Graduation Plan

Master of Science Architecture, Urbanism & Building Sciences

Graduation Plan: All tracks

Submit your Graduation Plan to the Board of Examiners (Examencommissie-BK@tudelft.nl), Mentors and Delegate of the Board of Examiners one week before P2 at the latest.

The graduation plan consists of at least the following data/segments:

Personal information	
Name	Valentijn Camiel Cloo
Student number	5436958

Studio		
Name / Theme	Building technology	
Main mentor	Dr. Barbara Lubelli	Heritage and Architecture
Second mentor	Dr. Azarakhsh Rafiee	Design Informatics (GIS Technology)
Argumentation of choice of the studio	I finished my bachelor's degree at The Hague University of applied sciences gaining knowledge on BIM Maturity assessment as my graduations thesis. I continued my studies at TU Delft CITG bridging program where I gained a basic understanding of mathematical concepts and computer programming. Finally during the MSc Building Technology courses Computational Intelligence and CORE I learned additional information about Computer vision, Point cloud technology and the machine learning.	

Graduation project	
Title of the graduation project	EXPLORING THE POTENTIAL OF DEEP LEARNING-BASED IMAGE ANALYSIS FOR DAMAGE RECOGNITION IN HERITAGE BUILDINGS
Goal	
Location:	Delft, The Netherlands.
The posed problem,	Advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have enabled promising developments in image-based damage detection. Techniques such as semantic segmentation and classification are commonly employed to identify specific damage patterns. However, accurately detecting and quantifying visually evident damage like efflorescence using automated methods remains a complex task due to variations in surface textures, lighting conditions, and the subtle nature of the damage itself. This research seeks to evaluate the performance of a known machine learning model in detecting efflorescence and explore enhancements to improve its accuracy and reliability,

