Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Engineering
Department of Civil and Environmental Engineering

Kamila Makuszewska

Image recognition applied to condition assessment of wastewater manholes

Master's thesis in Civil and Environmental Engineering
Supervisor: Rita Maria Ugarelli
June 2019

NTNU
Norwegian University of Science and Technology

Kamila Makuszewska

Image recognition applied to condition assessment of wastewater manholes

Master's thesis in Civil and Environmental Engineering
Supervisor: Rita Maria Ugarelli
June 2019

Norwegian University of Science and Technology
Faculty of Engineering
Department of Civil and Environmental Engineering

NTNU
Kunnskap for en bedre verden

Description

Development of an assessment framework for condition of wastewater manholes. The aim of the research is the classification of manhole failures through the categorization of defects. Innovative contribution of the study is the use of machine learning for visual recognition of the manhole defects. The framework and visual recognition will lead to automatic classification of manholes from manhole images. The master's thesis follows the work performed by the student in her project work.

Objectives:

1. Define and describe the general framework for assessing the condition of wastewater manholes:
    a. Characterization of relevant functions (hydraulic and structural) of manholes.
    b. List the defects with potential to reduce the performance towards the described functions.
    c. Define levels of reduction of performance (e.g. in %) and propose a table combining % of manhole performance reduction with severity of the defects. The severity of the defects could be based on the DANVA standard or described based on experience of water operators.
    d. Propose a scoring system to classify condition of manholes depending on the impact of existing defects on the performance reduction (e.g. 1 defect can produce 10% reduction of hydraulic performance and another 50% of the same function. What will be the final score for the manhole and what does the score mean in terms of rehabilitation need?) – refer to the scoring system for wastewater pipes classification.
2. Visual recognition of manhole classes:
    a. Investigate further the technique used and described in literature for visual recognition of pipe's defects (machine learning approach and software applied).
    b. Select the type of manhole to be "recognized" (the master will use only one type).
    c. Select defects easy to recognize in images and with potential for easy categorization of levels of severity, reflecting the severity define at task *c* and *d* of the framework described above.
    d. Train the visual recognition software to recognize the severity level of the defects and therefore to provide, if possible, the corresponding level of reduction of the performance. After the training, it would be interesting to test the software with a manhole image including more than one defect used for the training, with different levels of severity to test the ability to recognize them and give a final score for the manhole.

Abstract

Manholes are important components of the sewer system. They provide access to the wastewater pipes for inspection and maintenance, accommodate all geometrical changes in the system and ensure convenient layout of the pipelines. However, compared to wastewater pipes, their assessment is receiving little attention in Norway. Several countries have already developed monitoring guidelines to ensure well-functioning manholes. Water agencies in USA and Denmark have developed manhole reports describing the execution of manhole inspection and condition assessment. Similar approach for standardization of manhole inspection and assessment is necessary in Norway. Inspection of manholes has not been prioritized and the information concerning the condition of manholes is often available in form of images. The inspection of manholes is often performed visually from the ground or by going inside the manhole. Therefore, it is time demanding and expensive. As a result, an optimization of this procedure is necessary. This could be achieved as the available databases of manhole images represent a good basis for the implementation of image recognition software. These images can be used to train the software to recognize different manhole defects and their severity. Utilization of image recognition software out in the field could be very helpful for the Norwegian water utilities.

One of the objectives of this master's thesis was to develop a framework for the Norwegian manhole condition assessment report. The proposed content will be structured in a way that ensures proper collection and analysis of the desired data concerning wastewater manholes. DANVA manhole manual «Brøndmanualen – Inspektion og registrering af brønde», CARE-S report D3 «WP2 – Structural condition. Classification systems based on visual inspection" and Norsk Vann report 235:2018 «Dataflyt – Klassifisering av avløpsledninger» were used as the basis for both inspection guidelines and the classification of manhole condition. The presented manhole condition assessment report was based on the principles of Infrastructure Asset Management as it will optimize prioritization of future work regarding the improvement of current manhole condition. Development of a such report will provide Norwegian water utilities with several benefits. Some of them include objective assessment of manhole condition, equal execution of the inspection and improved decision-making regarding the maintenance, rehabilitation and replacement of manholes.

The second objective of the work presented in this thesis was to train Custom Vision model on a set of manhole images showing settled deposits. The goal of the training was to acquire a model that can recognize different defect grades of settled deposits. Custom Vision is an image recognition application provided by Microsoft. It was trained on a set of 344 images and tested with 12 images. The performed classification was a supervised classification, where the areas showing settled deposits were marked and tagged manually prior to the training of the model. The areas were tagged into one of four categories representing the defect grades. After completed training, the trained model was tested. Testing images were not a part of the training set and were uploaded to the model in order to get predictions. The model was able to predict correctly 38 of 39 settled deposits areas within the testing images with varying certainty. However, these results could be improved with increased image count during training, enhanced image manipulation, tagging of additional elements present in the images or labelling of all images.

Sammendrag

Kummer er viktige komponenter i avløpssystemet. De gir tilgang til inspeksjon og vedlikehold av avløpsrør, imøtekommer alle geometriske endinger i systemet, og sørger for en praktisk utforming av ledningene. Sammenlignet med evalueringen av avløpsrør, får tilstandsvurderingen av kummer lite oppmerksomhet i Norge. Flere land har allerede utviklet retningslinjer som omhandler overvåkning av kumtilstanden for å sikre velfungerende kummer i deres systemer. Vann- og avløpsetater i USA og Danmark har publisert kumrapporter som beskriver gjennomføringen av inspeksjoner og tilstandsvurderinger av kummer. En lignende tilnærming til standardiseringen av disse prosedyrene er nødvendig i Norge. Kuminspeksjonene har ikke blitt prioritert de siste årene, og informasjonen om deres tilstand er ofte tilgjengelig i form av bilder. Ettersom inspeksjonen av kummer ofte blir utført visuelt fra bakken eller ved å gå ned i kummen, er gjennomføringen av denne prosedyren både tidskrevende og kostbar. En optimalisering er dermed nødvendig. Databasene med kumbildene representerer et godt grunnlag for implementering av bildegjenkjenningsprogramvarer. Disse bildene kan brukes til å trene slik programvare til å gjenkjenne forskjellige feil og deres alvorlighetsgrader. Utnyttelse av bildegjenkjenning for automatisk gjenkjenning av kumfeil kan være svært nyttig for norske vann- og avløpsetater.

Ett av målene for denne masteroppgaven var å utvikle et rammeverk for en Norsk tilstandsvurderingsrapport for kummer. Den foreslåtte rapporten vil bli strukturert på en måte som sikrer riktig innsamling og analyse av ønsket data om avløpskummer. DANVA kumrapport «Brøndmanualen – Inspektion og registrering af brønde», CARE-S rapport D3 «WP2 – Structural condition. Classification systems based on visual inspection" og Norsk Vann rapport 235:2018 «Dataflyt – Klassifisering av avløpsledninger» ble brukt som grunnlag for både inspeksjonsretningslinjer og klassifiseringen av kumtilstanden. Den presenterte prosedyren for tilstandsvurderingen av kummer ble basert på prinsippene for kapitalforvaltningen av infrastruktur (IAM – Infrastructure Asset Management), da den vil optimalisere prioriteringen av fremtidig arbeid med forbedring av nåværende kumtilstand. Utvikling av en slik rapport vil resultere i flere fordeler for norske kommuner. Noen av dem inkluderer en objektiv vurdering av kumtilstand, lik utførelse av inspeksjoner og en forbedret beslutningsprosess angående vedlikehold, rehabilitering og utskifting av kummer.

