pixels to be mostly connected, the requirement for regions to be thin along a long path, and the demand for smooth variations in width across the region. Additionally, photometric constraints were considered, which involved evaluating the intensity values of pixels, significant differences from the surrounding background, smooth changes in color along the main direction of the structure, and specific intensity profiles across the structure resembling a valley or U-shape.

The labelling process involved the following main steps:

- Upload the image into the labelling tool and create a duplicate layer.
- Adjust various settings to isolate cracks effectively while reducing noise and unwanted features.
- Manually trace the cracks on the duplicate layer using the pen tool to create a binary mask.
- Apply personalized pre-processing techniques tailored to each image's unique characteristics.
- Optimize the visibility of cracks and minimize interference from other elements.

Throughout this process no formal quality control measures were implemented beyond visual observation. Once the annotations were complete, the images were saved in .png format.

5.3.1 Dataset 1 – Bucklow

Given the lack of public datasets, JTA proposed the challenge of creating two public datasets with different characteristics, one with color artworks (RGB), and the other with grayscale artworks.

The following sub-chapter provides a statistical overview of the grayscale dataset derived from the Bucklow collection. These statistics include the pixel distributions and overall characteristics of the images and masks, providing insights into the structure and quality of the dataset. Kernel Density Estimate (KDE) plots were also generated to further visualize the pixel value distributions for the dataset.

The images in Dataset 1 were graciously provided by S. Bucklow, a renowned expert in the field of art conservation [71]. These grayscale images represent various countries and centuries, encompassing a diverse range of artwork from different historical periods and cultural contexts (Figure 9 only shows 11 out of 20 total images). The dataset comprises 20 images in the .jpg format, with resolutions falling into two distinct categories: 1181x1772 and 1181x1181 pixels. The images were captured at a resolution of 300 pixels per inch (ppi) both vertically and horizontally, ensuring a high level of detail and clarity. The file sizes range from 200 KB to 650 KB, with a bit depth of 8 bits per pixel.

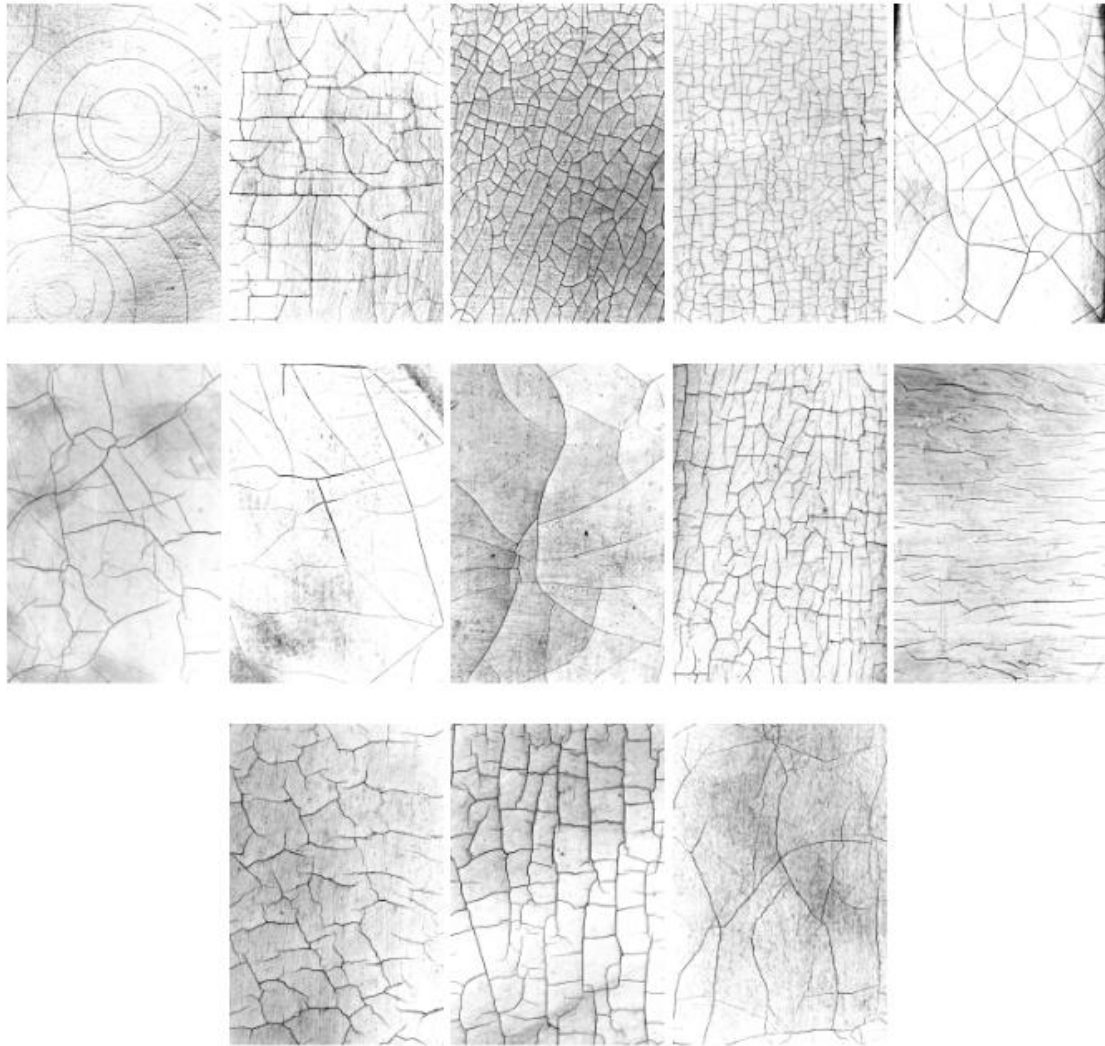


Figure 9. Bucklow dataset.

The criteria for image selection were designed to ensure that at least one image was included for each country represented in the dataset, maximizing the diversity of craquelure patterns. Pre-processing steps were undertaken in Adobe Photoshop, where various settings were adjusted to reduce noise and enhance the visibility of craquelure patterns as much as possible. The respective masks created for the images showed in Figure 9 are presented below in Figure 10.

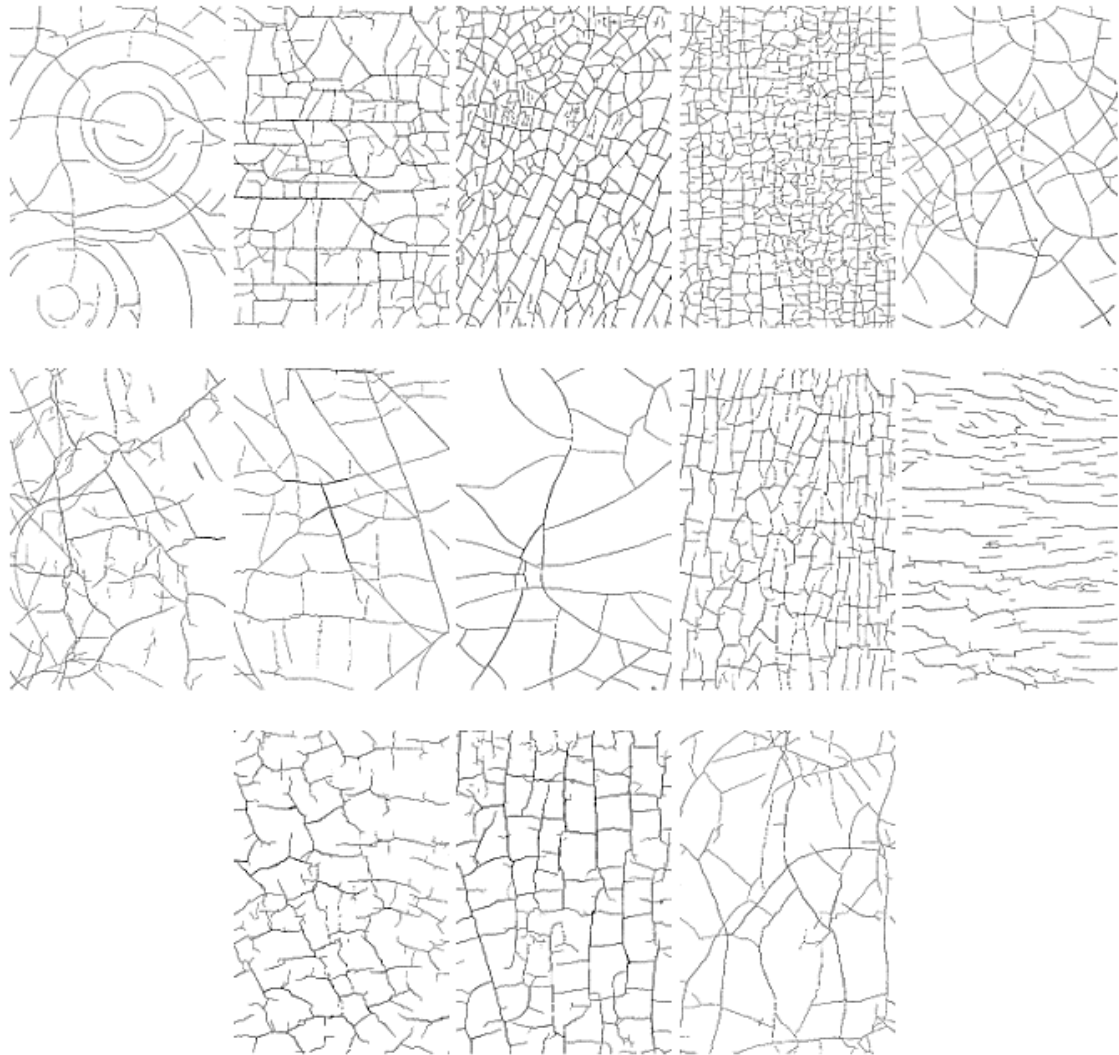


Figure 10. Masks for Bucklow dataset.

An analysis of the pixel and image statistics for masks, as well as the pixel values distribution for the Bucklow's dataset is presented below.

- **Pixel statistics for masks**

The binary masks in the grayscale dataset exhibit a clear contrast between labeled and unlabeled regions, where pixels are either black (representing the background) or white (indicating craquelure patterns). Table 5.1 summarizes the pixel statistics for the masks.

Table 5.1. Pixel statistics for Bucklow's masks.

Statistic	Value
Total White Pixels	35,777,241
Total Black Pixels	1,191,602
Total Pixels Processed	36,968,843

- **Image statistics for masks**

For the grayscale images, the pixel intensity primarily falls into high values, which is consistent with the bright areas representing cracks and other features. The pixel value distribution is summarized in Table 5.2.

Table 5.2. Image statistics for Bucklow's masks.

Statistic	Value
Mean Pixel Value	246.78
Median Pixel Value	255.00
Standard Deviation	45.04
Min Pixel Value	0
Max Pixel Value	255

This distribution reveals that most of the pixel values are near 255, indicating that most of the image areas are bright, with limited variations in pixel intensity due to the black-and-white nature of the masks.

- **Pixel value distribution**

The KDE plot below illustrates the distribution of pixel values in the grayscale dataset, showing a high peak at 255, corresponding to the white pixels in the masks (as displayed in Figure 11).

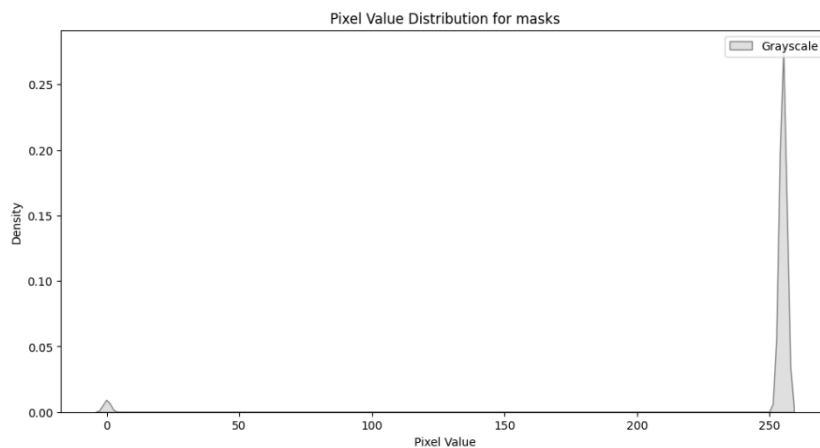


Figure 11. Pixel value distribution for Bucklow's dataset.

5.3.2 Dataset 2 – Public Domain Paintings

The following sub-chapter provides a statistical overview of the RGB dataset from public domain paintings (PDP). These statistics include the pixel distributions and overall characteristics of the images and masks, providing insights into the structure and quality of the dataset. KDE plots were also generated to further visualize the pixel value distributions for the dataset.

For Dataset 2, the source material comprised digital images of real paintings obtained from an online database of PDP. This dataset includes 28 different images extracted from 6 distinct paintings by 3 different authors (Figure 12). All images in this dataset share a consistent resolution of 770x770 pixels, with a bit depth of 24 bits per pixel and a .png file format. The average file size for each image is approximately 1 MB.



Figure 12. PDP's dataset.

The selection criteria for Dataset 2 required that the images have a minimum resolution of 20 pixels per millimeter, ensuring sufficient detail for craquelure analysis. The digitalized images have resolutions in the order of 15000 pixels by 15000 pixels, so a python script was developed to create patches of 770x770, which were the final images used to perform the labelling. Some examples of the masks created are presented below in Figure 13.