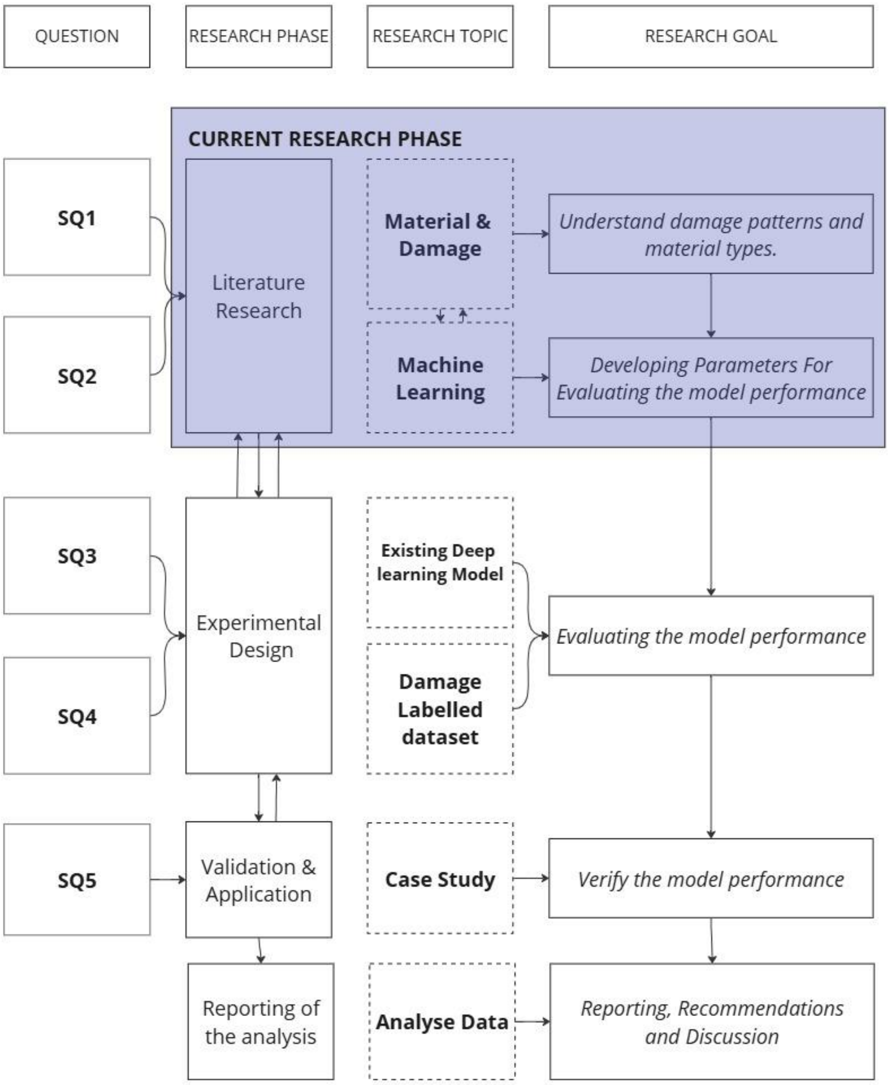
	contributing to more efficient and effective damage assessment methods.
research questions and	MQ: How can the performance of an existing deep learning model for detecting efflorescence damage in heritage masonry buildings in the Netherlands be improved by incorporating additional data and parameters? SQ1: Which visible surface characteristics and material properties of heritage masonry most significantly influence the detection and classification of efflorescence damage, and how do these factors present challenges for detection? SQ2: Which state-of-the-art deep learning models (e.g., CNNs, semantic segmentation models) are most suitable for detecting and classifying efflorescence damage in heritage masonry buildings based on performance criteria such as accuracy and generalizability? SQ3: How can additional parameters, such as image quality, angle, color, spatial context, and near-infrared imaging, be integrated into the model to potentially enhance its detection performance? SQ4: How do the individual and combined effects of parameters like image quality, angle, and near-infrared imaging impact the detection accuracy, precision, and reliability of the selected deep learning model for moisture-related damage? SQ5: How well does the enhanced model perform when evaluated on unseen datasets and applied to real-world case studies of moisture-related damage in heritage masonry buildings?
design assignment in which these result.	This study aims to bridge the gap between traditional preservation techniques and modern technology by leveraging machine learning methods for the accurate diagnosis of efflorescence damage in masonry within heritage buildings. Specifically, it seeks to evaluate the capabilities of a pre-existing deep learning framework, utilizing techniques such as Convolutional Neural Networks (CNNs), to detect and analyse moisture-related damage, including efflorescence, discoloration, and spalling. Furthermore, the research aims to identify and implement enhancements to improve the model's accuracy and reliability, addressing challenges posed by variations in surface textures, lighting conditions, and the subtle characteristics of such damage. Through this approach, the study aspires to contribute to the development of efficient, automated methods for visual damage assessment in heritage preservation.
[This should be formulated in such a way that the graduation project can answer these questions.	

The definition of the problem has to be significant to a clearly defined area of research and design.]

Process

Method description

This research study is divided into four different stages illustrated in figure 1: *Research Design Overview*. (1) Literature Research, (2) Experimental Design, (3) Validation & Application and finally (4) Reporting of the analysis.



Literature Research

The Literature Research phase consists of two main topics that will be researched, firstly there is a need for a broad understanding of heritage masonry and damages that could be found in The Netherlands. The objective of the literature research is to get a better understanding of damage patterns and material types. This research forms a basis for developing the general outline of the experiments and what metrics could be used to evaluate the models performance. The characteristics and history of masonry will be briefly discusses following the damage processes and causes to the masonry structures. Additionally the extensively researched damage atlas and MDDS[1] or MDCS[2] hosted by TNO, TU Delft and the Cultural Heritage Agency of the Netherlands will be briefly discussed due to their significance in the field of heritage damage diagnostics.

Secondly a research is required towards the understanding and mathematical concepts of state-of-the-art machine learning models and their application in the field of heritage based computer vision aided diagnostics. A literature review is required on the fast expanding and existing world of machine learning models are analyzed and classified while their differences are discussed. Lastly the required datasets are reviewed as well as the labels and the limitations currently posed to grasp a knowledge gap for the next research phase.