Det andre målet for masteroppgaven, var å trene Custom Vision-modellen med et sett av bilder som viser ulike typer av avsetning i avløpskummer. Målet med denne opplæringen var å erverve en modell som kan gjenkjenne ulike alvorlighetsgrader av avsetning i kummer. Custom Vision er en bildegjenkjenningsapplikasjon fra Microsoft. Den ble trent med et sett på 344 bilder og testet med 12 bilder. Klassifiseringen utført i denne masteroppgaven var en overvåket klassifisering, der områdene som viste avsetningen ble merket og tagget manuelt før treningen av modellen. Hvert område ble tagget i en av fire mulige kategorier som representerte alvorlighetsgradene. Modellen ble testet etter fullført trening med et bildesett som ikke var en del av bildesettet brukt for treningen av modellen. Disse bildene ble lastet opp til modellen for å få prediksjoner. Modellen var i stand til å forutsi riktig 38 av 39 områder med avsetning vist på bildene. Sikkerheten av disse prediksjonene var varierende. Dette resultatet kan forbedres med økt bildeopptelling, bildemanipulering, merking av ytterligere elementer som er tilstede i bildene eller forbedret merking av bilder brukt til treningen av modellen.

Preface

This master's thesis and its research is the final product of the course TVM4905 Water Supply and Wastewater Systems, Master's Thesis. It has been conducted at the Norwegian University of Science and Technology (NTNU) in Trondheim, during spring 2019. It equals 30 ECTS and is the end of the two-years master's degree program of Civil and Environmental Engineering, with the course specialization Water and Wastewater Engineering.

First and foremost, I would like to express my gratitude to my supervisor Rita Maria Ugarelli who has given me feedback and advices. Thank you for inspiration and guidance during the writing process, as well as great support throughout the whole last year.

I would also like to thank my other supervisors, Sveinung Sægrov and Jon Røstum. Thank you for the help you provided throughout both specialization project and this thesis.

I would also like to thank:

- Water Utility of Trondheim for allowing me to use their database with manhole images for the training and testing of image recognition software.
- My family and friends for their support during the whole study path.

Trondheim, 11th of June 2019

Kamila Makuszewska

Kamila Makuszewska

Table of contents

List of figures .... **XV**

List of tables .... **XVI**

List of equations .... **XVI**

List of abbreviations .... **XVII**

1.0 Introduction **1**

1.1 Thesis structure *5*

2.0 Infrastructure Asset Management **6**

3.0 Reliability **9**

4.0 Wastewater manhole design and functional requirements **11**

4.1 Definition of a wastewater manhole *11*

4.2 Structural and operational requirements for wastewater manholes *12*

4.3 Hydraulic design of wastewater manholes *13*

4.3.1 Hydraulic reliability of wastewater manholes 14

4.4 Wastewater manhole defects *15*

5.0 Method for classification of manholes **21**

6.0 Proposed manhole condition assessment report **24**

6.1 Structure of the proposed manhole report *24*

6.2 Assessment of the hydraulic reliability of wastewater manholes *28*

6.2.1 Defects with potential to affect the hydraulic reliability 28

6.2.2 Grading of the hydraulic defects 30

6.2.3 Weighting values for hydraulic defects 34

6.2.4 Hydraulic condition classes with corresponding total score thresholds 36

6.2.5 Registration scheme 37

7.0 Discussion of the proposed manhole condition assessment report and recommendations for future research **41**

7.1 Suggestions for future work *43*

7.2 Position of this work with regards to other national initiatives *45*

8.0 Artificial Intelligence, Machine Learning and Deep Learning **46**

8.1 Microsoft Azure Cognitive Services and Custom Vision *48*

9.0 Training and testing process of the Custom Vision model **51**

9.1 Case: The municipality of Trondheim *52*

10.0 Custom Vision results **53**

11.0 Discussion of the Custom Vision performance 56

12.0 Conclusion 59

13.0 References... 61

Appendix... 65

List of figures

Figure 1: Flow chart of the proposed condition assessment of wastewater manholes. 3
Figure 2: Principle sketch of a PDCA-loop (Rokstad, 2018). 7
Figure 3: Sketch of a wastewater manhole. The illustration is adjusted from DANVA manhole manual (DANVA, 2010). 11
Figure 4: Important factors for proper hydraulic design of a wastewater manhole. The illustration is adjusted from Norsk Vann report 172:2009 "Trykktak i avløpsnett", 2009. 14
Figure 5: Flow chart summarizing the proposed manhole condition assessment. 26
Figure 6: Hydraulic condition class H1 paired with different structural condition classes resulting in different types of desirable preventive actions. 27
Figure 7: Hydraulic condition class H5 paired together with different structural condition classes resulting in different types of desirable preventive actions. 27
Figure 8: Possible locations of defects observed in a manhole labeled by numbers. The illustration is adjusted from DANVA manhole manual (DANVA, 2010). 37
Figure 9: Clockface references for circumferential location of manhole defects (DANVA, 2010). 38
Figure 10: Flow chart for development of an official condition assessment report for Norwegian wastewater manholes. 41
Figure 11: Representation of relationship between Artificial Intelligence, Machine Learning and Deep Learning (Salvaris, et al., 2018). 47
Figure 12: Custom Vision main page (www.customvision.ai). 48
Figure 13: Training image tagged into category "HSD over 90%" and "HSD 0-10%". 53
Figure 14: Overall performance of the trained Custom Vision model. 53
Figure 15: Distribution of areas with prediction above probability threshold of 50%. 55
Figure 16: Flow chart of the development of an application that can inspect and assess the condition of manholes. 56
Figure 17: One of the manhole images used for testing. Predictions above the probability threshold of 0% are shown on the image to the left, while predictions above probability threshold of 40% are shown in the image to the right. 57

List of tables

Table 1: Overview of the three planning levels in Infrastructure Asset Management for water and wastewater systems (Ugarelli, 2018).. 7
Table 2: Hydraulic and structural defects observed in wastewater manholes. 15
Table 3: Hydraulic and structural manhole defects with corresponding failure modes. ...19
Table 4: Weighting values utilized for defects observed during CCTV-inspections of Norwegian wastewater pipes. Translated from "Dataflyt – Klassifisering av avløpsledninger", 2018. 22
Table 5: Weighting values utilized for defects observed during CCTV-inspections of Danish wastewater pipes. Translated from "Fotomanualen – beregning af fysisk indeks ved TV-inspektion", 2005. 23
Table 6: Example of categorization and coding of manhole defects in category "Structural condition". The table is adjusted from "Implementing Asset Management and Inspection Procedures to Wastewater Manholes", 2017. 25
Table 7: Grading of defect "Fissure/rapture" with corresponding description of each grade (DANVA, 2010). 25
Table 8: Weighting values for defects "Fissure/rupture" and "Surface damage" observed in wastewater pipes (Haugen, 2018). 25
Table 9: Condition classes for wastewater pipes presented in Norsk Vann report 235:2018 (Haugen, 2018). 26
Table 10: Description of the defects from defect category "Hydraulics" with corresponding defect codes and types. 28
Table 11: Grades of hydraulic defects with corresponding description of each grade. 31
Table 12: Weighting values for hydraulic defect grades...35
Table 13: Hydraulic condition classes with corresponding total score thresholds. 37
Table 14: Definitions of the locations labeled by numbers. 38
Table 15: Registration scheme. 39
Table 16: Available domains for image classification and object detection classifiers accessible in Custom Vision (Microsoft Azure, 2018)..49
Table 17: Performance per category. 54
Table 18: Summary of all predictions with corresponding probability ranges. 54