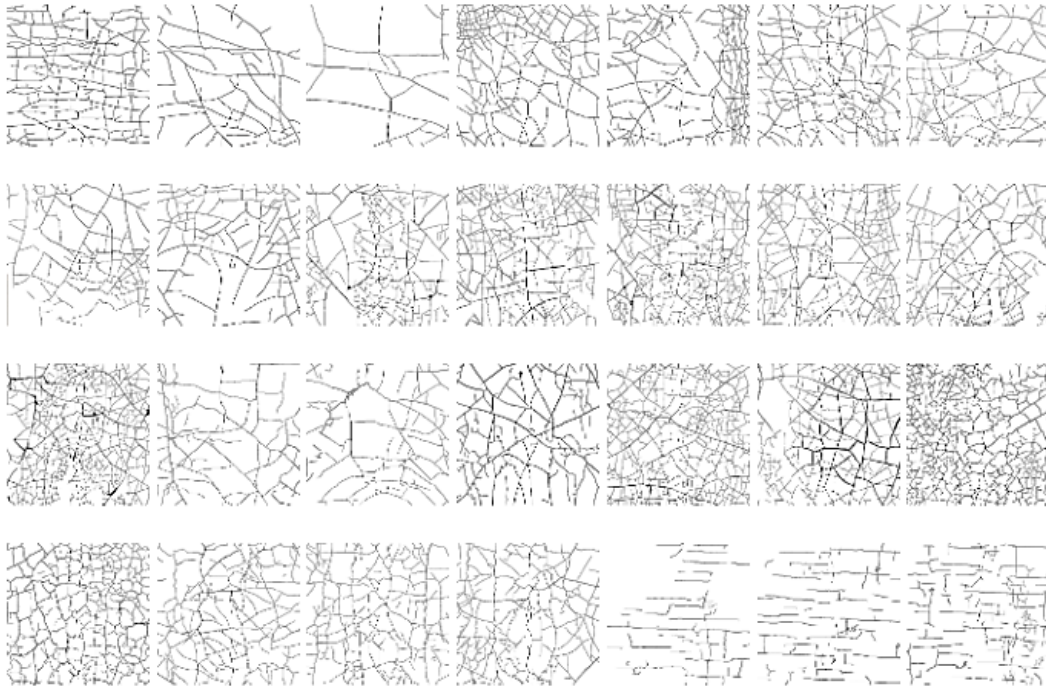


Figure 13. Masks for PDP dataset.

The RGB dataset contains more complex color variations due to the nature of the paintings, which include more diverse textures and colors. Below are the pixel statistics for the masks and the color channels of the original images.

- **Pixel statistics for masks**

As with the grayscale dataset, the masks are binary, representing areas of interest (craquelure patterns) and background. The statistics are presented in Table 5.3.

Table 5.3. Pixel statistics for RGB's masks.

Statistic	Value
Total White Pixels	15,721,868
Total Black Pixels	879,332
Total Pixels Processed	16,601,200

- **Image statistics for RGB images**

The pixel intensity across the red, green, and blue channels varies significantly, reflecting the diversity of colors in the original artworks. Table 5.4 summarizes the statistics for each color channel.

Table 5.4. Image statistics for each color channel (RGB).

Red Channel	Value	Green Channel	Value	Blue Channel	Value
Mean Pixel Value	149.75	Mean Pixel Value	138.73	Mean Pixel Value	114.21
Median Pixel Value	166.00	Median Pixel Value	151.00	Median Pixel Value	124.00
Standard Deviation	62.88	Standard Deviation	61.19	Standard Deviation	59.10
Min Pixel Value	0	Min Pixel Value	0	Min Pixel Value	0
Max Pixel Value	255	Max Pixel Value	255	Max Pixel Value	255

These statistics reflect the varying color distributions across the paintings, with the blue channel exhibiting the lowest average pixel intensity, while the red and green channels show higher mean values, indicating warmer colors dominating the images.

- **Pixel value distribution**

The following KDE plot (Figure 14) provides a visual representation of the pixel value distributions across the red, green, and blue channels. It illustrates how pixel intensities are distributed differently for each color, with more diversity in intensity in the blue and green channels compared to the red channel.

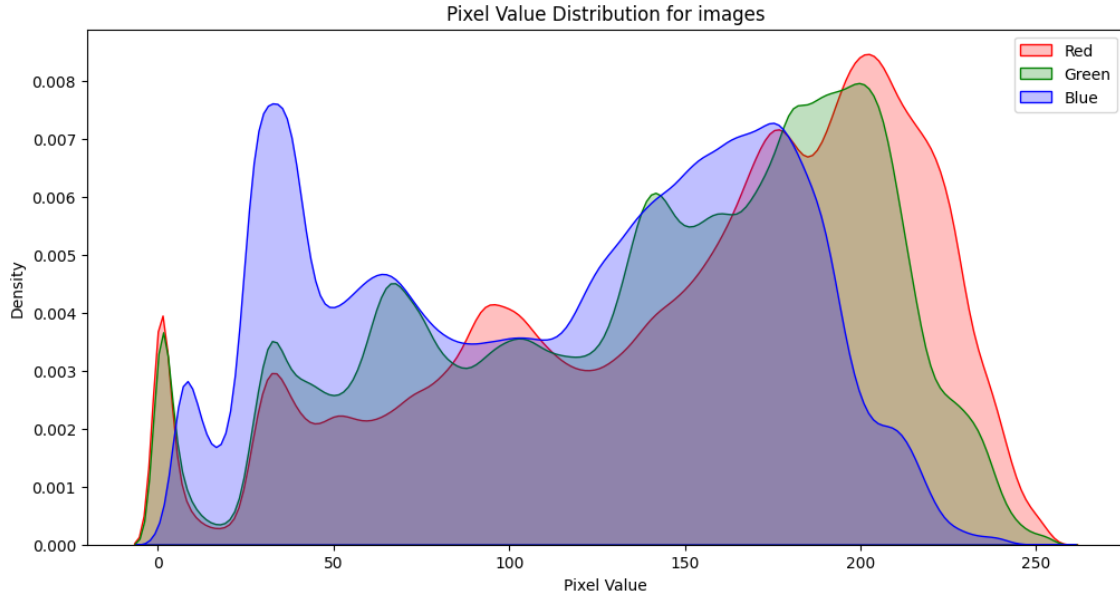


Figure 14. Pixel value distribution for the PDP's dataset.

5.3.3 Main Challenges

In the creation of both datasets, several challenges emerged that impacted on the accuracy and consistency of the labeling process. These challenges can be categorized into two main areas: annotation consistency and noise handling.

5.3.3.1 Annotation Consistency

One of the primary challenges during the annotation process was achieving consistent labeling across all images, particularly when distinguishing between true craquelure patterns and other textures present in the artworks. Craquelure patterns can often blend with other structural or textural features, making it difficult to consistently differentiate cracks from these elements.

While maintaining a certain level of textural complexity is crucial for simulating real-world scenarios, excessive noise or overlapping patterns can obscure cracks, making segmentation more difficult. As a non-expert in the field of art conservation, the subjective nature of craquelure definition posed an additional challenge, as crack patterns could vary significantly between artworks, periods, and geographic origins.

Moreover, challenges arose in determining whether to label crack intervals and deciding on the appropriate width for crack delineation. These decisions were based on pixel intensity, but the complex lighting conditions and color variations across the paintings required careful consideration.

To mitigate these issues, the annotation process prioritizes consistency in decision-making. An empirical set of criteria was followed throughout the labeling process to ensure that similar scenarios were handled in a uniform manner. This ensured that the labeled masks were as accurate as possible given the variability of the input images.

Figure 15 illustrates differences between craquelure patterns and other textures.

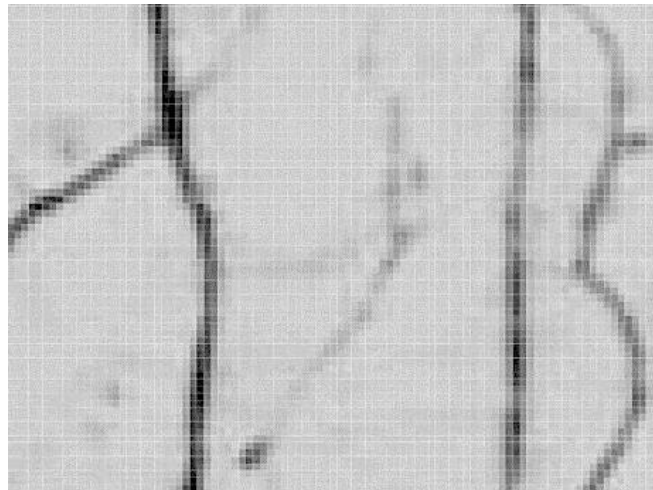


Figure 15. Example of the restraints followed by [3].

5.3.3.2 Noise Handling

Another challenge that emerged during the dataset creation was related to noise and artifacts that were introduced during the various stages of image manipulation, from Adobe Photoshop to data loading and pre-processing.

During quality control, abnormal values were returned, prompting individual inspection of the images. It was discovered that artifacts such as those shown in Figure 16 (b) were being introduced into the binary masks. These artifacts were primarily caused by inconsistencies in the Photoshop labeling process, where the pencil color was not always exactly black (RGB value of 0) or white (RGB value of 255). As a result, near-black or near-white artifacts passed unnoticed during visual inspections, leading to inaccuracies in the masks.

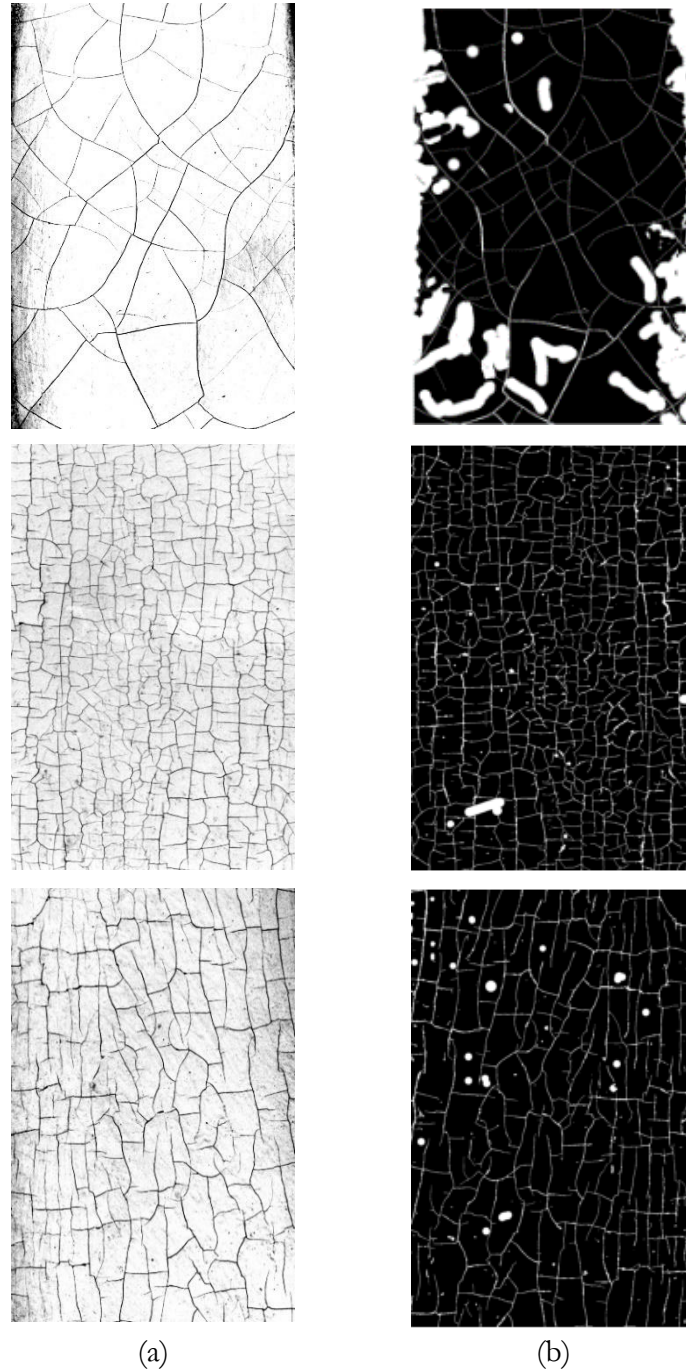


Figure 16. Example of portions from artworks. (a) Original image. (b). Artifacts encountered on the image.

The artifacts, particularly those caused by slightly off-black pixels, could lead to misclassifications during segmentation. This was compounded by the fact that some cracks were not entirely uniform in width or intensity, adding complexity to the noise removal process.

To address these issues, additional pre-processing steps were introduced to automatically correct pixel values before feeding the data into the segmentation models. This involved enforcing strict binary thresholds (0 for black and 255 for white) to eliminate any near-black or near-white artifacts. Post-processing steps also included noise reduction techniques to minimize the interference caused by these artifacts, ensuring cleaner input data.

By implementing these strategies, the overall quality of the datasets was significantly improved, allowing for more accurate segmentation of craquelure patterns.

5.4 Experimental Procedure

This sub-chapter provides a detailed description of each element in the workflow, following the architecture outlined in Figure 8. Each step is crucial to the segmentation task and contributes to the results. The experimental procedure steps are:

1. Dataset creation
2. Data loading and pre-processing
3. Model configuration and initialization
4. Hyperparameter tuning and grid search execution
5. Data splitting
6. Performance metrics
7. Logging to MLflow
8. Results and visualization

5.4.1 Dataset Creation

The dataset creation process involved the collection, annotation, and organization of images used for craquelure segmentation. Given the lack of pre-existing datasets specifically tailored to this task, two datasets were created: one grayscale dataset and one RGB dataset.

- **Grayscale dataset (Bucklow collection)**

This dataset was provided by S. Bucklow, an art conservation expert. The images represent a diverse collection of artworks from various countries and

periods, covering different craquelure patterns. Each image was processed to highlight cracks and then annotated manually.