Experimental Design

The experimental Design phase focusses on the development of multiple hypothesis and experiment set ups where firstly a benchmark will be developed to identify the current accuracy of the referred machine learning model from the literature research phase, and possible performance gap of accuracy can be identified. To ensure the experiments are both feasible and impactful, their design will be informed by expert consultation and aligned with the scope and time constraints of this study. The experiments are based on the results of the literature research results and will be structured into several steps to ensure a comprehensive analysis.

First, based on insights from the literature research, specific hypotheses will be formulated. For example, hypotheses might test whether integrating additional parameters, such as near-infrared imaging or spatial context, improves the model's performance. These hypotheses will guide the design of individual experiments and ensure that each step contributes to answering the sub-research questions.

Secondly, The first set of experiments will establish a benchmark by testing the unmodified machine learning model on a selected dataset. Key performance metrics such as accuracy, precision, recall, and F1-score will be recorded to assess the current state of the model. This step is essential to quantify the initial performance and identify gaps or areas of potential improvement.

Continuing, The experiments will systematically incorporate additional parameters identified during the literature research phase. Examples include: Image quality variations (e.g., resolution, contrast), environmental conditions (e.g., lighting and angle of images), spatial context and proximity to surrounding structures, inclusion of near-infrared imaging to enhance the detection of moisture-related damage. Each parameter will be tested individually and in combination to determine its impact on model performance. Based on the results of the parameter integration, the machine learning model will be fine-tuned to optimize its performance. Techniques such as *transfer learning, hyperparameter tuning, and augmentation strategies* will be employed to maximize accuracy and reliability. Specific attention will be paid to balancing sensitivity to damage detection while minimizing false positives.

The experiments will employ a range of evaluation metrics related to the context of heritage damage diagnostics. These metrics may include: **Segmentation Accuracy:** For localized damage detection.

[1] Masonry Damage Diagnostics System
[2] Monument Diagnosis and Conservation System

Classification Accuracy: For distinguishing between different types of moisture-related damage, such as efflorescence and spalling. **Processing Time:** To assess the feasibility of real-time diagnostics. **Robustness:** Evaluating model performance across diverse datasets and conditions.

Datasets will be carefully chosen based on the literature research, with consideration for the availability of annotated heritage damage images. If datasets are limited, the datasets will be expanded by field research validated by experts.

The experiments will follow an iterative cycle where results from initial tests inform adjustments in subsequent ones. For instance, if integrating near-infrared imaging yields significant improvements, further tests will optimize its inclusion. This iterative approach ensures continuous refinement and learning throughout the experimental phase.

Validation & Application

The Validation and Application phase aims to assess the practical effectiveness and reliability of the enhanced machine learning model in a real-world context. This phase involves two main components: testing the model on a selected heritage site and gathering expert feedback to evaluate its performance comprehensively.

An appropriate heritage site in the Netherlands will be chosen as the focus of the case study. Selection criteria will include: The presence of moisture-related damage such as efflorescence, discoloration, or spalling. Accessibility for capturing high-quality images or data for validation. Representativeness of the site in terms of materials, and damage types found.

The results obtained during the experimental phase will be reproduced using real-world data collected from the selected site. This involves: Capturing new datasets under varying conditions (e.g., different lighting or angles). Applying the enhanced model to detect and classify damages. Comparing model predictions with visual inspections or documented damage reports from conservation experts.

Reporting & Analysis

The Reporting & Analysis phase serves as the finalization of the research, concluding all findings, insights, and evaluations from the previous phases into a complete document. This phase ensures that the research outcomes are presented clearly and meaningfully, while also providing recommendations for future research and practical applications.