List of equations

Equation 1: Reliability function (Ugarelli, 2018). 9
Equation 2: Proposed calculation of the total score. 36

List of abbreviations

AI – Artificial Intelligence
AM – Asset Management
API – Application Programming Interface
AWARE-P – Advanced Water Asset Rehabilitation in Portugal
CARE-S – Computer Aided Rehabilitation of Sewer networks
CCTV – Close Circuit Television
DANVA – Danish Water and Wastewater Association
DNN – Deep Neutral Network
IAM – Infrastructure Asset Management
IEC – International Electrotechnical Commission
LTP – Long-Term Planning
mAP – Mean Average Precision
ML – Machine Learning
NORVAR – Norwegian Water and Wastewater Association
PDCA – Plan, Do, Check, Act

1.0 Introduction

Main pipelines, lateral lines and manholes are all integral components of the wastewater system. As all components are deteriorating continuously, proper operation and maintenance are very important in order to provide sufficient levels of service (Ugarelli, 2018). Pipelines represent the largest part of the network and most critical failures normally occur in the pipes (Malvik, 2017). Therefore, the condition monitoring and assessment of pipes has been prioritized in the recent years. In Norway, several reports concerning the evaluation of wastewater pipes were developed and are extensively utilized. However, none of them include guidelines regarding the assessment of manholes. Development of a manhole condition assessment report should be a priority in order to ensure satisfactory condition and performance of these assets. This will also contribute to an improved performance of the whole sewer system.

Manholes are important components of the sewer network as they provide access to the pipes for inspection and maintenance. In addition, they ensure convenient layout of the pipelines and accommodate all geometrical changes in the system (DANVA, 2010). Norwegian sewer system consists of a large number of manholes, where the municipality of Oslo alone owns nearly 10 000 wastewater manholes (Makuszewska, 2018). Despite the essential function and amount, the assessment of manholes has been neglected as both inspection and evaluation of manholes are not normally performed. In most of the Norwegian municipalities, the inspection and rehabilitation of manholes are often done in connection with projects concerning pipes (Malvik, 2017). Only the nearby manholes, that are a part of the pipeline evaluated, are assessed. The lack of proper maintenance has resulted in an increased number of deteriorated manholes where more frequent collapses, blockages, basement backups and overflows may become a major concern. Just as any other component of the wastewater system, manholes require regular and effective maintenance. Continuous monitoring and conservation of the condition of manholes will save money for the water utilities in a long-term time perspective as it will identify urgent repairs before total replacements become a necessity (Federtion of Canadian Municipalities and National Research Council, 2002). In addition, regular maintenance will extend the expected life of these assets, ensure optimal performance and maintain their reliability at the demanded level. Systematic monitoring of the deterioration will also result in records of deterioration that can help utilities to prioritize interventions, plan future rehabilitation and maintenance, and organize budget for the repairs. Additionally, systematic monitoring will provide input to risk analyses and facilitate asset management programs (Federtion of Canadian Municipalities and National Research Council, 2002). Such planning and actions are essential as manholes represent a large number of assets within a wastewater system.

As the evaluation and maintenance of pipes is continuously being improved, it is important to develop proper procedures for the condition assessment of manholes. These assets are susceptible to the similar forms of deterioration as pipes, thus effective manhole inspection and maintenance plans are necessary to improve their structural integrity. Manholes should be assessed and maintained in a way that guarantees the best management of these assets throughout their entire life-cycle. Reasonable management of manholes will require a systematic approach that ensures maintenance of their reliability and condition under reasonable budget (Ugarelli, 2018). Therefore, the condition assessment of manholes should be based on proper Infrastructure Asset

Management (IAM). As the sewer network does not solely consist of pipes, water utilities should start proper collection of manhole condition data. Further analysis of the data will then represent a good basis for proper maintenance and rehabilitation plans for manholes (Ugarelli, 2018). Future maintenance and rehabilitation needs might be high since the assessment of manholes has not been performed to a large extent in Norway. Therefore, a balance between cost, risk and desired level of service will be important. To ensure proper prioritization of manhole projects, the evaluation process should include a risk assessment. However, as the implementation of IAM is based on the data obtained during inspection and further evaluation, the whole process of developing a manhole condition assessment report starts at the proper description of how condition monitoring and assessment should be performed. This will be the main objective of the proposed manhole condition assessment report, with the primary focus on the hydraulic reliability of wastewater manholes.

Condition monitoring and assessment are essential elements of IAM. As there is not enough of manhole condition data available in Norway today, proper condition monitoring will be important. The data can be collected by conducting a visual inspection from the ground, by going inside the manhole, or by camera during close circuit television (CCTV) inspection of wastewater pipes. The execution of the inspection should be standardized in order to ensure proper collection of all desired information. The inspector will then know what to look for during an inspection, how the observations should be interpreted and thereafter registered. Therefore, all defects that can be observed in a manhole should be categorized according to manhole functions, described and coded. As for pipes, all defects present in the assessed manhole should also be graded according to their severity (Bernhus, et al., 2007). In addition, the inspected manhole must be photographed, and the resulting image must be included in the documentation. The picture should be of a good quality and reflect accurately the current state of the manhole condition. After the collection and registration of needed data, assessment of the manhole condition should be performed.

A proposal for the content and structure of a theoretical manhole condition assessment report will be presented in this master's thesis. The proposed method is a reliability-based condition assessment of manholes, meaning that the possible condition classes are defined according to the effect or the impact of the possible defects on to the functional requirements of manholes. This allows for a transparent decision-making considering the method of rehabilitation or maintenance based on the nature of the worst type of the condition class. The goal of the presented manhole report is to guide to data collection supporting a proper condition monitoring and assessment of wastewater manholes. The rationale behind the followed methodology consists in categorizing and weighting of the defects based on their effects on the expected functional requirements of manholes. Specifically, the main focus of the proposed report is the effect on the hydraulic functions of the wastewater manholes. Therefore, a hydraulic reliability approach will be followed. The defects will be selected, described and graded based on the available theory for manhole hydraulics. These defects will be a part of the defect category labeled "Hydraulics". In addition, the proposed manhole condition assessment report will contain weighting values for all defect grades and present a way to calculate the total score for the inspected manholes. The score is designed to reflect the current hydraulic condition state of the inspected manhole. Based on the calculated score the manholes will be assigned into hydraulic condition classes. Future research should focus on defects that have an impact on the structural functions of manholes. These defects will then be a part of a new defect category, which for now will be labelled "Structural condition". All defects should be described, graded and weighted in a similar way as defects in category "Hydraulics". This will lead to new group of total score thresholds which will reflect the structural condition of a manhole construction and will consequently assign manholes into structural condition classes. The presented manhole report also proposes how to assess both hydraulic and structural condition classes together in order to achieve a complete assessment of the inspected manholes. Assignment of manholes into condition classes according to the critical functions will make the understanding of the calculated score much clearer. Additionally, different types of intervention actions should be implemented depending on the nature of the function affected by either hydraulic or structural defects. Therefore, a structure of the manhole report where manholes are assigned to functional condition classes will contribute to easier decision-making regarding the implementation of preventive measures. The person performing the assessment will know better whether the improvement of the manhole condition requires an operational intervention such as flushing, a structural intervention such as reconstruction of manhole components, or a combination of both. A flow chart of the proposed reliability-based condition assessment procedure is presented in Figure 1.