- **RGB Dataset (PDPs)**

This dataset was generated from an online collection of public domain paintings. The RGB dataset includes paintings from different artists, and patches of 770x770 pixels were created using a Python script to ensure uniformity and facilitate the annotation process.

In both datasets, the images were processed using **Adobe Photoshop** to manually create binary masks of the craquelure patterns. This annotation process involved carefully tracing the cracks using a Wacom tablet to ensure pixel-wise precision. Once annotated, the masks were stored in .png format for subsequent analysis.

5.4.2 Data Loading and Pre-processing

The next stage in the workflow involved loading the images and applying pre-processing techniques to prepare the data for input into the model. Two steps were applied: data loading and pre-processing.

1. Data Loading

Images and corresponding binary masks were loaded from their respective directories. A Python script handled the organization and loading of image/mask pairs, ensuring that the data were consistent and correctly matched.

2. Pre-processing

Several transformations were applied to ensure the data met the model requirements:

- **Grayscale conversion**

For RGB images, the color images were first converted to grayscale to facilitate the analysis of curvilinear structures. This reduced dimensionality while preserving critical information.

- **Inversion**

The grayscale images were inverted so that the cracks were represented by darker pixels on a lighter background. This step ensured that the models could focus on detecting crack-like features more effectively.

- **Normalization**

After inversion, the pixel values were normalized to a [0, 1] range. This normalization step helps in standardizing the input data and improving model convergence during training.

These pre-processing steps were critical for enhancing the visibility of cracks, reducing the impact of noise, and ensuring that the data were in the correct format for the next stages of the workflow. The original algorithm used the green color channel as pre-processing step since it allowed for the better segmentation of the blood vessels. However, in the case of real historical paintings (or even grayscale images), the background tends to be much more complex, with many more variations in intensity and as such that approach was not taken.

5.4.3 Model Configuration and Initialization

Two models were selected for comparison and evaluation in this study: the **B-COSFIRE algorithm** and a **state of the art model** for craquelure segmentation. The configuration and initialization of each model were critical in preparing for the parameter tuning process.

- **B-COSFIRE algorithm**

This model was configured based on its original design for blood vessel detection but modified for craquelure segmentation. Key parameters, such as the number of symmetric angles, scale, and different intervals were set based on initial experiments and qualitative testing.

- **Our method**

We developed an extended version of the B-COSFIRE algorithm that includes additional tuning parameters specifically for detecting cracks in artworks.

- **Comparison model**

A state of the art segmentation model [1] was selected for comparison to benchmark the performance of B-COSFIRE in this task. This model was configured with default settings optimized for segmentation tasks.

Each model was initialized with pre-set parameters and configurations, preparing them for hyperparameter optimization.

5.4.4 Hyperparameter Tuning and Grid Search Execution

To achieve optimal performance, a Grid Search was employed for hyperparameter tuning. This systematic search explores different combinations of hyperparameters to find the best configuration for each model.

- **Hyperparameter tuning**

Key hyperparameters, described in section 4, were tested and optimized (Table 5.5). The hyperparameter search space was defined based on prior knowledge and experimentation.

Table 5.5. Hyperparameter's values for the both datasets.

Hyperparameter	Feature descriptor	Bucklow	PDP
σ	DoG standard deviation	[0.1, 0.3]	[1.1]
ρ	Radial distance	[1, 2, 3]	[1, 2, 3,4]
n_p	Number of radial positions	[2, 3, 5]	[2, 3]
ρ_{step}	Step size for p	[0, 2, 4]	[4,6]
σ_0	Base blurring	[0.1, 0.3]	[0.4, 0.6]
α	Scale	[0.5, 1]	[1.1]
n_{angles_symm}	Number of symmetric orientations	12	12
n_{angles_asymm}	Number of asymmetric orientations	24	24
homogeneity_offset	Offset for computing homogeneity responses	[5, 7, 9]	[5, 7, 9]
intra-sensitivity	Sensitivity for intra-homogeneity	[0, 2, 4]	[2,5,7]
inter-sensitivity	Sensitivity for inter-homogeneity	[0, 2, 4]	[2,5,7]

- **Grid Search Execution**

A custom grid search was implemented to perform the search by evaluating the model for each hyperparameter combination across multiple folds of the dataset (using K-fold cross-validation). By iterating through each combination, the grid search identifies the set of parameters that yield the best performance.

This grid search process ensured that the models were trained with the most suitable configurations, maximizing their potential for accurate segmentation.

With this combination of parameters, a total of 5832 combinations of parameters were tried for the B-COSFIRE model, and 437 for the comparison model.

5.4.5 Data Splitting

Once the grid search was complete, the dataset was split into training, validation, and testing sets to evaluate the model's performance across unseen data.

K-fold cross-validation was employed with k set to 4. This strategy involves partitioning the dataset into k subsets (folds). The model is trained on $k - 1$ folds and validated on the remaining fold. This process is repeated k times, with

each fold serving as the validation set once. This approach maximizes data utilization and provides a robust estimate of model performance

5.4.6 Performance Metrics

To evaluate the performance of the models, an extended set of metrics was employed, providing a comprehensive understanding of their segmentation accuracy. These metrics are discussed in Section 2.6 and they were calculated for each individual prediction, allowing us to assess the models' performance in detail.

To calculate these metrics, the raw inputs of the segmentation were processed to fit the specific metric calculation. This ensured that the metrics accurately reflected the models' performance. These metrics were implemented using the scikit-learn library, which provides a robust and efficient way to calculate a wide range of metrics.

5.4.7 Logging to MLflow

Throughout the training and evaluation processes, MLflow was employed to track and log experiments. This included logging the following information:

- **Hyperparameters**

The configuration of each model and the selected hyperparameters for every experiment.

- **Performance metrics**

All relevant performance metrics mentioned in sub-chapter 5.4.5 were logged for easy comparison.

- **Model artifacts**

Saved versions of trained models, segmentation outputs, and other artifacts were stored in MLflow.

The use of MLflow provided transparency and reproducibility, allowing for easy comparison of models and parameter sets. This ensured that the best-performing model and configuration were identified and could be revisited if needed.

5.4.8 Results and Visualization

Finally, after evaluating the models, the results were analyzed and visualized. This final step ensured that the most effective model was identified and that its performance was thoroughly documented.

6 RESULTS AND DISCUSSION

In this chapter, the results obtained are presented and analyzed. Using the logs from MLflow, the best-performing parameter sets were identified based on training scores, and the corresponding test scores were used for evaluation. This allowed for the optimization of parameters for the B-COSFIRE algorithm, the proposed method, and a comparison method. Additionally, a comparison between these algorithms is discussed.

The results are reported for two distinct datasets: Bucklow's grayscale image dataset and the PDP image dataset. The initial results from Bucklow's dataset are highlighted, followed by those from the PDP dataset. It is important to note that the default parameter configuration in the original work was designed for segmenting vascular structures in retinal fundus images, which differs from the task of craquelure segmentation. Therefore, a direct comparison between these configurations and our task is not entirely appropriate. Nevertheless, the results are presented to demonstrate the potential for systematically searching for optimal parameters in a structured manner.

6.1 Quantitative Results

After the algorithms selected for this project had been executed following the proposed methodology, the results obtained by the chosen classification metrics were collected. In Table 6.1 are the best hyperparameters of the models.

Table 6.1. Hyperparameters' values for the Bucklow's dataset.

Hyperparameter	Original	Extension
σ	0.1	0.1
ρ	2	2
n_ρ	3	3
ρ_{step}	2	2
σ_0	0.1	0.3
α	0.5	0.5
n_{angles_symm}	12	12
n_{angles_asymm}	24	24
homogeneity_offset	-	5
intra-sensitivity	-	4
inter-sensitivity	-	2

In Table 6.2, the best hyperparameters for the PDP dataset are presented.

Table 6.2. Hyperparameters' values for the PDP dataset.

Hyperparameter	Original	Extension
σ	1.1	1.1
ρ	4	4
n_ρ	2	2
ρ_{step}	4	4
σ_0	0.4	0.4
α	1.1	1.1
n_{angles_symm}	12	12
n_{angles_asymm}	24	24
homogeneity_offset	-	5
intra-sensitivity	-	7
inter-sensitivity	-	5

6.1.1 Dataset 1 – Bucklow

The Bucklow dataset was used for the initial evaluation of the models. The results presented in Table 6.3 show the highest performance scores for both the fine-tuned models and the baseline models across all metrics. Notably, the table highlights the best performance for each metric, even though these scores may stem from different parameter configurations. This ensures a comprehensive view of the improvements achieved through parameter tuning.

The B-COSFIRE models, both original and extended, demonstrated significant performance improvements over the baseline, particularly in terms of Precision and Dice score, indicating better segmentation of fine details. However, the comparison model displayed a higher Recall score, meaning it detected more cracks, though it was more prone to false positives.

Table 6.3. Best performance scores for different parameters configurations of B-COSFIRE and comparison models fine-tuned with the Bucklow’s dataset.

Metric	Fine-tuned						Baseline			
	Extension		Original		Comparison		Original		Comparison	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
Accuracy	0.9893	0.9892	0.9893	0.9892	0.9557	0.9555	0.9752	0.9752	0.9457	0.9457
AUC	0.9914	0.9914	0.9914	0.9914	0.9599	0.9599	0.9850	0.9850	0.9438	0.9438
DSC	0.8221	0.8221	0.8221	0.8221	0.5412	0.5412	0.6821	0.6821	0.5145	0.5145
F1	0.8221	0.8221	0.8221	0.8221	0.5412	0.5412	0.6821	0.6821	0.5145	0.5145
IoU	0.6993	0.6981	0.6993	0.6981	0.3754	0.3754	0.5190	0.5190	0.3522	0.3522
MCC	0.8184	0.8175	0.8184	0.8175	0.5608	0.5519	0.6867	0.6867	0.5483	0.5483
Precision	0.8861	0.8861	0.8788	0.8788	0.4135	0.4108	0.5663	0.5663	0.3740	0.3740
Recall	0.8374	0.8362	0.8374	0.8362	0.9566	0.9566	0.8622	0.8622	0.8859	0.8859

6.1.2 Dataset 2 – PDP

The results for the PDP dataset, shown in Table 6.4, indicate more variability compared to Bucklow’s dataset. Across the metrics, there is a slight decrease in overall performance due to the higher complexity of the PDP dataset. The B-COSFIRE extension again outperforms the original model in terms of finer detail segmentation, while the comparison model achieved the highest accuracy. As noted earlier, however, accuracy is less informative due to the highly imbalanced nature of the dataset, where most pixels belong to the background.

Table 6.4. Best performance scores for different parameters configurations of B-COSFIRE comparing models fine-tuned with the PDP dataset.

Metric	Fine-tuned						Baseline			
	Extension		Original		Comparison		Retinal		Comparison	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
Accuracy	0.9007	0.9006	0.9007	0.9006	0.9440	0.9435	0.8911	0.8911	0.9349	0.9349
AUC	0.9071	0.9071	0.9071	0.9071	0.8058	0.8058	0.9126	0.9126	0.7925	0.7925
Dice	0.4844	0.4845	0.4844	0.4845	0.4369	0.4257	0.4595	0.4595	0.4239	0.4239
F1	0.4844	0.4845	0.4844	0.4845	0.4369	0.4257	0.4595	0.4595	0.4239	0.4239
IoU	0.3462	0.3462	0.3462	0.3462	0.2900	0.2804	0.3124	0.3123	0.2792	0.2792
MCC	0.4801	0.4801	0.4801	0.4801	0.4169	0.4077	0.4568	0.4568	0.4046	0.4046
Precision	0.5641	0.5588	0.5149	0.5149	0.4454	0.4438	0.3851	0.3851	0.3781	0.3781
Recall	0.6820	0.6705	0.6820	0.6705	0.5523	0.5504	0.7096	0.7096	0.5181	0.5181

6.1.3 Discussion

When comparing the results on the training and test datasets, overall performance remained consistent after parameter tuning. For the Bucklow dataset - which is less complex and uses simpler grayscale images - the models tended to adopt parameter configurations that closely resembled the original B-COSFIRE model. In this context, the B-COSFIRE algorithm itself already demonstrated robust performance. Nonetheless, the slight improvement in Precision observed when using the proposed extension suggests that incorporating this optional enhancement can help the algorithm more accurately detect true craquelure patterns where necessary.

For the more challenging PDP dataset, involving colored images and complex textures, the extended B-COSFIRE model showed improvements in segmenting craquelure. Although scores were generally lower compared to the Bucklow dataset, the extension again proved beneficial. Conversely, the comparison model's high Accuracy largely reflected the dominance of background pixels, emphasizing that Accuracy alone can be misleading in these scenarios. Overall, these results highlight B-COSFIRE's inherent strengths in handling grayscale craquelure segmentation while illustrating how the extension can serve as a targeted enhancement to further refine precision, especially when tackling more intricate, colored images.

6.2 Qualitative Results

The qualitative results for both datasets are presented below.

6.2.1 Dataset 1 – Bucklow

A qualitative assessment of the segmentation results for the Bucklow dataset is presented in Figure 17. The visual evaluation demonstrates that the extended B-COSFIRE model provides more detailed segmentation compared to both the original B-COSFIRE model and the comparison model. The extended model excels in capturing intricate craquelure lines, particularly in images with more complex patterns. While the original B-COSFIRE model also performs well, it tends to miss finer details. The comparison model, although quantitatively scoring high in accuracy, frequently produces false positives and negatives, particularly in areas with subtle craquelure.