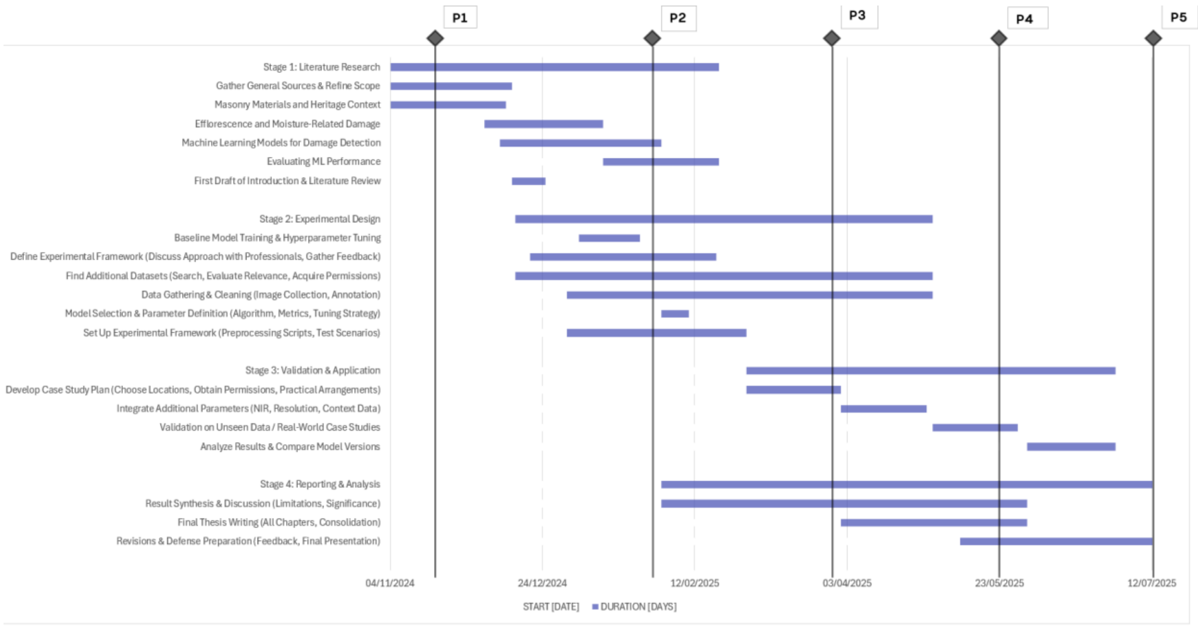


Figure 1 Proposed time schedule

Literature and general practical references

Masonry Materials and Heritage Context

Masonry Material Properties

[brick composition and porosity]

Keshmiry, A., Hassani, S., Dackermann, U., & Li, J. (2024). Assessment, repair, and retrofitting of masonry structures: A comprehensive review. Construction and Building Materials, 442, 137380. https://doi.org/10.1016/J.CONBUILDMAT.2024.137380

Cultural Heritage Agency of the Netherlands. (n.d.). Masonry. Retrieved January 4, 2025, from https://kennis.cultureelerfgoed.nl/index.php/Baksteenmetselwerk

[lime mortar properties and aging]

Cultrone, G., Sebastián, E., & Huertas, M. O. (2007). Durability of masonry systems: A laboratory study. Construction and Building Materials, 21(1), 40-51.

Branco, F. G., Belgas, M. D. L., Mendes, C., Pereira, L., & Ortega, J. M. (2021). Mechanical performance of lime mortar coatings for rehabilitation of masonry elements in old and historical buildings. Sustainability, 13(6), 3281.

Lubelli, B., van Hees, R., & Nijland, T. G. (2018). Steenreparatiemortels: criteria voor het maken van een keuze. In WTA-studiedag'Reparatie van steenachtige materialen'. WTA Nederland-Vlaanderen.

[Dutch masonry typologies]

Keshmiry, A., Hassani, S., Dackermann, U., & Li, J. (2024). Assessment, repair, and retrofitting of masonry structures: A comprehensive review. Construction and Building Materials, 442, 137380.

Maldonado, N. G., Martín, P., del Solar, G. G., & Domizio, M. (2019). Historic masonry. In Heritage. IntechOpen.

Goudeau, J. J. W. (2015). Biografie van de baksteen 1850-2000 Zwolle/Amersfoort: WBooks/Rijksdienst voor het Cultureel Erfgoed, 2012 9789040007569 Historisch metselwerk: instandhouding, herstel en conservering Zwolle/Amersfoort: WBooks/Rijksdienst voor het Cultureel Erfgoed, 2012 9789040007576.