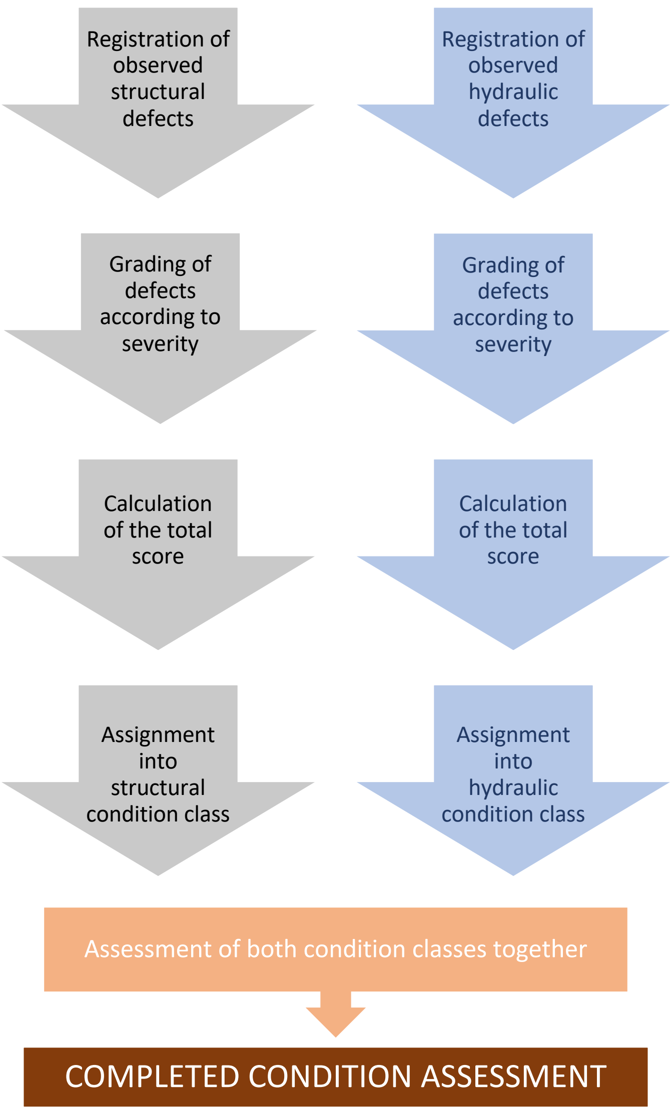


Figure 1: Flow chart of the proposed condition assessment of wastewater manholes.

The development of a manhole report will ensure that the Norwegian municipalities dedicate more focus to the manholes. As the inspection and assessment of manholes have not been performed extensively before, a significant number of manholes needs to be inspected. The visual inspection is both time demanding and expensive. Therefore, an optimization of this procedure is necessary. Majority of Norwegian water utilities have significant databases containing images of manholes. These images represent a good basis for the implementation of image recognition software. Recently, similar methodology has been implemented on CCTV footage from inspections of wastewater pipes. It has shown to be efficient in detecting sewer faults in a range of sewer shapes and construction materials (Myrans, et al., 2018). Similar results can be achieved for manholes as the image recognition software could be trained to recognize different manhole defects and their severity.

An attempt of implementation of a such software on manhole images will be presented in this thesis. Custom Vision application provided by Microsoft will be used as the image recognition software. Images showing manholes with "Settled deposits" defect from category "Hydraulics" will be utilized for the training of the software to recognize different grades of this defect. After completed training, the software will be tested with a new set of manhole images. The trial presented here was successful, as the software managed to predict correctly the majority of testing images. Therefore, it is encouraged to continue the training of the software to recognize other manhole defects. Currently, the Custom Vision software is not able to calculate the total score of the photographed manholes and assign them into hydraulic condition classes. Digitalization of the assessment procedure will require development of an additional software, which is also encouraged as the results from this trail were satisfactory. An application that combines image recognition and a digitalized assessment will optimize and simplify both manual inspection and assessment of manhole condition out in the field.

The presented work is pioneer in the field of Norwegian wastewater systems as both condition assessment of manholes and use of image recognition on manhole images are fairly new concepts. However, it represents only the beginning of the development process of an official manhole report. The proposed framework of the manhole report needs to be verified and adjusted as the weighting values proposed here should be based on a sensitivity analysis. This will lead to further adjustments of the proposed total score thresholds for hydraulic condition classes. In addition, the list of defects should be expanded with defect categories concerning other functions of manholes, such as the structural condition. The total assessment of all condition classes together will also require adjustments depending on how many defect categories the defects will be divided into. As for the image recognition of the manhole defects, the software will require to be trained with pictures representing other defects with corresponding grades. In order to digitalize the whole assessment, the calculation of the total scores and corresponding assignment of manholes into condition classes will require a development of a new software that can cooperate with the image recognition software. Hopefully, at the end of this process the personnel of the Norwegian water utilities can be equipped with an app that can be utilized out in the field. This will make the both inspection and assessment of manholes more objective, less time demanding and thus more affordable.

1.1 Thesis structure

The content covering the objectives of this master's thesis will be presented in two parts according to theme. The first part will review the content considering the first objective which is the development of a manhole condition assessment report. This part is presented through 5 chapters, starting with *Chapter 2: Infrastructure Asset Management* and ending with *Chapter 7: Discussion of the proposed manhole condition assessment report and recommendations for future research*. Chapter 2-4 present the necessary background theory, Chapter 5 presents the followed method, Chapter 6 presents the obtained results, while Chapter 7 presents the discussion of the presented results.

The second part will review the content considering the second objective which is the implementation of the image recognition software on manhole images. This part is presented through 4 chapters, starting with *Chapter 8: Artificial Intelligence, Machine Learning and Deep Learning* and ending with *Chapter 11: Discussion of the Custom Vision performance*. Chapter 8 presents the necessary background theory, Chapter 9 presents the followed method, Chapter 10 presents the obtained results, while Chapter 11 presents the discussion of the presented results.

The thesis was structured in the following way in order to focus the reader at one distinguished theme at a time. This will ensure an easier understanding of the presented content, as well as simplified navigation among the chapters.

2.0 Infrastructure Asset Management

Infrastructure Asset Management (IAM) is a discipline that develops, improves and provides guidelines for a systematic approach concerning the management of infrastructure assets (Too & Tay, 2008). There are several definitions of IAM in use today. According to the publication "Implementing Asset Management: A Practical Guide", IAM is: "An integrated set of processes to minimize the life-cycle costs of infrastructure assets, at an acceptable level of risk, while continuously delivering established levels of service." (AMWA, NACWA and WEF, 2007). The methodology supports the realization of assets' value while balancing social, financial and environmental costs, risk, service quality and assets' performance (International Organization for Standardization, 2014). The overall goal of IAM is to optimize the utility of the asset over its life-cycle by intervening at the right time (Ugarelli, 2018). This can be done by direct repairs, preventive maintenance and rehabilitation of the asset within reasonable budget. The prioritization of assets is based on the quantification and assessment of risk produced by the failure or incapability of infrastructure assets to provide their intended functions or demanded levels of service (AMWA, NACWA and WEF, 2007). The risk is assessed based on the probability and consequence levels of risk scenarios that are related to the asset. Probability represents the possibility of asset failure, while the consequence is the resulting impact on established levels of service. Management of infrastructure assets based on the guidelines provided by IAM could result in improved satisfaction of the costumers, enhanced governance and accountability, managed risk, improved efficiency, effectiveness and sustainability (International Organization for Standardization, 2014).