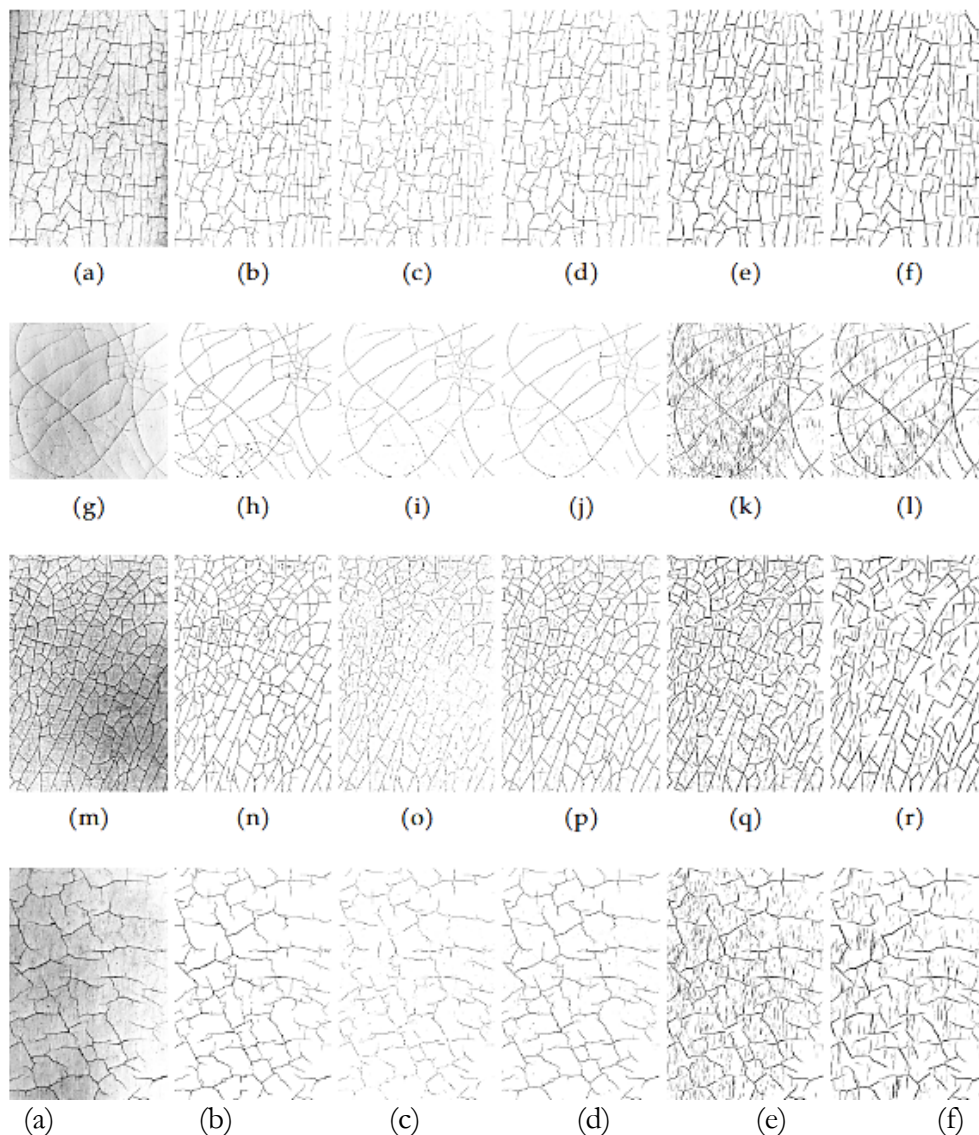


Figure 17. Segmentation results on Bucklow dataset. (a) Original PDP images. (b) Ground truth. (c) Extension. (d) Original. (e) Comparison baseline (f) Comparison fine-tuned

6.2.2 Dataset 2 – PDP

Qualitative results for the PDP dataset are shown in Figure 18. These images reflect the complexity of the dataset, which includes multiple textures, colors, and artifacts that complicate segmentation. The extended B-COSFIRE model again demonstrates better segmentation of craquelure patterns, effectively managing variations in texture and color intensity. The original B-COSFIRE model, while accurate, struggles with finer details, particularly in more complex areas of the images. The comparison model produces a higher number of false positives and struggles to maintain segmentation precision in such complex conditions.

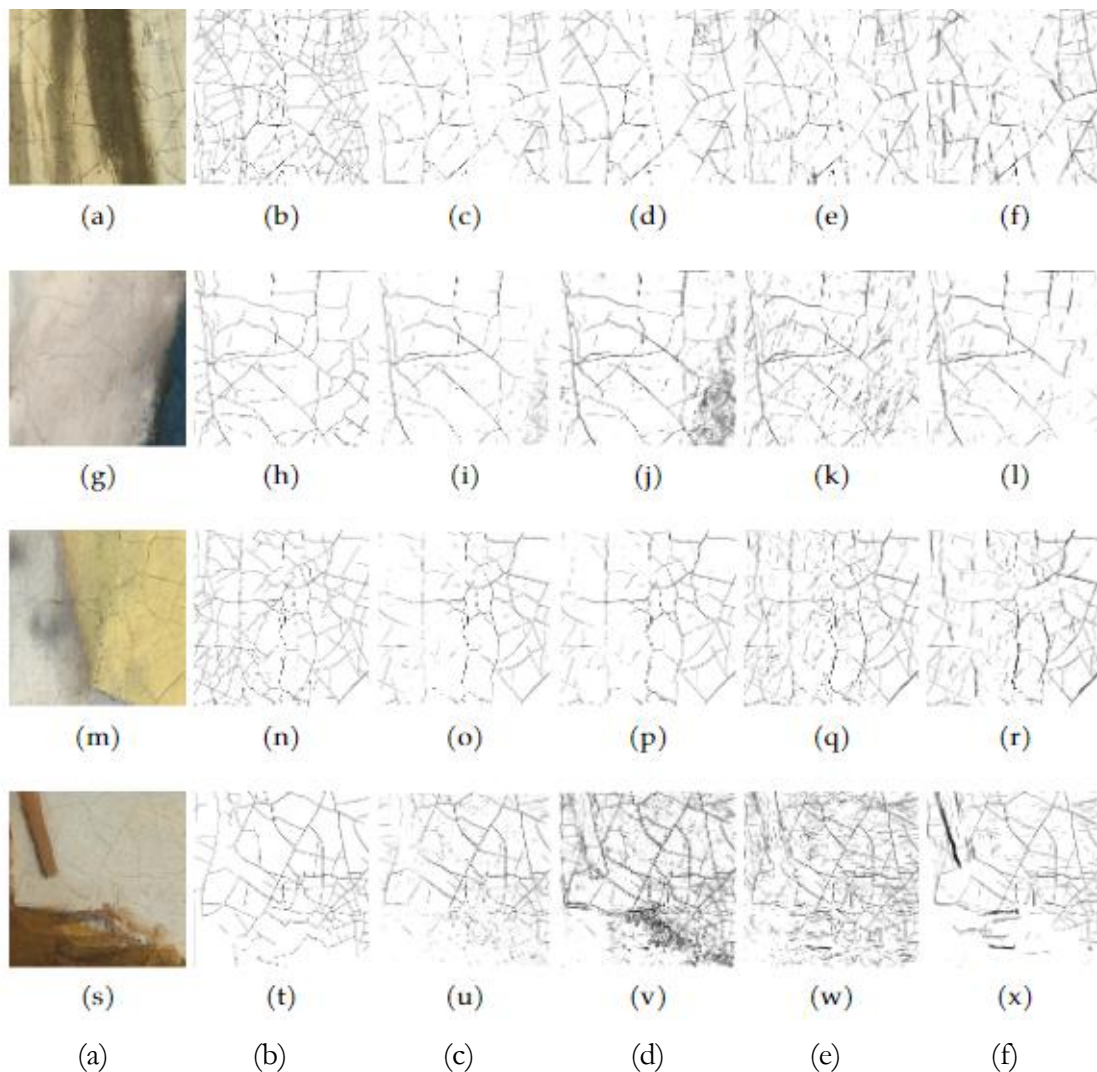


Figure 18. Segmentation results on PDP dataset. (a) Original PDP images. (b) Ground truth. (c) Extension. (d) Original. (e) Comparison baseline (f) Comparison fine-tuned.

6.2.3 Discussion

The qualitative results, particularly in Figure 17, highlight how the simplicity of the Bucklow dataset benefits all models, reducing the difference in performance

between them. In this case, the original B-COSFIRE model performs comparably to the extension, as the data does not demand more intricate parameter configurations. The models display improved segmentation due to the dataset's relative simplicity.

Conversely, the more complex PDP dataset, as seen in Figure 18, illustrates the value of algorithmic extension. The extended B-COSFIRE model performs notably better in distinguishing craquelure patterns from non-craquelure structures, such as changes in color intensity and unrelated image features (e.g., a windmill paddle). This dataset demonstrates the utility of the extension in handling challenges that the original algorithm and comparison methods struggle with, further justifying its introduction.

7 CONCLUSIONS

The project bridged a methodological gap in the application of SS techniques to art conservation, a domain that has historically lagged in other fields such as medical imaging and road crack detection.

The B-COSFIRE algorithm was adapted and optimized for the segmentation of craquelure patterns, and a specialized dataset was created to support this effort. The project demonstrated the potential of integrating advanced segmentation techniques, such as those used in medical imaging, into the field of artwork conservation. The thorough evaluation of various segmentation methods provided valuable insights into their effectiveness in this specific context, contributing to a deeper understanding of the intersection between technology and the preservation of cultural heritage.

The project also made significant contributions to the interdisciplinary community by showing how these advanced techniques can be adapted for other fields where accurate segmentation of curvilinear structures is critical, such as artwork analysis and conservation.

7.1 Strengths

By tailoring the B-COSFIRE algorithm for artworks-specific applications, this project has not only provided a novel approach to craquelure segmentation but also highlighted the broader potential of these techniques across a domain that has not been widely explored. This methodological innovation plays a crucial role in leveling the technological playing field, ensuring that artworks conservation can benefit from the same advancements that have revolutionized other disciplines. The successful application of these methods in artworks conservation demonstrates the viability of transferring technologies across fields, paving the way for future interdisciplinary collaborations.

A key strength of the project was the creation of two specialized datasets tailored specifically for the segmentation of craquelure patterns. In the field of ML, the quality and specificity of datasets are often just as important as the algorithms applied to them. By developing a dataset that captures the unique characteristics of craquelure, the project not only supported its immediate research goals but also laid the groundwork for future studies in art analysis and conservation. These datasets might be valuable resources for other researchers working in the domain, enabling them to build upon the foundation laid by this project. Additionally, the creation of these datasets demonstrates the importance of developing domain-specific resources when applying general algorithms to specialized fields, ensuring that the results are both accurate and relevant.

Furthermore, the project provided a comprehensive evaluation of multiple segmentation techniques, rigorously testing each against the specialized datasets. This evaluation presented a critical comparison of various approaches, identifying their strengths and weaknesses. This analysis serves as a roadmap for future advancements, offering guidance on the most effective techniques for different contexts within artworks conservation. The findings from this evaluation are not only relevant to the immediate application in craquelure segmentation but also hold broader implications for other fields where curvilinear structure segmentation is critical, opening new paths for exploration in others, reinforcing the value of cross-disciplinary innovation.

7.2 Limitations

The project has faced several limitations. Hyperparameter tuning involves systematically adjusting various parameters of an algorithm to identify the combination that yields the best performance. However, due to the limited time available for this specific task, the project may not have been able to explore the full range of potential configurations. As a result, the algorithm's performance could have been suboptimal, with certain parameter settings not fully optimized. This limitation is particularly relevant for the complex tasks of craquelure segmentation, where fine-tuning can have a substantial impact on the accuracy and efficiency of the algorithm. The inability to thoroughly explore the hyperparameter space means that there may be unexplored configurations that could significantly enhance the algorithm's effectiveness, potentially leading to even better segmentation results.

Another major limitation encountered in the project was the lack of a reliable baseline for comparison, which poses a significant challenge in the evaluation of the algorithm's performance. In the domain of craquelure segmentation within artworks conservation, there is a noticeable scarcity of consistent evaluation metrics and quantitative results in the existing literature. This absence of standardized benchmarks made it difficult to directly compare the algorithm's performance with other state of the art methods. The lack of quantitative results in related studies further exacerbated this issue, leaving a gap in the ability to validate the algorithm's performance against a recognized standard. Consequently, while the project made strides in presenting an approach to segmentation, the inability to rigorously benchmark against other methods limits the ability to definitively assess its relative success.

7.3 Future Work

For the future, one of the most immediate opportunities lies in the implementation of data augmentation techniques. This approach can be particularly valuable in this domain, where acquiring large amounts of labeled data can be challenging. By augmenting the existing datasets, the model can be

exposed to a wider variety of scenarios, which in turn can improve its robustness and generalization ability. This is especially important in dealing with the inherent variability in craquelure patterns across different artworks, as a more diverse training dataset would enable the model to perform better in recognizing and segmenting these complex structures in new and unseen images.

Another exciting direction for future work is the application of DL models to the segmentation of craquelure patterns. Incorporating DL into the framework of craquelure segmentation could potentially lead to significant improvements over the current state of the art approaches. For instance, a well-trained U-NET could automatically learn to identify the nuanced features of craquelure patterns that are difficult to capture with more traditional algorithms. Furthermore, the transfer learning approach, where a model pre-trained on a large dataset is fine-tuned for a specific task, could be employed to leverage the knowledge gained from broader image segmentation tasks, thereby enhancing the performance of the B-COSFIRE algorithm when adapted for art conservation.