Cultural and Structural Significance of Heritage Buildings

[Netherlands-specific heritage regulations]

Koster, H. R. A., & Rouwendal, J. (2017). Historic amenities and housing externalities: evidence from the Netherlands. Economic Journal, 127(605), F396–F420. https://doi.org/10.1111/ecoj.12477

Ruijgrok, E. C. M. (2006). The three economic values of cultural heritage: a case study in the Netherlands. Journal of Cultural Heritage, 7(3), 206–213. https://doi.org/10.1016/J.CULHER.2006.07.002

[value of preserving historic masonry]

Sabbioni, C., Brimblecombe, P., & A Bonazza. (2007). Mapping climate change and cultural heritage. Academia.Edu. https://www.academia.edu/download/31157702/A-1_182.pdf#page=137

Sabbioni, C., Cassar, M., … P. B.-… and M. M., & 2008, undefined. (2008). Vulnerability of cultural heritage to climate change. Coe.Int, 44. http://www.coe.int/t/dg4/majorhazards/activites/2009/ravello15-16may09/Ravello_APCAT2008_44_Sabbioni-Jan09_EN.pdf

Strlič, M., Thickett, D., Taylor, J., Conservation, M. C.-S. in, & 2013, undefined. (2013). Damage functions in heritage science. Taylor & Francis, 58(2), 80–87. https://doi.org/10.1179/2047058412Y.0000000073

[discussing conservation principles]

Makoond, N., & Pela, L. (2021). A risk index for the structural diagnosis of masonry heritage (RISDiMaH). ElsevierN Makoond, L Pela, C MolinsConstruction and Building Materials, 2021•Elsevier. https://www.sciencedirect.com/science/article/pii/S0950061821001938
Fino, M. De, Galantucci, R., Heritage, F. F.-, & 2023, undefined. (2023). Condition assessment of heritage buildings via photogrammetry: A scoping review from the perspective of decision makers. Mdpi.ComM De Fino, RA Galantucci, F FatigusoHeritage, 2023•mdpi.Com. https://doi.org/10.3390/heritage6110367

Efflorescence and Moisture-Related Damage

Causes and Mechanisms of Efflorescence

[explaining salt crystallization processes in brick]

Proietti, N., Calicchia, P., Colao, F., De Simone, S., Tullio, V. Di, Luvidi, L., Prestileo, F., Romani, M., Tatì, A., Rosina, E., & Lubelli, B. (2021). Moisture damage in ancient masonry: a multidisciplinary approach for in situ diagnostics. Mdpi.Com. https://doi.org/10.3390/min11040406
Nijland, T. G., Lubelli, B., & van Hees, R. P. (2018). Een plaag van alle tijden: zout. Omgaan met Vocht en Zout, 12.
van Hees, R. P. J., & Lubelli, B. (2012). Schade door vocht, vorst en zouten: Fenomenen verklaard. In Historisch Metselwerk (pp. 141-149). Wbooks.

[capillary action and rising damp]

Lubelli, B., van Hees, R. P. J., & Bolhuis, J. (2018). Optrekkend vocht: hoe kiest u een geschikte interventie?. Omgaan met Vocht en Zout, 74.
van der Grijp, E. 4. Oorzaak en gevolg. Karakteristiek Duurzaam Erfgoed in Gelderland, 57.
Pel, L., van Gils, N., & Voronina, V. (2008). De fysische principes achter en de effectiviteit van ontzoutingsmethoden. In conference; WTA, Bergen op Zoom, 25 April 2008; 2008-04-25; 2008-04-25.

[linking environmental conditions to salt damage]

Miranda Dias, J., Henriques, M., Matias, L., Ribeiro, M. S., & Raposo, S. (2018). NDT techniques for the analysis of anomalies related with durability-heritage buildings with masonry walls and confining concrete elements.

Diagnostic Methods for Moisture and Efflorescence

[visual inspection for salt deposits]

Siedel, H. (2018). Salt efflorescence as indicator for sources of damaging salts on historic buildings and monuments: a statistical approach. Environmental earth sciences, 77(16), 572.