The framework of Asset Management (AM) distinguish between the methodology and tools (Alegre & Coelho, 2012). The methodology of AM for water and wastewater infrastructure is an integrated approach that is a result of study performed during AWARE-P project, which stands for Advanced Water Asset Rehabilitation in Portugal (Alegre, et al., 2012). AWARE-P methodology approaches IAM as management process that must be adopted at three defined decisional levels (AWARE-P, 2011). The long-term direction of the water utility is defined at the strategic level. This level is driven by the corporate, long-term views and concerns the whole system at a macro scale (Alegre & Coelho, 2012). It results in several strategies aiming at the accomplishment of the defined direction. The next step of planning is performed at the tactical level. The purpose of this level is to define the path in the medium-term and establishment of priorities for possible interventions and solutions (Ugarelli, 2018). The planning at this level is implemented on subsystems and results in tactics. The operational level is the last planning level where short-term actions, such as operational plans, are planned and implemented (Alegre & Coelho, 2012). These actions are implemented on groups of components on a detailed scale in order to follow the previously defined path (Ugarelli, 2018). An overview of the planning levels utilized in the IAM methodology for water and wastewater infrastructure is presented in Table 1. In addition to the decisional levels, the methodology requires cooperation between the competence of business management, engineering and information (Alegre & Coelho, 2012).

Table 1: Overview of the three planning levels in Infrastructure Asset Management for water and wastewater systems (Ugarelli, 2018).

Levels	Strategic	Tactical	Operational
Scale	Macro	Medium	Detail
Scope	Global system	Trunk system / subsystems	Groups of components
Type of action	Define directions	Define path	Implement action
Responsible	Asset owner (or administrator)	Asset manager	Head of operations
Results	Strategies	Tactics	Operational plans
Time horizon	Long term (10-20 years)	Medium term (3-5 years)	Short term (1-3 moths)

The AWARE-P approach to IAM planning procedure is based on Plan-Do-Check-Act (PDCA) principles (AWARE-P, 2011). Therefore, a PDCA-loop is performed at each decisional level. The principle of this cycle is illustrated in Figure 2. The implementation of PDCA-cycle throughout the decisional levels is aiming at the continuous enhancement of the IAM process (Alegre & Coelho, 2012). During the PDCA-cycle the objectives, assessment criteria, planning and analysis of time horizon, scenarios, metrics and several other factors are defined in order to ensure proper planning procedure at each level (Ugarelli, 2018).

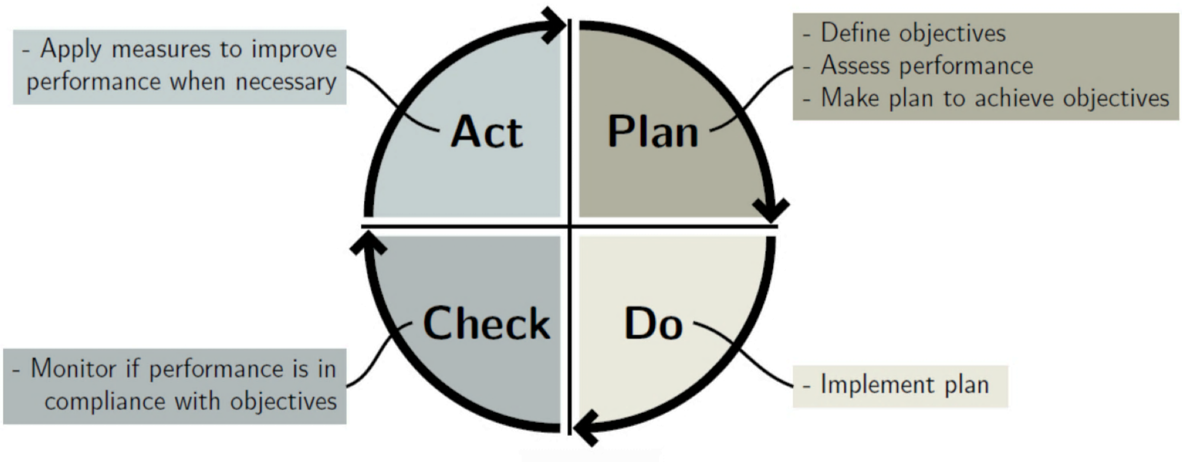


Figure 2: Principle sketch of a PDCA-loop (Rokstad, 2018).

Condition monitoring and assessment are essential elements of Infrastructure Asset Management. Proper execution of condition monitoring and assessment will provide a large volume of information related to the condition and performance of the asset (Ugarelli, 2018). The purpose of the condition monitoring is to identify changes in the assets' condition through systematic collection of data, while the goal of condition assessment is to establish the performance of the asset based on the detected conditions (Ugarelli, 2018). During this process the collected data is evaluated. The data obtained from both processes represents the basis for proper implementation of IAM (AMWA, NACWA and WEF, 2007).

IAM tools include several types of models that are utilized in order to optimize the planning process and ensure the best possible decision-making. Condition-based deterioration models are used to predict the future condition and performance of the investigated assets (Ugarelli, 2018). They aim at planning of the preventive measures in a cost-effective manner to preserve the reliability of the asset. Markovian models are some of the models that are used to predict the future conditions. Assets are divided into classes according to their current condition state and the models will predict the probability of the transition to a worst class (Ugarelli, 2018). The transition is a function of numerous influences such as structural condition, construction material and quality, and environmental factors that affect the deterioration rate (Ugarelli, 2018). The model has to be provided with the information about condition classes of different age, together with variables that influence the condition of today's classes and the deterioration speed (Ugarelli, 2018).

Cohort survival models are used for Long-Term Planning (LTP) of strategic rehabilitation of urban water and wastewater systems. These models are utilized at the strategic level since the model is applied at the network level and not a single pipe (Bruaset, 2018). The assets are divided into groups or cohorts according the material, construction year and norm, and failure rates (Bruaset, 2018). These models are based on the Herz function which allows for prediction and comparison of the network behavior in the long-term time horizon. This behavior is provided in terms of the life expectancy and the predicted failure rate for each cohort of assets (Bruaset, 2018).

3.0 Reliability

Reliability is a characteristic of an asset or item (Birolini, 2007). It is expressed by the probability that an asset or an item will perform its intended functions for a specific period of time under given operational and environmental conditions (Gulati & Smith, 2009). Reliability is generally designated by R and can be determined and quantified through the use of several formulae depending on the type of function under analysis. From a qualitative point of view, the term can be defined as “the ability of the asset or item to remain functional” (Birolini, 2007). Quantitatively, reliability expresses the probability that no operational interruptions of the selected function will occur during a stated time interval under specified operational conditions (Birolini, 2007).

To be able to analyze reliability of an asset, the concept of reliability has to be accompanied by the definition of the required function, failure, failure mode and operating environment. Additionally, it is also essential to know whether the asset is considered to be new at the start of the mission time (Birolini, 2007).

International Electrotechnical Commission (IEC) defines the term “Required function” as “a function or a combination of functions of an item which is considered necessary to perform a given service” (International Electrotechnical Commission, 1990). The specified functions are often stated with corresponding functional requirements. For example, the essential function of a water pump is simply to pump water. However, corresponding functional requirement related to this function might be the specification of the water output as for instance an interval of 100-110 liters of water per minute. The definition of all functions related to an item with associated functional requirements is the starting point of any reliability analysis as it is the basis for future identification of potential failures and failure modes (Ugarelli, 2018).

The complementary way of studying reliability in probabilistic terms is to analyze it as probability of an asset to fail as presented in Equation 1 (Ugarelli, 2018). If an asset is 90% reliable for a given function/functional requirement, it means that it has a 10% probability of failure. In that case, one will be assessing the probability of an asset to fail.