In addition to exploring new models, refining the existing pipeline through the application of advanced pre-processing and post-processing techniques presents another valuable research avenue. Pre-processing techniques such as noise reduction, contrast enhancement, and edge detection can significantly improve the quality of input images, leading to better segmentation outcomes. In the context of craquelure detection, pre-processing could help in isolating the crack patterns from other visual noise present in the artworks, thereby providing the algorithm with cleaner, more relevant data to work with. Similarly, post-processing techniques such as morphological operations can be used to refine the output of the segmentation algorithm, reducing errors like over-segmentation or under-segmentation. By systematically experimenting with different combinations of these techniques, future research can optimize the segmentation pipeline, making it more accurate and reliable.

Finally, there is considerable potential in developing the B-COSFIRE algorithm into a domain-agnostic filter, extending its applicability beyond the specific context of artworks conservation. A domain-agnostic filter is one that can be effectively applied across a wide range of disciplines without requiring extensive reconfiguration for each new application. The current adaptation of the B-COSFIRE algorithm for craquelure segmentation demonstrates its flexibility, but further research could explore how to generalize this approach so that it can be seamlessly integrated into other fields where the segmentation of curvilinear structures is critical.

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APPENDICES

Appendix A – Oral Presentation at CM2024

Oral Presentation at the Twentieth International Conference on Condition Monitoring and Asset Management (CM2024) in Oxford, United Kingdom.

Extending B-COSFIRE for Automatic Extraction of Craquelure

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Abstract—This study addresses the segmentation of craquelure patterns in fine arts, a complex challenge due to the varied textures, color transitions, and canvas deformations typical in paintings. We advance this field by introducing supervised learning, manually labeling two distinct image datasets: one comprising grayscale images from the established Bucklow’s dataset, and the other consisting of image patches extracted from historical paintings, reflecting more realistic scenarios. We employ the B-COSFIRE model, originally developed for medical imaging, to enhance the detection and delineation of these complex patterns. This approach significantly boosts performance by optimizing the model’s parameters using our labeled datasets. We qualitatively compare the B-COSFIRE model’s effectiveness against a state-of-the-art segmentation model. Our findings demonstrate that supervised learning significantly improves the ability of the model to accurately identify and segment craquelure, underscoring its potential in the domain of fine art analysis.

Keywords — Curvilinear Structure Segmentation, Craquelure Extraction, Computer Vision, Supervised Learning, Fine-Arts

I. INTRODUCTION

Extracting lines in digital images stands as a fundamental low-level task in the realm of computer vision [1]. This critical process facilitates the identification and extraction of linear features in structures that are ubiquitous in nature and that appear in a wide range of scales, from a microscale to macroscale. Central to this task is the concept of curvilinear structures, which are essentially thin, long, elongated line-like regions distinguished by their differing intensities from the surrounding pixels. These types of structures are observable in many different applications including biomedical, satellite, and geological imagery.

In the realm of fine arts, particularly in painting conservation and authentication, these curvilinear patterns manifest distinctly as craquelure—networks of fine cracks that form naturally as paintings age due to the expansion and contraction of their canvas or wooden supports. These patterns not only act as indicators of a work’s age and condition but also serve as unique identifiers akin to “fingerprints”, providing insights into the materials used by the artist and the artwork’s provenance. Thus, the detailed analysis of craquelure is crucial for authenticating paintings and detecting forgeries, as well as understanding structural issues that may impact the artwork’s long-term preservation [2].

This preliminary approach develops the work carried out in some of the scientific fields mentioned above [3]-[6]. It employs model supervision with annotated data to enhance the performance of craquelure segmentation, a novel application in this context to the best of our knowledge.

Specifically, we employ the B-COSFIRE (Bar Combination of Shifted Filter Responses) algorithm, initially developed for the segmentation of vessel trees in retinal fundus images [7] for the automated extraction of craquelure patterns in paintings. This adaptation aims to improve the precision and efficiency of craquelure extraction, contributing significantly to both the understanding and preservation of artworks.

This structured approach aims to make a substantial contribution to art conservation by providing new methodologies for the analysis and understanding of artworks. The main contributions of this work are:

1) *Bridging Methodological Gap*: This work addresses the existing gap in the application of Supervised Learning (SL) methods for craquelure analysis. Different works involving the segmentation of different structures utilize publicly available labeled data along with SL. However, to the best of our knowledge, this approach has not been previously applied in the field of art conservation due to a lack of suitable SL frameworks. In this work, not only do we adapt a supervised method from other fields to the art domain, but our preliminary results also show that implementing supervision on previously developed methods for this domain also drastically improves the results.

2) *Development of two Manually Labeled Datasets*¹: We have curated two distinct image datasets, both manually labeled. The first dataset includes grayscale images from the established Bucklow’s dataset [2], frequently used in the literature. To complement this and extend the methodological framework previously discussed, we created a second dataset from scratch, named the Public Domain Paintings dataset (PDP dataset). This new dataset consists of RGB images, created by extracting and labeling patches from real historical paintings. Together, these datasets not only facilitate ongoing research in art conservation but can also support machine learning applications that depend on precise, labeled data for effective segmentation.

By enhancing the precision and effectiveness of craquelure analysis, this research not only aids in the authentication and preservation of artworks but also deepens our understanding of art history and theory, facilitating the integration of advanced technological methods with traditional art conservation practices. The remainder of this work is organized as follows: Section II offers an overview of the state of the art; Section III introduces the proposed method; Section IV presents the main results and includes a discussion; finally, the conclusions of the study are drawn in Section V.

¹Permission to publicly share the labeled Bucklow’s dataset from [2] is pending author approval. The PDP dataset, containing public domain images, is ready for use.

II. STATE OF THE ART

This section outlines the evolution of curvilinear structure segmentation and its journey from more traditional techniques to more advanced ones, using deep learning (DL) approaches, and sets the stage for discussing the specific challenges and advancements in the analysis of craquelure patterns in artwork, highlighting the significance of these developments for this work.

A. Evolution of the Segmentation of Curvilinear Structures

The evolution of curvilinear structure segmentation has advanced from traditional techniques such as template filter[8], morphology [9], multiscale [10], based to more sophisticated machine learning methods [11]. This progression has been powered not only by significant advancements in DL algorithms and enhanced computational power, enabling more complex and accurate analyses data availability but also by an increase in data availability. This shift has significantly enhanced segmentation precision by using SL methods, which train on expert-annotated images. Meanwhile, Unsupervised Learning (UL) methods aim to autonomously identify curvilinear structure's patterns without relying on labelled data, marking a shift towards a greater need for annotated datasets in SL for improved results.

The review of curvilinear structure segmentation across multiple disciplines underscores the critical advancements in both methodology and technology that have shaped the current landscape of digital image analysis, and this exploration serves as a foundational basis for this work. By understanding the successes and limitations encountered in other fields, this research aims to leverage the most effective strategies and innovations, adapting them to meet the unique requirements of craquelure segmentation in artworks.

B. Advancements in Artwork Craquelure Analysis

In the world of artwork, prior methods for extracting and analyzing craquelure mainly based on morphological operations [12] often led to incomplete recognition and segmented results with poor continuity, while others fail to distinguish between genuine craquelure and color transitions in artworks, leading to inaccurate continuous crack identification [13]. Despite significant advances in imaging and computational techniques, the complex nature of craquelure patterns still presents substantial obstacles to achieving precise segmentation. Some common limitations found in the literature include dependence on manual intervention of the user while using the algorithm (for example, threshold levels, and structuring elements sizing), provision of statistical information about the craquelure only, its exclusive segmentation of feature points and constraints in processing multi-modal data (regular photographs, infrared photography and X-Ray images) [14]-[16].

C. Methods for Craquelure Patterns Segmentation

The literature on craquelure pattern segmentation (Figure 1) in artworks reveals a diverse array of methods aimed at enhancing the visibility and detail of these intricate features. Early techniques, such as morphological transformations and the use of multiscale filters [14] have been fundamental in preparing the field of craquelure segmentation for deeper analysis, using different methods and approaches.

For instance, advanced segmentation methodologies employ neural networks and sophisticated frameworks like



Figure 1 – Example of craquelure and respective mask in a small painting patch (Girl with a Pearl Earring Painting by Jan Vermeer).

ResNet-50 and U-Net, as demonstrated in the work of [13] and [15] which enable precise feature extraction, respectively. Moreover, approaches like Graph Neural Networks [16] and 3D imaging technologies, including Optical Coherence Tomography, have provided substantial insights into the structural and dimensional aspects of craquelure patterns [17].

Among these diverse methods, the method developed by [18] for the segmentation of craquelure patterns in artworks uniquely combines advanced morphological processing with the Radon transform, offering a precise way to extract intricate crack patterns critical for tasks such as authentication and preservation. The process begins with enhancing image contrast through adaptive histogram equalization, making craquelure patterns distinct enough from the background for subsequent analysis. It then applies multi-scale, multi-orientation morphological processing using linear structuring elements, effectively highlighting potential craquelure lines while minimizing other textural elements like brush strokes. The results from various scales and orientations are aggregated to reinforce areas where craquelure is consistently detected, enhancing the segmentation's reliability (Figure 2).

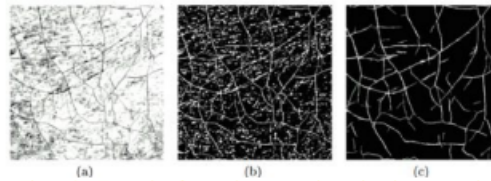


Figure 2 – Example of craquelure extraction using the proposed method in [18]. (a) Original image; (b) Segmentation using Top-hat and adaptive threshold; (c) Segmentation using the method in [18].

The technique used in [18] stands out for its precision in both enhancing the visibility of cracks and removing unwanted structures, establishing it as a benchmark for craquelure segmentation. This robust approach not only exemplifies the evolution of segmentation techniques but also validates the potential of sophisticated image processing methods to analyse and understand the complex phenomena of craquelure in artworks. Given its demonstrated precision and robustness, this approach [18] will serve as a baseline comparison for our own developments, aiming to further refine and adapt these techniques to the specific challenges presented by our dataset.

III. PROPOSED METHOD

A. B-COSFIRE

The B-COSFIRE algorithm is a highly configurable filter designed for the detection and delineation of elongated structures in images, such as blood vessels in retinal fundus images, lines, and other curvilinear structures. Inspired by the biological processing mechanisms in the primary visual cortex, specifically the functionality of simple cells selective to specific orientations, this algorithm exemplifies how computational models can mimic biological perception [7], [19].

1. Configuration of B-COSFIRE Filters

The configuration of a B-COSFIRE filter begins with an example-driven procedure utilizing a prototype pattern. This pattern, typically a line or bar of a designated orientation and scale (depending on the goal of the segmentation task), sets the stage for initializing the filter parameters reflective of the dominant orientations and scales present in the prototype. The prototype is convolved with a series of Difference of Gaussians (DoG) filters denoted by Equation (1):

$$DoG_{\sigma}(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) - \frac{1}{2\pi(0.5\sigma)^2} \exp\left(-\frac{x^2+y^2}{2(0.5\sigma)^2}\right) \quad (1)$$

With σ being the standard deviation of the outer Gaussian function. The collected responses, which are the geometric mean of the responses of its sub-units, are instrumental in defining the operational parameters of the B-COSFIRE filter (Figure 3).

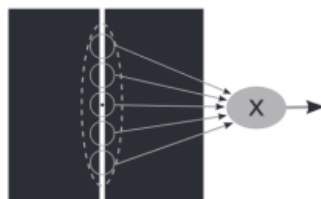


Figure 3 – Illustration of an example B-COSFIRE filter. The center of the filter support is marked by a black dot in the middle of the white bar, depicted within a dashed ellipse. The B-COSFIRE filter combines the outputs of several DoG filters (shown as solid circles) through a multiplication process.

2. Position and Parameter Selection

In this crucial step, every significant response captured during configuration helps pinpoint exact positions and parameters such as orientation and scale. These recorded positions correspond precisely with the locations where the combined responses from the DoG filters align with the prototype pattern's structure, thereby facilitating targeted and accurate detections.

3. Operation of B-COSFIRE Filters

Once the filter is configured, its operation can be systematized as:

- **Input Image Processing:** The same array of DoG filters, used during configuration, processes the input image, capturing specific features based on the earlier derived settings from the prototype.
- **Combination of Responses:** The individual DoG filter responses are aggregated according to a pre-determined

spatial arrangement. This aggregation, typically a weighted geometric mean, markedly enhances the filter's selectivity to patterns similar to the prototype.

- **Output Generation:** The final output from the B-COSFIRE filter is a comprehensive map that delineates the locations and intensities of detected patterns that match the prototype. This detailed output is pivotal for subsequent analyses or integration into broader image processing applications.

4. Features and Applications

B-COSFIRE filters demonstrate inherent robustness through their tolerance to rotation and scale, detecting possibly different patterns (Figure 4) across a range of orientations and sizes [20].

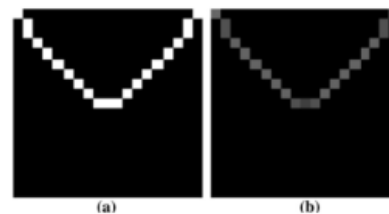


Figure 4 – a) Prototype used for configuring a U-COSFIRE filter and b) the response map obtained [20].

This capability is complemented by a high degree of selectivity, as these filters are finely tuned to recognize specific patterns, making them crucial for precision-driven applications such as medical imaging and traffic analysis [21][22]. Additionally, the design of B-COSFIRE filters is modular, which allows for configurations to adapt to various patterns and complexities. This modularity is paired with trainability, meaning the algorithm can optimize its parameters based on the specific demands and characteristics of the input data. This enhances the effectiveness and adaptability of the filters across different scenarios, as shown in [22].