[non-destructive testing (NDT) for moisture]

Fort, R., Feijoo, J., Varas–Muriel, M. J., Navacerrada, M. A., Barbero-Barrera, M. M., & De la Prida, D. (2022). Appraisal of non-destructive in situ techniques to determine moisture-and salt crystallization-induced damage in dolostones. Journal of Building Engineering, 53, 104525.
Binda, L., Cardani, G., & Zanzi, L. (2010). Nondestructive testing evaluation of drying process in flooded full-scale masonry walls. Journal of Performance of Constructed Facilities, 24(5), 473-483.
Büyüköztürk, O., Taşdemir, M. A., Colla, C., Molari, L., Gabrielli, E., & de Miranda, S. (2013). Damp and salt rising in damaged masonry structures: Numerical modelling and NDT monitoring. In Nondestructive Testing of Materials and Structures (pp. 1151-1156). Springer Netherlands.
[in-situ sampling and lab tests]

Machine Learning Models for Damage Detection

Overview of Deep Learning and Computer Vision

Tapeh, A. T. G., & Naser, M. Z. (2023). Artificial intelligence, machine learning, and deep learning in structural engineering: a scientometrics review of trends and best practices. Archives of Computational Methods in Engineering, 30(1), 115-159.

Zhao, Z., Wu, J., Li, T., Sun, C., Yan, R., & Chen, X. (2021). Challenges and opportunities of AI-enabled monitoring, diagnosis & prognosis: A review. Chinese Journal of Mechanical Engineering, 34(1), 56.

[CNN fundamentals for image classification]

Dhruv, P., & Naskar, S. (2020). Image classification using convolutional neural network (CNN) and recurrent neural network (RNN): A review. Machine learning and information processing: proceedings of ICMLIP 2019, 367-381.

Jogin, M., Madhulika, M. S., Divya, G. D., Meghana, R. K., & Apoorva, S. (2018, May). Feature extraction using convolution neural networks (CNN) and deep learning. In 2018 3rd IEEE international conference on recent trends in electronics, information & communication technology (RTEICT) (pp. 2319-2323). IEEE.

Chen, L., Li, S., Bai, Q., Yang, J., Jiang, S., & Miao, Y. (2021). Review of image classification algorithms based on convolutional neural networks. Remote Sensing, 13(22), 4712.

[semantic segmentation frameworks]

Pang, B., Yang, J., Xia, T., Zhang, A., Zhang, K., Xu, Q., & Wang, F. (2025). Automated heritage building component recognition and modelling based on local features. Journal of Cultural Heritage, 71, 252-264.

Liu, Z., Brigham, R., Long, E. R., Wilson, L., Frost, A., Orr, S. A., & Grau-Bové, J. (2022). Semantic segmentation and photogrammetry of crowdsourced images to monitor historic facades. Heritage Science, 10(1), 1-17.

[object detection (e.g., YOLO, MASK R-CNN)]

Pratibha, K., Mishra, M., Ramana, G. V., & Lourenço, P. B. (2023, September). Deep Learning-Based YOLO Network Model for Detecting Surface Cracks During Structural Health Monitoring. In International Conference on Structural Analysis of Historical Constructions (pp. 179-187). Cham: Springer Nature Switzerland.

ML Applications in Heritage Conservation

[AI-based efflorescence detection in historic structures]

Marin-Garcia, D., Bienvenido-Huertas, D., Carretero-Ayuso, M. J., & Della Torre, S. (2023). Deep learning model for automated detection of efflorescence and its possible treatment in images of brick facades. Automation in Construction, 145, 104658.

Mishra, M., & Lourenço, P. B. (2024). Artificial intelligence-assisted visual inspection for cultural heritage: State-of-the-art review. Journal of Cultural Heritage, 66, 536-550.

Giannuzzi, V., & Fatiguso, F. (2024). Historic Built Environment Assessment and Management by Deep Learning Techniques: A Scoping Review. Applied Sciences (2076-3417), 14(16).

Mishra, M., Barman, T., & Ramana, G. V. (2024). Artificial intelligence-based visual inspection system for structural health monitoring of cultural heritage. Journal of Civil Structural Health Monitoring, 14(1), 103-120.