Equation 1: Reliability function (Ugarelli, 2018).

$$\boldsymbol{R(t) = 1 - F(t) = \int_t^{\infty} f(u)\, du}$$

where

$\mathrm{R(t)}$ = the probability that the item will survive at least to time t

According to IEC 60050-191:1990, a failure is defined as “the termination of the ability of an item to perform a required function” (International Electrotechnical Commission, 1990). In other words, a failure is simply a nonfulfillment of a functional requirement (Ugarelli, 2018). Considering the water pump described earlier, a failure will be observed if the output of water is outside the specified interval of 100-110 liters of water per minute.

Failures can occur suddenly or gradually, at varying frequencies (Birolini, 2007). In addition, their duration may be intermittent or extended (Ugarelli, 2018). The time without occurrence of any failures, also called failure-free time, can be reasonably long or relatively short thus it is generally a random variable. Besides the failure frequency, it is also important to classify failures according to the mode, cause, effect and mechanism (Birolini, 2007). A failure mode is the effect or symptom by which a failure is observed on a failed item (Ugarelli, 2018). Possible failure mode of the previously mentioned water pump can be the leakage out of the pump. The occurrence of the failure may be caused by weaknesses of the item, wear out, or mishandling during the design, manufacturing or use (Birolini, 2007). The consequences of a failure can be of different levels of criticality. The failures may be classified as not relevant, partial, complete or critical. In addition, they can be classified as primary and secondary depending on their ability to cause further failures. Lastly, the classification according to the failure mechanism distinguish between physical, chemical or other processes that can result in a failure (Birolini, 2007).

Every item is designed with a certain level of reliability (Gulati & Smith, 2009). This reliability is defined as inherent reliability and is the maximum level of reliability that can be achieved by an asset. Only replacements or redesigning can change or improve the inherent reliability of an asset after installation (Gulati & Smith, 2009). However, it can be preserved at a certain level by establishment of proper maintenance plans. Such plans should include required maintenance and descriptions of additional actions needed to identify potential failures before they cause unprepared interruptions or shutdowns (Birolini, 2007).

Operating environment also has a significant impact on the reliability as it reflects the conditions that the item has to operate under and how it is used (Birolini, 2007). In addition, the capability of the operators and maintenance technicians has also to be taken under account when considering operating environment. The main reason for this is the fact that poorly trained operators and maintenance crew will eventually lead to less reliable assets (Gulati & Smith, 2009).

Analysis of the reliability of a single asset does not take into account the redundancy of the system the asset belongs to (Ugarelli, 2018). Hence, a failed single asset can be stated to be not reliable. However, if the asset under analysis is a part of a system then the reliability or function expected by the system has to be defined first. In such case, an asset can be a water pipe that is a part of a network, which is an example of a system. The expected function of such system can be supplying water demand at every hour in all operational conditions. This network/system is created by interconnected assets with their own functions and reliability. Here, the inherent reliability is the result of individual components' reliability, the way they are designed and how they interact with each other (Gulati & Smith, 2009). Therefore, if the network is redundant it can still be reliable as a system even if some of the assets fail. These parts can be repaired but without operational interruptions at the system level (Birolini, 2007).

4.0 Wastewater manhole design and functional requirements

4.1 Definition of a wastewater manhole

A manhole is an access point to an underground utility network, here wastewater system. They consist of pipes or half-pipes that go in and out of the manhole. The pipes inside the manhole may have additional equipment such as flowmeters. The main purpose of a manhole is to provide access to pipes and equipment inside the manhole (Buttler & Davies, 2011).

Wastewater manholes are used to carry out inspections, cleaning and removal of obstructions in the sewer line. In addition, they serve for maintenance and rehabilitation of sewers, aeration and deaeration of flow and as emergency overflow during clogging, uncontrolled flooding or flood seasons (Hager, 1999). Manholes are provided at changes in pipe direction, changes in pipe size, heads of runs, changes in gradient, points where pipes meet and where additional equipment is necessary (Buttler & Davies, 2011). Figure 3 shows a sketch of a wastewater manhole together with the tags of different parts (DANVA, 2010).

Manholes facilitate the laying of pipelines in convenient lengths throughout the system (Buttler & Davies, 2011). They are installed at regular intervals depending on the diameter of the pipes and the requirements set by the municipality owning the system. In Larvik, the highest allowed distance between two wastewater manholes equals 70 meters for pipes with diameters lower than 200 millimeters, and 100 meters for pipes with diameters higher than 200 millimeters (Larvik kommune, 2018).

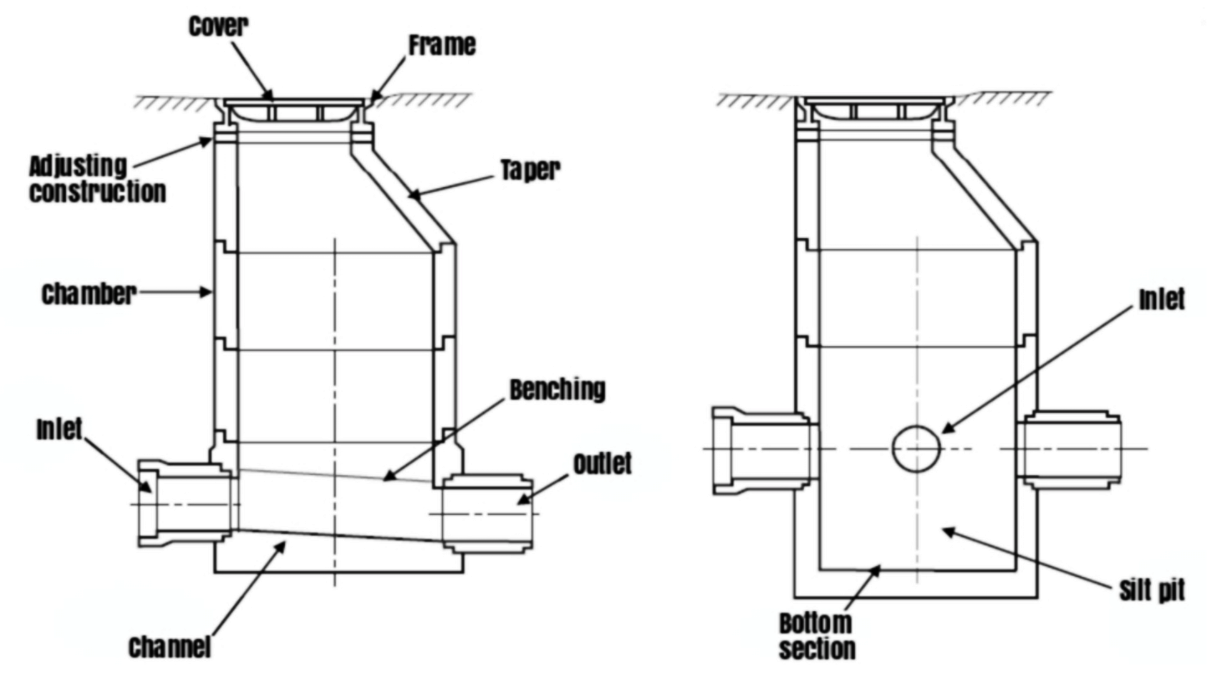


Figure 3: Sketch of a wastewater manhole. The illustration is adjusted from DANVA manhole manual (DANVA, 2010).

Manholes are often divided in three categories; shallow, normal and deep (Buttler & Davies, 2011). The type of applied manhole depends on the location and depth of the pipeline, the size of the pipeline, and the function that it is supposed to provide. Access to manholes is limited to authorized workers with training and necessary safety equipment to prevent accidents due to falls, and exposure to harmful gases like methane and hydrogen sulfide. Manholes are secured by manhole covers which prevent people, objects and debris from entering the system.