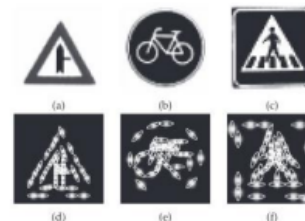


Figure 5 – Three reference traffic signs: (a) an intersection, (b) compulsory give-way for bikes, and (c) a pedestrian crossing. (d)-(f) the structures of the corresponding COSFIRE filters [22].

B. Dataset and Ground Truth

The study of craquelure patterns in artworks requires attention to the complexity of the image backgrounds. In grayscale images, like the ones present in Bucklow's dataset, the background tends to be plain, allowing the cracks in the foreground to stand out distinctly. This simplicity contrasts sharply with that of more realistic images of artwork, where the backgrounds are significantly more complex. Here,

brushstrokes mimic elongated-like structures similar to cracks, and the canvas's texture adds further complexity. These contrasting conditions require different approaches for the labelling phase of the datasets but also provide the necessary change and variation in the data to further improve the quality of the SL.

For the development of this preliminary work, two image datasets were constructed to enable a more detailed analysis of these craquelure patterns. These datasets underwent pixel-wise labelling and were assessed through empirical evaluation, a method distinct from the expert annotator approach typically found in the literature regarding biomedical data. This empirical and subjective evaluation focused on the distinctiveness of foreground features against their backgrounds.

The empirical criteria employed for segmentation involved both geometric constraints - such as the necessity for pixels to be mostly connected, the requirement for regions to be thin along a long path, and the demand for smooth variations in width across the region - and photometric constraints, which consider the intensity values of pixels and require significant differences from the surrounding background, smooth changes in color along the main direction of the structure, and specific intensity profiles across the structure resembling a valley or U-shape. These criteria can be found in more detail in [3]. The datasets constructed for this analysis, each comprising an original image and its corresponding ground truth depicting craquelure segmentation, are categorized into two distinct types of image data:

- **Bucklow's dataset:** This dataset, obtained from source [2], includes 20 grayscale images that enhance the visibility of foreground cracks against simple backgrounds. The images vary in size from 1181x1181 pixels to 1181x1772 pixels and feature a variety of artworks from Italy, France, and other European regions, spanning from the 15th to the 18th Century. We contacted the original author to access these images and selected a representative sample from the available collection provided. Prior to labelling, each image was processed in Adobe Photoshop to further enhance the visibility of the craquelure patterns, ensuring precise annotations.
- **PDP Dataset:** In contrast, the PDP dataset (described in more detail in [3]), includes images with more complex backgrounds, where brushstrokes and canvas textures mimic the appearance of cracks, adding to the visual complexity. This dataset comprises color patches of 770x770 pixels extracted from six historical paintings,

processed and labelled with the same care as the grayscale images to highlight the craquelure patterns effectively.

Both datasets were meticulously labelled to support the intended analysis, and both will be publicly available¹.

C. Approach Methodology

Consequently, we progressed to evaluate the B-COSFIRE algorithm, utilizing a supervised approach. The experiment procedure can be depicted as follows:

1. **Data Loading and Preprocessing:** The images were loaded and converted to grayscale to operate on lesser data, thus simplifying processing [13]. An inversion transformation was applied to standardize the background to black and the foreground to white across all images. Normalization was carried out to adjust the pixel values to a range between 0 and 1. The original work [7] has a different preprocessing step which consists in isolating the green channel of the RGB images and using a contrast-limited adaptive histogram equalization (CLAHE) algorithm to enhance the image. However, and unlike the retinal image's dataset, craquelure is present in paintings with different colours intensities and variations, and the data in the fine-art case exhibits more complex structures and textures, this preprocessing step was not adopted.
2. **Model Configuration:** We selected a sensible range of parameters for iteration to ensure precise craquelure segmentation while minimizing the unintended enhancement of brush strokes, canvas textures, or other background features.
3. **Optimization Loop:** Implementation of an extensive grid search to fine-tune the B-COSFIRE model parameters using k-fold cross-validation. The splitting of the source data into training and testing was carried out to validate the correctness of the algorithm.
4. **Comparison with State of the Art:** For a robust and fair comparison, we also executed a grid search for the method in [18] using our datasets for supervision. We replicated the method as closely as possible based on available descriptions, despite the absence of publicly accessible software.

Optimization of both methods was conducted using Bucklow's dataset in this study. The optimized parameters were then applied to the PDP dataset for testing. Note that these parameters, while optimal for grayscale data, may not be ideal for the PDP dataset due to its different characteristics.

Table 1 – Dataset description for the research of this work.

<i>Title</i>	<i>Author</i>	<i>Year</i>
The Lacemaker	Anonymous	-
The mill	Rembrandt van Rijn	1645-1648
Woman Holding a Balance	Johannes Vermeer	1664
Girl with a Pearl Earring		1665
A Lady Writing		1665
Girl with the Red Hat		1669

¹Permission to publicly share the labeled Bucklow's dataset from [2] is pending author approval. The PDP dataset, containing public domain images, is ready for use.

IV. RESULTS AND DISCUSSION

A. Qualitative results

To assess the performance of our method under supervision, we conducted a series of experiments focusing on the qualitative evaluation using the two distinct types of image datasets created, with random samples being chosen for each dataset. Bucklow’s dataset, as anticipated, provided a simplified scenario that allowed the algorithm to focus on intensity variations. These conditions are ideal for detecting craquelure patterns due to the stark contrast between the cracks and their backgrounds, resulting in a more precise segmentation and a high recognition rate as evidenced in Figure 6. Even in images with significant background noise (Figure 6a and Figure 6k), where dark areas closely match the

intensity of craquelure, the algorithm’s optimized parameters effectively eliminated background interference while preserving the integrity of craquelure segmentation.

The evaluation of the PDP dataset, which poses more significant challenges due to multiple color and complex textures, revealed some of the algorithm’s ability to discriminate between structural features and background disturbances like brush strokes and color variations. A notable instance is the mill paddle depicted in Figure 7a, where the algorithm successfully identified craquelure within the paddle but struggled with accurately delineating its outer edges, mistakenly recognizing them as craquelure. Similarly, Figure 7p illustrates the algorithm’s proficiency in segmenting wider cracks amidst strong color intensity variations and differing crack widths, although it occasionally omitted finer cracks.

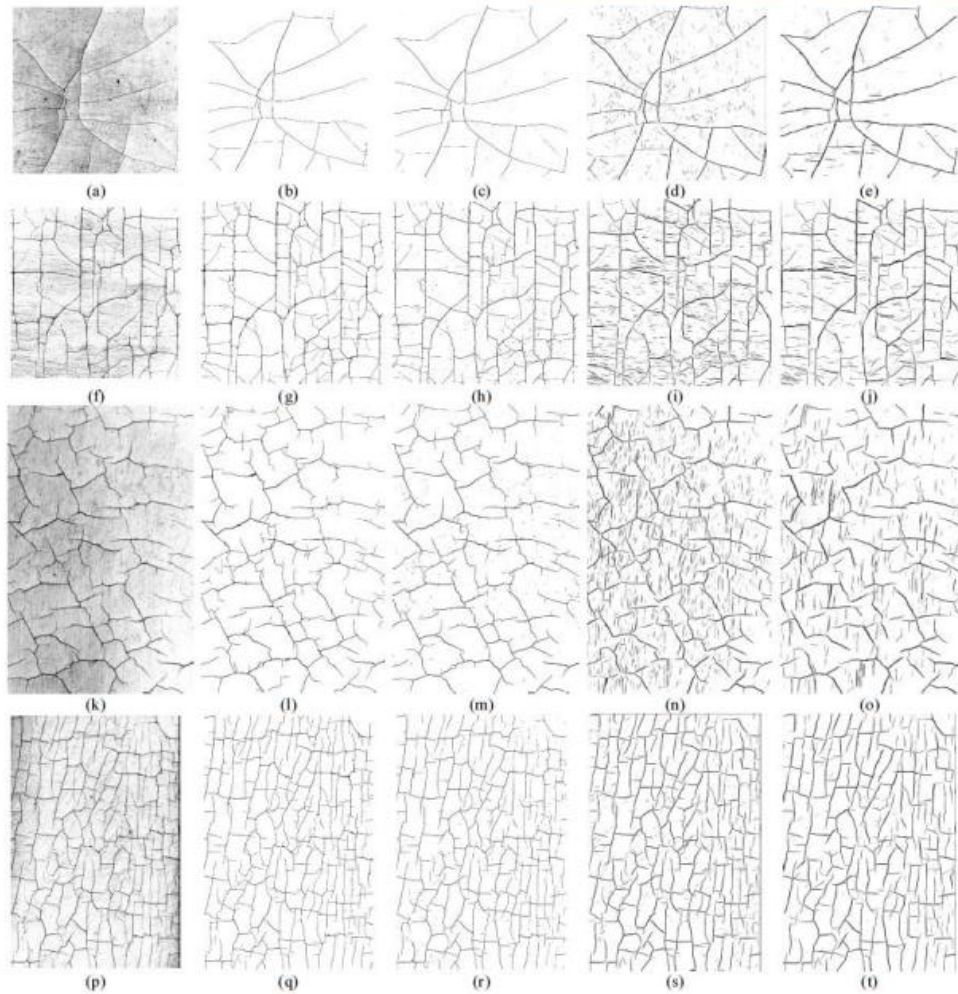


Figure 6 – Results Output: The first column displays the original grayscale images; the second shows the corresponding ground truths; the third presents the segmentation outputs from the implemented B-COSFIRE method; the fourth and fifth columns illustrate the results from the method in [18], using default and optimized parameters, respectively.

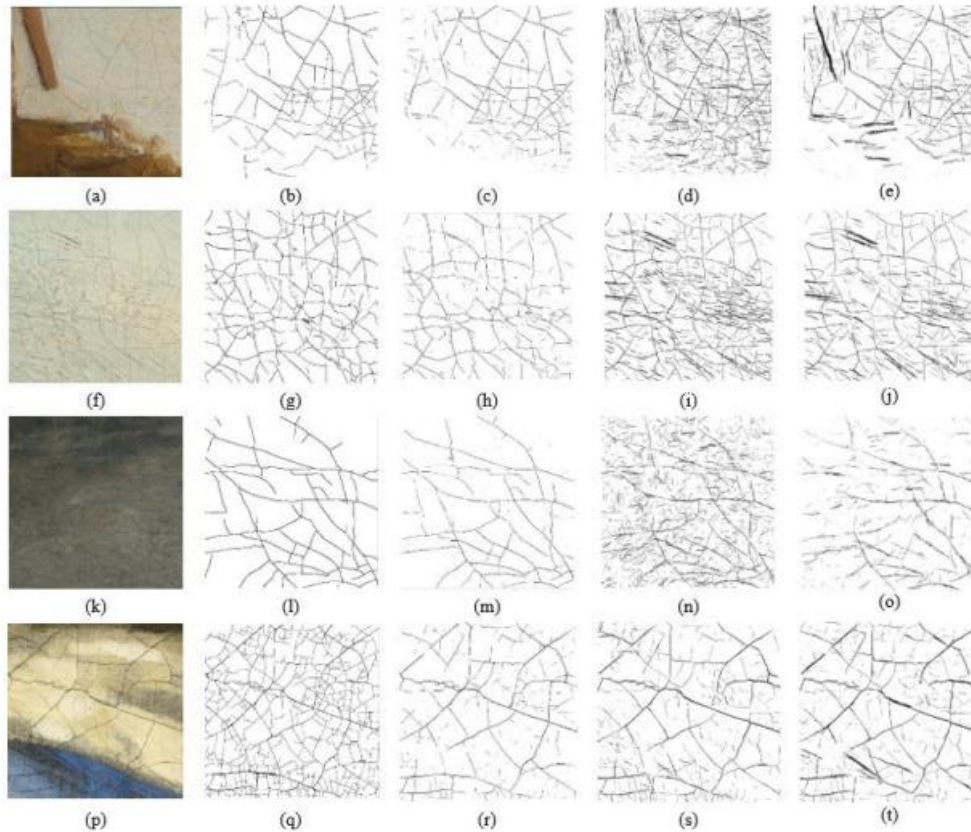


Figure 7 – Results Output: The first column displays the original RGB image; the second shows the corresponding ground truths; the third presents the segmentation outputs from the implemented B-COSFIRE method; the fourth and fifth columns illustrate the results from the method in [18], using default and optimized parameters, respectively.

Our results show that the B-COSFIRE settings adapted dynamically to these complexities, demonstrating an improved capability to segregate and identify craquelure patterns accurately.

B. Results Comparison

The algorithm developed by [18] highlighted the advantages of introducing a supervision component in parameter optimization, evident in Bucklow's dataset. This approach generally improved segmentation by eliminating unwanted structures such as background noise and minor artifacts, as shown across multiple scenarios in Figure 6. However, this occasionally resulted in the discontinuity of actual crack patterns, as seen in Figure 6n and Figure 6o, due to the increased size of the structuring elements used for noise removal.

When applying the same parameters optimized for the grayscale images to the PDP dataset, the results varied. Although the segmentation improved significantly for some tests, it was less consistent across images with similar

complexities. For instance, the segmentation outcomes in Figure 6o and Figure 6j demonstrate that when the orientation of background noise aligns closely with that of craquelure, the algorithm struggles to differentiate between the two. This issue was also evident in Figure 7e and Figure 7t, where the algorithm failed to accurately distinguish the boundaries of the paddle against varied color backgrounds, confusing these edges with craquelure.