[image-based damage classification in masonry] *[Mostly Cracks]*

Mishra, M., & Lourenço, P. B. (2024). Artificial intelligence-assisted visual inspection for cultural heritage: State-of-the-art review. Journal of Cultural Heritage, 66, 536-550.

Zou, J., & Deng, Y. (2024). Intelligent assessment system of material deterioration in masonry tower based on improved image segmentation model. *Heritage Science*, *12*(1), 252.
Jothiraj, S., Balu, S., Rengarajan, N., & Nagarani, N. (2024). Monitoring Ancient Buildings Using UAV and Instant Image Segmentation Using Masked R-CNN. In *Artificial Intelligence for Multimedia Information Processing* (pp. 3-17). CRC Press.
Hacıefendioğlu, K., Altunışık, A. C., & Abdioğlu, T. (2023). Deep Learning-Based Automated Detection of Cracks in Historical Masonry Structures. Buildings, 13(12), 3113.

Evaluating Machine Learning Performance
Metrics and Validation Techniques

[accuracy, precision, recall, F1-score, IoU]
Zhou, J., Gandomi, A. H., Chen, F., & Holzinger, A. (2021). Evaluating the quality of machine learning explanations: A survey on methods and metrics. Electronics, 10(5), 593.
Naser, M. Z., & Alavi, A. H. (2023). Error metrics and performance fitness indicators for artificial intelligence and machine learning in engineering and sciences. Architecture, Structures and Construction, 3(4), 499-517.

[cross-validation methods for small datasets]
Allgaier, J., & Pryss, R. (2024). Cross-validation visualized: a narrative guide to advanced methods. Machine Learning and Knowledge Extraction, 6(2), 1378-1388.

[performance benchmarks for AI in structural health monitoring]
Zinno, R., Haghshenas, S. S., Guido, G., & VItale, A. (2022). Artificial intelligence and structural health monitoring of bridges: A review of the state-of-the-art. *IEEE Access*, *10*, 88058-88078.

Challenges and Limitations
[overfitting in deep learning for damage detection]
Seventekidis, P., & Giagopoulos, D. (2022). Model-based damage identification with simulated transmittance deviations and deep learning classification. Structural Health Monitoring, 21(5), 2206-2230.
Bejani, M. M., & Ghatee, M. (2021). A systematic review on overfitting control in shallow and deep neural networks. Artificial Intelligence Review, 54(8), 6391-6438.

[data scarcity in heritage contexts]
…. MDDS, MDCS,

Additional Parameters and Data Sources [This will be further developed in the coming stages]
Imaging Techniques
[near-infrared (NIR) imaging for moisture]
[thermal imaging for surface temperature differentials]
[high-resolution vs. low-resolution imagery in detection accuracy]

Environmental and Contextual Data
[integrating climate or groundwater data]
[geographical or hazard-mapping overlays]

[temporal data (time-lapse) for progression of efflorescence]

Reflection

Relation Between Graduation Topic, Studio Topic, Master Track, and Master Programme

My graduation project focuses on using machine learning to detect efflorescence in heritage masonry buildings. This aligns with the overarching theme of the studio, which emphasizes the intersection of digital technologies and sustainable design strategies for the built environment. As part of the Building Technology track in the MSc Architecture, Urbanism, and Building Sciences, this project integrates **material science,** computational methods (**Design Informatics**), and conservation principles (**Heritage Architecture**), reflecting the multidisciplinary nature of the master programme. By combining technical analysis with architectural context, the research addresses both the preservation of cultural heritage and advancements in digital heritage diagnostics.

Relevance in a Larger Social, Professional, and Scientific Framework

Socially, enhancing methods for detecting masonry damage supports the **sustainable conservation** of heritage buildings, thereby preserving cultural identity and **community value**. Professionally, the project contributes to state-of-the-art deeo-learning best practices in damage diagnostics, offering architects, engineers, and conservators new tools for proactive maintenance and renovation. Scientifically, it advances the application of machine learning in structural and materials research, potentially guiding future studies on predictive damage modeling and automated assessments in construction and heritage fields. Additionally the research could help validate statistical lab results in combination with field work studies.