4.2 Structural and operational requirements for wastewater manholes

Wastewater manholes have to provide several functions according to the current Norwegian requirements. One of these is the structural function which requires that a manhole is able to carry the loads it is subjected to (Stiftelsen VA/Miljø-blad, 2018). Therefore, a manhole structure must have a sufficient structural reliability, which is here defined as the ability of sewer manhole components to provide continuing and long-term operation without the need for frequent repairs, modifications or replacements. Structural reliability of a manhole may also be defined as the probability that the component performs its expected function of carrying loads and experiences no structural failures for a given period of time in specified environment (Ugarelli, 2018). Hence, manholes must have sufficient strength in order to withstand and absorb both internal and external loads (Keseler, et al., 2018). In addition, their strength should not decrease with time (Loe Rørprodukter AS, 2017). They should also prevent leakage of stormwater and sewage, and infiltration of groundwater as these water movements may disturb the soil that supports the structure (Keseler, et al., 2018). In order to achieve that, the elements of a manhole structure are required to have sufficient material density. Furthermore, manholes should have resistance to mechanical wear as well as chemical and thermal influences from both inside and outside of the construction (Loe Rørprodukter AS, 2017). The expected life time of a wastewater manhole construction is 100 years (Mosevoll, 2008).

Proper hydraulic design of wastewater manholes is also required and essential for proper functionality (Stiftelsen VA/Miljø-blad, 2018). The description of an optimal hydraulic design will be provided in the following section together with a definition of hydraulic reliability and hydraulic failure. However, the wastewater manholes must have an appropriate roughness and flow capacity, as well as a self-cleansing ability (Keseler, et al., 2018).

Inside a wastewater manhole, it should be possible to perform maintenance work, take necessary flow measurements and samples, and use equipment for pipe inspection and flushing (Loe Rørprodukter AS, 2017). Additionally, wastewater manholes have to ensure safe working environment for the operational workers of water utilities (Mosevoll, 2008). Based on the previously described requirements, the operational reliability is here defined as the ability of sewer manholes to provide safe and adequate access to the wastewater pipes to carry out inspections and maintenance, as well as take necessary flow measurements and samples.

4.3 Hydraulic design of wastewater manholes

Manholes are very important for the hydraulic capacity of the whole wastewater system. However, they are often undervalued parts of the system when it comes to contribution to the roughness and flow capacity of the system (Hafskjold, 2009). The pressure loss caused by the surcharged manholes may be in the same order of magnitude as the pressure loss caused by the pipe friction. This depends mainly on the distance between the manholes, as well as the condition and design of the manholes (Hafskjold, 2009). A water and wastewater system with manholes of a good hydraulic design may have up to 15% greater hydraulic capacity than a system with manholes of a bad hydraulic design (Lindholm, et al., 2012).

The hydraulic performance of a wastewater manhole may be affected by factors such as number and angles of incoming streams, water level in incoming pipes and changes in roughness coefficients (Malvik, 2017). Invert channels in manholes represent nodes that ensure availability to the pipes; therefore, it is important that they are designed appropriately. Inadequate hydraulic design can lead to deposition and increased singular losses (Keseler, et al., 2018). Hence, it is important to account for proper design of channels with proper depth and curve radius in order to ensure good hydraulic properties of the manhole (Hafskjold, 2009). Dimension, direction, material or cross-sectional transition from incoming to outgoing pipes will also have an impact on the manhole hydraulics as it will contribute to increased singular losses. Consequently, the proper hydraulic design of wastewater manholes should contribute to minimalization of these losses (Hafskjold, 2009).

There are several important factors to consider when designing a wastewater manhole with the optimal hydraulic design (Hafskjold, 2009). Norsk Vann report 172:2009 "Trykktap i avløpsnett" outlines following factors as the most important:

- Depth of the channels in wastewater manholes must be equal to or greater than the diameter of the connected pipe.
- A conical fitting outside the manhole at the inlet and outlet to increase the diameter of the channel in the manhole reduces headloss.
- Whenever two flows meet in a manhole, even a relatively small flow from either side will negatively affect the main flow going straight through the manhole, increasing pressure loss.
- A directional change in the manhole is better directed through the manhole in a Y-manhole with 45-degree angles than an X-manhole with 90-degree angles.

An illustration of the important factors for proper hydraulic design described above is presented in Figure 4. In addition to the elements presented in this figure, the elevation to the bottom side channel should be greater than the elevation of the main inlet whenever it is possible (Hafskjold, 2009). Manholes without slope are not recommended. Preferably, the slope through the manhole should be greater than or equal to the slope of the outlet pipe (Hafskjold, 2009).

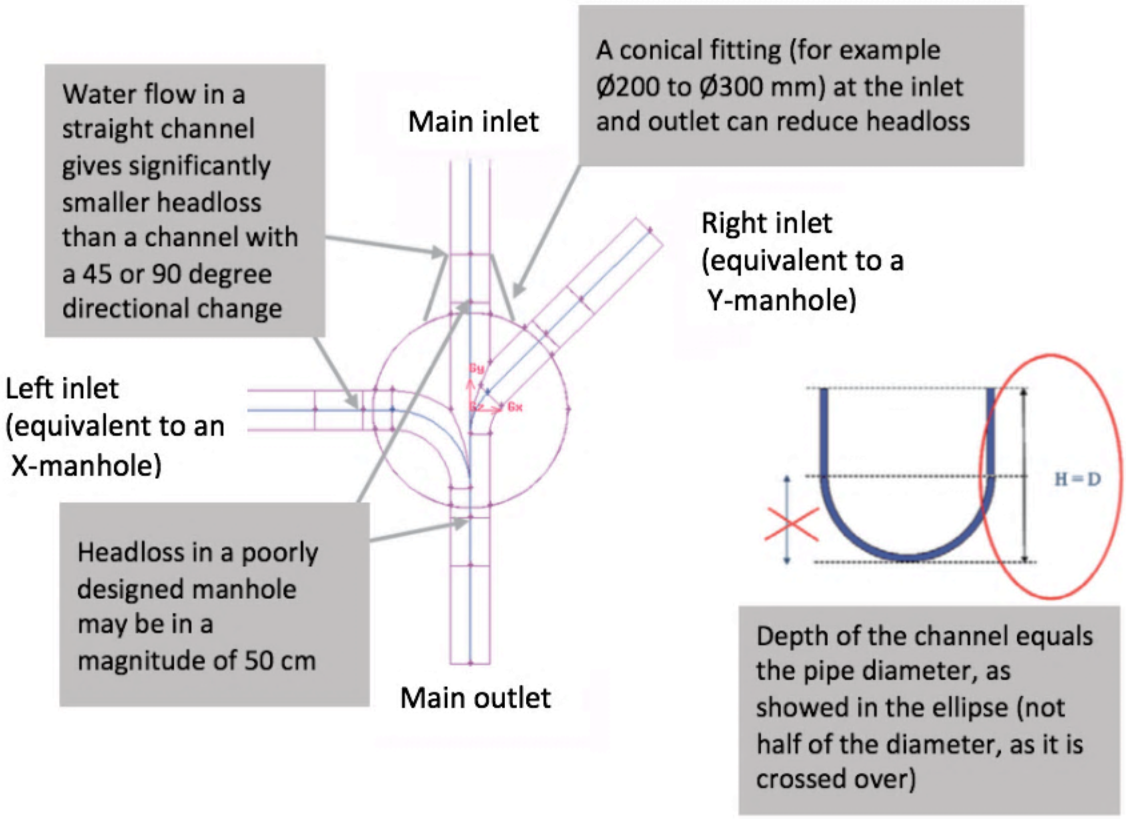


Figure 4: Important factors for proper hydraulic design of a wastewater manhole. The illustration is adjusted from Norsk Vann report 172:2009 "Trykktak i avløpsnett", 2009.