C. Role of Labelled Data in Method Adaptation

The introduction of labelled data played a pivotal role in our experimental approach, enabling both the B-COSFIRE method and the comparative algorithm [18] to dynamically adjust their parameters to the specific challenges posed by craquelure segmentation. This adaptive parameter tuning is crucial for enhancing the methods ability to accurately segment craquelure while effectively suppressing unwanted structural elements that could confound the analysis. In particular, the presence of labelled data facilitated a more nuanced approach to parameter optimization, allowing for an

iterative refinement process that closely aligns the algorithms with the complexities of the datasets.

D. Comparative Performance and Method Improvements

Our work demonstrates that the introduction of supervision using the labelled datasets significantly enhanced the performance of the segmentation methods. The method from the authors in [18], when applied to Bucklow's dataset, showed remarkable improvements in eliminating background noise and minor artifacts that often obscure or mimic craquelure patterns, leading to cleaner and more accurate segmentations crucial for subsequent analytical or conservation work in comparison to its application in an unsupervised setting. However, when these same parameters, optimized for Bucklow's dataset, were applied to the more complex PDP dataset, the challenges of distinguishing craquelure from similar-looking elements such as brush strokes or varied color intensities became apparent. This scenario underscores the necessity of introducing supervision to improve models' segmentation overall.

V. CONCLUSIONS AND FUTURE WORK

The application of the B-COSFIRE model to the segmentation of craquelure in fine arts represents a significant advancement in the field of curvilinear structure analysis. The model's effectiveness in various fields has now been demonstrated in art conservation, largely attributed to the integration of a labeled dataset that facilitated the fine-tuning of model parameters. This supervision element was particularly evident in the improvements observed with the method developed in [18], where the optimized configuration led to notably better segmentation results. The success of these methods emphasizes the critical importance of developing and employing advanced segmentation techniques that can be precisely adjusted through SL.

Furthermore, the optimization performed on Bucklow's dataset underscores the necessity for further refinement and enhancement of our method. It is crucial to conduct qualitative testing and additional trials using the PDP dataset to not only evaluate results qualitatively but also to optimize the model's parameters for this specific type of data. Such testing will confirm that the B-COSFIRE model maintains its effectiveness when applied to complex color datasets, thereby improving both its accuracy and utility across varied artwork.

Moreover, a key area for future work involves extending our methodology to effectively handle the complexities associated with artworks that include different textures or feature prominent brushstrokes. Enhancing our segmentation algorithms to adeptly navigate these real-world complexities would substantially improve our capacity to isolate craquelure from other textural distractions. This advancement is crucial for accurately identifying and extracting only the intended structures like craquelure, minimizing the impact of extraneous elements. These developments have the potential to optimize art conservation practices and expand the applications of these technologies in fields that require intricate texture and pattern recognition.

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Appendix B – Poster Presentation at RECPAD'24

Poster Presentation at RECPAD 2024 - 30th Portuguese Conference on Pattern Recognition.

Extending the B-COSFIRE Algorithm for Craquelure Segmentation

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Abstract

This study proposes a novel extension of the B-COSFIRE algorithm for accurate craquelure segmentation in historical paintings. We introduce two new manually annotated datasets of historical paintings and demonstrate superior precision and robustness of our approach compared to existing techniques. Our method addresses the lack of supervised learning techniques in art conservation and offers valuable tools for analyzing intricate craquelure patterns, even in the presence of complex backgrounds and color variations.

1 Introduction

Craquelure, the network of cracks that develops on paintings over time, provides crucial insights into an artwork's history, materials, and environmental exposure [1]. Its accurate detection and segmentation are vital for art historians, conservators, and researchers and for the development of various applications, ranging from the analysis of craquelure patterns to blockchain applications [2][3].

Traditional methods for craquelure analysis, such as morphological operations and thresholding techniques have evolved significantly, with early approaches like Abas and Martinez's morphological top-hat transform [4] and Ruzic's multiscale morphological approach developing solid foundational implementations. With the development of more powerful digital imaging techniques new and improved methods were developed like Cornelis et al.'s conditional Bayesian tensor factorization or CBTF [5]. The field further advanced with machine learning techniques, exemplified by Polatkan et al.'s use of Hidden Markov Trees for forgery detection.

Deep learning has also brought additional improvements, with Sizyakin et al.'s CNN-based approach [6] and Sindel et al.'s CraquelureNet [7] demonstrating enhanced accuracy in crack detection and feature description. However, existing studies face limitations such as the chosen data (multimodal type, specific patches of the same painting with no variability, among others), poor reproducibility and high computational complexity. To address these issues, we propose an extension of the B-COSFIRE (Bar-Combination of Shifted Filter Responses) algorithm, originally used for vessel segmentation in biomedical imaging [8]. Our approach incorporates local homogeneity analysis to differentiate true cracks from unwanted structures such as brushstrokes, changes in intensity or other artifacts, aiming to enable accurate craquelure segmentation across diverse paintings.

2 Methodology and Data

To improve craquelure segmentation in historical paintings, we propose a methodology based on five phases, represented by Figure 1. First, we collected and curated two datasets of historical painting images featuring craquelure patterns. Second, we performed data pre-processing to clean and prepare our data for model fitting. Third, we utilized our extension of the B-COSFIRE algorithm that applies local homogeneity analysis and defined an extended range of sensible parameters. Fourth, we conducted an extensive parameter optimization process to find the optimal configuration. Finally, we evaluated the performance of our method using various metrics and compared it to existing techniques.

Dataset: We created two datasets: (1) Bucklow's dataset of 20 grayscale images from European artworks, provided by Dr. Spike Bucklow[9], and (2) the Public Domain Paintings dataset of 28 patches from historical paintings (obtained in website¹). Both datasets were pixel-labelled for craquelure patterns.

Data pre-processing: images were converted to grayscale, inverted to standardize background and foreground, and normalized to adjust pixel values to a range between 0 and 1.

¹<https://www.nga.gov/>

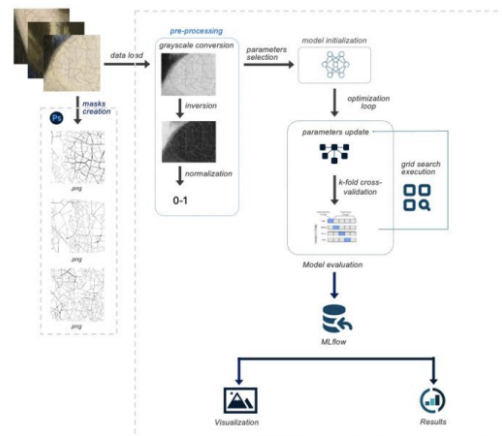


Figure 1: Diagram of the architecture workflow.

Extended B-COSFIRE algorithm: We incorporated local homogeneity analysis into the original B-COSFIRE algorithm. Our method computes responses for the main crack structure and four adjacent "bars" using both symmetric and asymmetric filters. We introduced three homogeneity measures: left intra-homogeneity, right intra-homogeneity, and inter-homogeneity.

Parameter optimization: We conducted a comprehensive grid search to fine-tune our method's parameters, employing 4-fold cross-validation. The optimization process explored a total of 5,832 distinct parameter combinations.

Evaluation: The datasets were split into 75% for training and 25% testing. We used various metrics to evaluate our method's performance, including Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), Area Under Curve (AUC), among others. Segmentation predictions were thresholded using the Otsu algorithm.

Comparison: We executed a grid search for a reference method [10] using our datasets to ensure a fair comparison with the state-of-the-art techniques.

This methodology enables us to accurately evaluate the segmentation efficacy of our method on the segmentation of craquelure patterns in diverse historical paintings, addressing the limitations of existing methods and providing a robust tool for art conservation and analysis.

3 Results

Our extended B-COSFIRE method demonstrated improved performance in craquelure pattern detection across two datasets. We evaluated our method using a comprehensive set of metrics to provide a holistic view of performance, as different studies in the literature have used varying evaluation criteria. The quantitative results of our experiment, summarized in Tables 1 and 2, show that on Bucklow's dataset, we achieved the highest precision of 0.8861, compared to 0.8788 for the original B-COSFIRE and 0.4108 for the reference method. Precision is particularly noteworthy as it indicates the method's ability to avoid false positives (false cracks), which is crucial in craquelure detection. The more complex PDP dataset showed similar trends, with our method maintaining superior performance at 0.5558 precision, versus 0.5149 and 0.4438 for the original and reference methods, respectively.

Table 1: Quantitative results for Bucklow's dataset

Metric	Our method	Original method	SOTA Comparison
Accuracy	0.9892	0.9892	0.9555
AUC	0.9914	0.9914	0.9599
DSC	0.8221	0.8221	0.5412
F1	0.8221	0.8221	0.5412
IoU	0.6981	0.6981	0.3754
MCC	0.8175	0.8175	0.5519
Precision	0.8861	0.8788	0.4108
Recall	0.8362	0.8362	0.9566

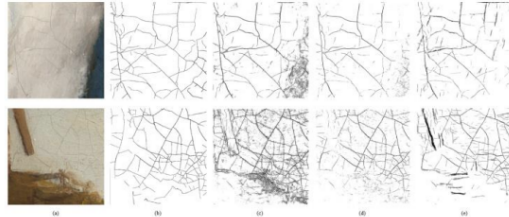


Figure 3: Qualitative results for PDP dataset: (a) Original image. (b) Ground truth. (c) Original B-COSFIRE. (d) Our method. (e) Comparison method.

Table 2: Quantitative results for PDP dataset

Metric	Our method	Original method	SOTA Comparison
Accuracy	0.9036	0.9006	0.9435
AUC	0.9071	0.9071	0.8058
DSC	0.4845	0.4845	0.4257
F1	0.4845	0.4845	0.4257
IoU	0.3462	0.3462	0.2804
MCC	0.4801	0.4801	0.4077
Precision	0.5558	0.5149	0.4438
Recall	0.6705	0.6705	0.5504

A qualitative analysis of the segmentation results, as illustrated in Figures 2-3, confirms this improvement in segmentation, with our extended B-COSFIRE method consistently producing more accurate and detailed craquelure patterns compared to the other approaches. On Bucklow's dataset (Figure 2), our method, along with the original implementation, clearly distinguishes fine craquelure lines from the background, even in images with complex patterns. For the PDP dataset (Figure 3), which presents more challenging conditions with coloured images and varying textures, our method effectively captures intricate craquelure structures while minimizing false positives.

The original B-COSFIRE method (Figure 3c) performs well but tends to miss some of the finer details captured by our extended version, particularly in areas with subtle crack patterns. The comparison method, while achieving decent quantitative metrics, often produces more false positives and misses some of the intricate craquelure lines, especially in areas with complex background textures or color variations. These results highlight the adaptive nature of our extension, which improves precision without compromising overall performance. The consistent enhancement across diverse datasets demonstrates the robustness of our approach, making it a valuable tool for art conservation and analysis.

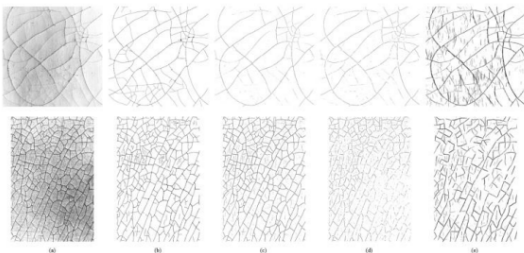


Figure 2: Qualitative results for Bucklow's dataset: (a) Original image. (b) Ground truth. (c) Original B-COSFIRE. (d) Our method. (e) Comparison method.

4 Conclusion

This study extends the B-COSFIRE algorithm for craquelure segmentation in historical paintings, demonstrating significant improvements in precision and robustness compared to traditional methods. Our key contributions include:

1. Development of a novel craquelure segmentation algorithm based on B-COSFIRE, applied in the domain of artwork, more specifically craquelure segmentation in real world paintings.
2. Creation of two new datasets of manually labelled paintings.
3. Implementation of a supervised learning framework for craquelure analysis.

Our method effectively detects and segments craquelure patterns, even in complex backgrounds and varying color intensities. The publicly available datasets we created will support ongoing research in craquelure analysis and cultural heritage preservation.

Future work could explore adapting this algorithm to different domains, optimizing parameter configurations for specific scenarios, and incorporating more advanced neural networks, such as those with attention mechanisms. The development of real-time monitoring and virtual restoration tools for art conservation also remains a promising direction.

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Appendix C – State of the Art Comparison

The structure of many papers found, particularly those from earlier years, often lacked the rigorous organization necessary for clear scientific communication of their research findings. Several studies, notably those published before 2015, did not adhere to a consistent template or organized structure, which is essential for scientific writing. This inconsistency often resulted in a disjointed presentation of the introduction, methodology, results, and conclusions.

In several cases, the papers prioritized the novelty of the approach over the clarity and completeness of the research process. For instance, some studies presented innovative methods without providing a detailed introduction to the problem or sufficient background information, making it difficult for readers to contextualize the research. Furthermore, the methodology sections in these papers often lacked the necessary detail to allow for reproducibility, a cornerstone of scientific research.

Moreover, the results and conclusions sections in these studies were sometimes underdeveloped, lacking quantitative evidence to support the claims made about the effectiveness of the proposed methods. This lack of evaluation metrics and comprehensive discussion of results further complicates the comparison of different techniques across studies. As a result, it is challenging to assess the relative strengths and weaknesses of the methods presented, which hinders the field's overall progress.

This trend underscores the importance of adhering to a clear and structured format in scientific writing. A well-organized paper, with a clearly defined introduction, detailed methodology, robust results, and thoughtful conclusions, is essential for advancing the field and facilitating the application of new techniques in real-world scenarios.

A comparative table of the remaining 17 papers can be found below in Appendix C - Table 1.

Table 1 - Summary of reviewed studies.

Author	Year	Method	Dataset	Main Results
Abas, F.; Martinez, K. [45]	2002	Eight differently oriented Gabor filters, also using a morphological thinning algorithm and chain code-based representation.	Xradiographs of paintings taken by the research labs of the Louvre Museum in Paris and the Hamilton Kerr Institute, Cambridge.	Lack of quantitative results. The authors concluded that the results showed that multi-oriented Gabor filters can be used to extract suspected crack patterns, showing its potential.
Abas, F.; Martinez, K. [47]	2003	Morphological top-hat operator and grid-based automatic thresholding, also using fuzzy k-means (FKM) clustering	Not mentioned.	Lack of quantitative results. The authors presented a single representation of their method's performance justifying the performance of the method with the difficulties of finding a dataset and a ground truth to improve the method's results, which turns the process even more complex.
Giakoumis, I., et. al. [48]	2006	Two segmentation approaches with top-hat transformation, the first one using a Median Radial Basis Function (MRBF) NN on hue and saturation data and the second one using a semi-automatic procedure based on region growing with crack filling using order statistics filters and controlled anisotropic diffusion.	12 images from the training dataset and 15 images (of the same artistic style and era) that did not belong to the training dataset) with no ground truth data.	Lack of quantitative results, only showing qualitative results. The authors concluded that it was found very effective by restoration experts. However, there are certain aspects of the proposed methodology that can be further improved. For example, the craquelures-detection stage is not very efficient in detecting craquelures located on very dark image areas.

Spagnolo, G.; Somma, F. [49]	2010	Gray-scale morphological dilation and erosion using top-hat transformation with opening top-hat operators (OTH) and top-hat operators (CTH) (or also known as the bottom-hat operator), as well as a median radial basis functions (MRBF) NN, which is a robust version of radial basis functions (RBF) network	Not mentioned.	Lack of quantitative results. After presenting the definition of the reconstruction of defective pixels (crack-filling methods), the author showed the result obtained with the used algorithm of reconstruction which was the best one presented within the scope of their study, showing the benefits of replacing several pixels together.
Sangeetha, T.A.; Saradha, A. [50]	2010	Morphological top-hat operator and grid-based automatic thresholding	Private dataset with no ground truth set.	Lack of quantitative results. The work concludes that the method presented can effectively detect and classify crack patterns in paintings. This method enhances the ability to analyze and preserve artwork by providing a structured approach to crack detection, feature extraction, and classification, which can assist in understanding the underlying causes of cracks and guide restoration efforts.
Gancarczyk, J. [51]	2012	Semi-automatic technique based on a region-growing algorithm, replacing the manual initial points selection by another process, based on a decision tree application	Private, provided by the Laboratory of Analysis and Nondestructive Investigation of Heritage Objects of the National Museum in Krakow.	Lack of quantitative results. For the author, the main difficulty in this method was defining an adequate set of descriptors forming a feature vector for the mining model. However, she considered the method achieved satisfactory identification of craquelure pixels in the whole area where crack pattern was darker from the background.

Gancarczyk, J.; Sobczyk, J. [52]	2013	Top-hat transformation, pixel-level data mining with k-means clustering and a decision tree, based on the Bayesian approach to learning causal interaction models with a uniform Dirichlet distribution of priors was chosen.	Private dataset.	The authors explained though none of these methods can replace the restorer's work completely, significant help is obtained, thus allowing more caution to be paid to further steps of the investigation and restoration of an artwork. The proposed method provides some improvement of the results when considering the misclassified pixels, and regarding the rate of manual pre-processing.
Gillooly, T., et. al. [53]	2018	Three segmentation post-processing approaches, the first one using thresholding or binarization applied to the output of spectral top-hat transform (THB) and the second one using a top-hat transformation, followed by a thresholding and a path opening (THBPO) and the third one using a top-hat, followed by a path opening and a thresholding (THPOB).	Dataset created with a group of five patches from a single artwork with a ground truth for each patch created by manually painting a binary crack map using photo editing software.	The authors concluded that the post-processing methods presented do not necessarily segment out non-thin structures, depending on how they are connected, and mentioned that when combined with a spectral top-hat operator it can detect the general shape of the crack map under certain conditions. However, extra processing is necessary to produce a better result. The evaluation metric chosen by the authors was Intersection over Union (IoU), for THB the best IoU value was 0.48312, while for THBPO was 0.40877 and for THPOB was 0.43171. Based on these results the authors concluded that the path opening operation typically induces a worse score, possibly from the removal of blob artifacts.
Dulecha, T. G; Giachetti, A.; et. al. [54]	2019	Edge detection and a CNN-based labeling of image patches around edges.	36 painted squares with different pigments and coatings and	Average classification accuracy for the dataset patches extracted on the 6 test painted squares of 76.83% and average accuracy in single patch

			presenting visible craquelures that can have been annotated by experts.	edge classification for selected elevation range of 71.92 % for an elevation range of 0-30 degrees, 77.75% for 30-60 degrees and 80.81% for 60-90 degrees. The results obtained on the multi-light data shown to be better than those obtained on the single image, based on the better quality of both the edge detection performed with the multi-light approach and the better classification accuracy obtained using CNN.
Sidorov, O.; Hardeberg, J. Y. [55]	2019	Graph representation and statistical features individually using novel Graph Neural Networks (GNNs) and SVM-model with linear kernel as a classifier.	Private dataset with 36 high-resolution grayscale photographs of Italian, French, Flemish, German, and Dutch panels and canvas paintings of XIV–XVIII centuries.	Lack of quantitative results. Authors indicated that the best performance they achieved happened when both techniques were merged into one framework. Also, they performed experiments on the dataset for artworks origin classification and concluded that their approach outperformed existing techniques by a large margin, mentioning that GNNs are robust to any kind of geometrical distortions, which is interesting to notice.
Sparavigna, A. [56]	2020	GNU Image Manipulation Program (GIMP) Retinex filter.	Not a dataset, just isolated artworks from famous artists.	Lack of quantitative results, only showing qualitative results, mentioning that the outcome of the filter can be adjusted selecting different levels, scales and dynamics. Based on the results, author mentioned that this method can be a proper option for preprocessing artworks, before any further analysis or also for measurements of craquelure domains.

Sizyakin, R.; Cornelis, B; et al. [57]	2020	Morphological filtering as pre-processing stage (morphological bottom-hat and top-hat operation, emphasizing bright objects and dark objects, respectively), deep CNNs for multimodal data (Morphological Convolutional Neural Network (MCNC)) with a compensation method for reducing excessive thickening of the crack boundaries.	Multimodal dataset Ghent Altarpiece with hand-labeled data with crack pixels represented with green labeled pixels and blue marks for the undamaged image parts.	The authors' results from the comparison of different methods show that classical classification methods such as Support Vector Machines (SVM), AdaBoost, and standard fully connected networks (FCNs) are inferior to DL methods in the task of crack detection in artworks. The MCNC method shows comparable performance to DL common approaches, with 0.8419 of recall, 0.8185 of precision and 0.8185 of F1-score.
Angheluta, L.; Chiroasca, A. [58]	2020	CNN uses a standard 16-layer VGG-16 model.	Private dataset of 2148 pictures.	Based on the results for craquelures detection, the model presented a precision of 0.87, a recall of 0.83, and a F1-score of 0.85. Authors concluded that to improve accuracy, hardware and software dependencies and the applicability of the model it will need to be changed to an encoder-decoder pattern that usually implements a Fully Convolutional Network (FCN)
Sindel, A.; Maier, A.; Christlein, V. [59]	2021	CraquelureNet for multi-modal image registration, also using ResNet.	Creation of a multi-modal dataset of historical paintings with key point pair annotations and class labels for craquelure detection and matching.	Based on the author's conclusion, the method demonstrates the best registration performance on the multi-modal dataset in comparison to competing methods, also presenting quantitative results that were or that helpful at the end of the day.

<p>Toorn, J.; & Wiersma, R.; et. al. [60]</p>	<p>2022</p>	<p>Scale Invariant Feature Transform (SIFT), Multispectral Feature Descriptor (MFD), and Self-Supervised Interest Point Description (SuperPoint).</p>	<p>2 images from different modalities with their original ground truth.</p>	<p>The authors indicated that SuperPoint starkly increased the description matching accuracy by 40% for modalities with few modality-specific artifacts. Further, performing craquelure segmentation and using the MFD descriptor results in significant description matching accuracy improvements for modalities with many modalities specific artefacts. The experiment concludes that the multimodal MFD descriptor slightly outperforms the classical SIFT descriptor, while the learned unimodal SuperPoint descriptor nearly doubles SIFT's performance.</p>
<p>Jamalabadi, M. [61]</p>	<p>2022</p>	<p>AI-based method (not specified) to extract and analyze crack patterns in panel paintings, transforming detected cracks into simplified lines, and assessing their distribution, orientation, and evolution.</p>	<p>Not mentioned.</p>	<p>Lack of quantitative results. The author concluded that AI effectively extracts and analyzes crack patterns in paintings, transforming them into simplified lines and providing valuable insights for conservation and restoration.</p>
<p>Yuan, Q.; He, X., et al. [62]</p>	<p>2023</p>	<p>Semantic segmentation method, ResUnet.</p>	<p>Private newly built dataset based on 600 images.</p>	<p>Authors showed experimental results supported by statistical tests show that Res-UNet is a capable method of craquelure recognition, with an accuracy rate of 98.19%, and F1-score of 93.42%. Hence, the proposed hybrid approach is a promising tool to support the preservation and restoration of valuable traditional Chinese polychrome architectural paintings.</p>

Appendix D – Data Labelling Tool

The materials (hardware and software) used to carry out the data labelling, as well as the selection criteria, are described below.

Initially, the open-source tool Label Studio was considered for data annotation, but it proved unsuitable due to a significant degradation in image quality and the inability to distinguish cracks effectively.

Furthermore, the available tools within Label Studio lacked the precision necessary for accurate pixel-wise segmentation since the pencil tool was often too large to accurately outline the intricate crack patterns, and at the optimal zoom level, the pen movement was restricted to 45-degree angles, making it impossible to trace the cracks with the required level of detail (Appendix D - Figure 1).

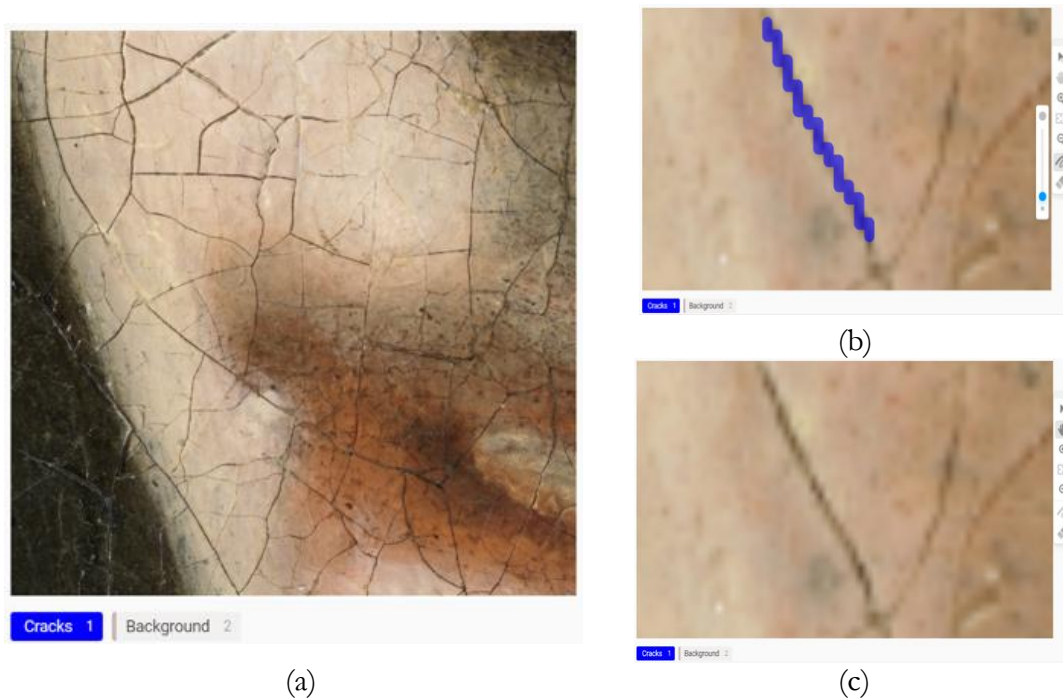


Figure 1 - Pixel-wise precision using Label Studio: (a) Portion extracted from the original artwork. (b) Single craquelure visualization. (c) Single craquelure segmentation.

Consequently, Adobe Photoshop was chosen as the software for the annotation process, offering a wider range of tools and techniques, albeit with a steeper learning curve. To facilitate pixel-wise segmentation across the images, a pen and a Wacom tablet were applied (Appendix D - Figure 2).



Figure 2 - Wacom One tablet.

Choosing the right data labelling tool was crucial for accurate labeling of craquelure patterns. The selection criteria included aspects such as user-friendliness, the ability to handle high-resolution images, features specific to curvilinear structure annotation, among others. Appendix D - Table 1 shows a comparison between the selection criteria defined to choose the tool to be used.

Table 1 - Comparison of Annotation Software Features.

Criteria	Photoshop	Label Studio
Cost	Paid	Free/Paid
Versatile Image Editing	✓	✗
Pixel-Precision Editing	✓	✓
Steep Learning Curve	✓	✗
User-Friendly for Annotation	✗	✓
High-Resolution Image Handling	✓	✓
Multi-Annotator Support	✗	✓
Tools for Complex Structures	✓ (with manual precision)	✓ (with ML integration)
Annotation Speed	Slow	Fast
ML Model Integration	✗	✓
Semantic Segmentation Support	✗	✓



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