4.3.1 Hydraulic reliability of wastewater manholes

Hydraulic reliability has not been defined for wastewater manholes in the available literature. Therefore, a definition for hydraulic reliability has been formulated based on the theory presented in the sections *4.2 Structural and operational requirements for wastewater manholes* and 4.*3 Hydraulic design of wastewater manholes*. Here, the hydraulic reliability is the ability of sewer manholes to interconnect and assist wastewater pipes in meeting the disposal capacity of wastewater from the users. The optimal interconnection of wastewater flow between the sewers by manhole invert channels is specified in terms of proper hydraulic design, which include specifications of; (i) channel depth, (ii) channel roughness, (iii) minimalization of energy and singular losses, (iv) self-cleansing ability, (v) flow capacity. Hydraulic failures occur when one or several features of the proper hydraulic design of invert channels are altered, thus the wastewater flow through the manhole is retarded, interrupted or blocked totally. As a result, the outgoing sewer is not receiving the flow capacity that it was designed to convey further down the system.

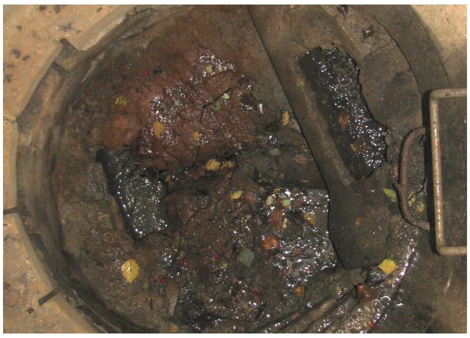
4.4 Wastewater manhole defects

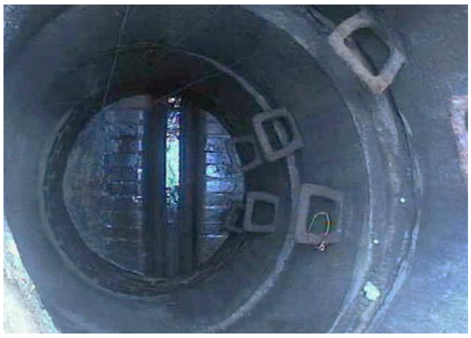
Table 2 presents several defects that can be observed during an inspection of a wastewater manhole and that might lead to hydraulic and structural failures. The failures are divided into two failure categories named "Hydraulic failures" and "Structural failures", respectively. The defects assigned into category "Hydraulic failures" have a direct impact on the hydraulic reliability of the wastewater manholes, while defects from category "Structural failures" have an impact on their structural reliability. The list of hydraulic defects is more comprehensive than the list concerning the structural defects, since the hydraulic reliability is in the main focus of the research presented in this thesis. Some defects appear in both categories since they have different impacts on both hydraulic and structural reliabilities. Therefore, these defects are described twice, but according to the considered failure category. Each defect is presented with a short description which refers to the elements constituting the manhole structure as depicted in *Figure 3: Sketch of a wastewater manhole* (DANVA, 2010). In addition, several of the presented defects are visualized through a picture example. The majority of the pictures presented in Table 2 are taken from the DANVA manhole manual "Brøndmanualen – Inspektion og registering af brønde", with exception of the pictures showing the "Water level", "Obstacle", "Sings of overflow" and "Transition during change of construction" defects. These pictures were taken from the database of the municipality of Trondheim. The descriptions of defects were determined based on the descriptions presented in DANVA manhole manual and the CARE-S report D3 "WP2 – Structural condition. Classification systems based on visual inspection". The descriptions presented in both reports were used interchangeably and were additionally adjusted in order to focus on the failure category that the described defects were assigned into.

Table 2: Hydraulic and structural defects observed in wastewater manholes.

Failure category: HYDRAULIC FAILURES		
Defect	**Description**	**Picture example**
Water level	The observed level of water inside the manhole. Intense turbulences in the water flow through the manhole can occur when the water level rises over the top of the channel resulting in the suction of air and consequently giving high energy losses (Hafskjold, 2009).	
Roots	Roots of trees or other plants are growing into the manhole through joints, defects or connections resulting in reduced cross-sectional area of the invert channel and/or increase of the invert channel roughness.	

Infiltration	Ingress of water through the wall of the manhole, joints or defects in the wall, benching or channel of the manhole resulting in increase of the flow through the manhole.	
Settled deposits	Deposited material such as sediments or other bottom deposits are observed in the invert channels, resulting in the reduction of the cross-sectional area of the invert channel and/or increase of the invert channel roughness.	
Attached deposits	Materials that stick to the invert channel resulting in the reduction of the cross-sectional area of the invert channel and/or increase of the invert channel roughness.	
Obstacles	Foreign objects in the bottom section of the manhole resulting in the reduction of the cross-sectional area of the invert channel.	
Surface damage of the channel	Inner side of the manhole channel is affected by aggressive media (corrosion) or wear (erosion) resulting in increased invert channel roughness.	

Manhole bottom	Condition assessment of the bottom section including benching, invert channels and corresponding slopes. A poor condition of the bottom section can contribute to operational disturbances, as well as inadequate, reverse or a complete lack of slope.	
Transition during change of construction	Transition during change of material, dimension, direction or cross-section resulting in contribution to operational disturbances. Depending on the type of observed change, the resulting impact may involve the reduction of the cross-section, increase of the channel roughness, and/or contribution to infiltration, exfiltration or build-up of inputs.	
Signs of overflow	Visible signs of overflow of wastewater into stormwater pipe or vice versa inside the manhole. The resulting impact on manhole hydraulics include increased flow in one pipe and decreased flow in the other pipe.	
Exfiltration	Visible leakage of flow out of the manhole resulting in decreased flow through the manhole and worsen self-cleansing properties.	
Deformation of bottom section	The cross-sectional shape of the manhole bottom has been deformed from its original cross-section shape resulting in flawed transition between the inlet pipe and invert channel, and consequently reduced cross-sectional area of the invert channel.	
Fissure/ fracture in bottom section	A fracture occurs in the material of the bottom section of the manhole resulting in contribution to infiltration or exfiltration of wastewater, or build-up of inappropriate or unwanted inputs.	

Failure category: STRUCTURAL FAILURES		
Defect	**Description**	**Picture example**
Fissure/ fracture	A fracture occurs in the manhole material as a result of the exceeded load bearing capacity or the structure is physically fractured, resulting in compromised integrity of the manhole structure.	
Surface damage	Inner side of the manhole structure is affected by aggressive media (corrosion) or wear (erosion) resulting in compromised integrity of the manhole material.	
Displaced joint	One of the manhole chamber elements is not centered. Adjacent chamber elements are displaced in relation to each other. The resulting impact represent compromised integrity of the manhole structure.	
Intruding sealing material	All of or part of the material used to seal a joint between two adjacent chamber elements is visible and intruding into the manhole.	

Production failure	A production failure is occurring in the manhole resulting in compromised integrity of the manhole material. Such failures include, but are not limited to, casting defect, honeycombing of concrete, defective lining, defective weld, porous material etc.	
Deformation	The cross-sectional shape of the manhole has been deformed from its original cross-section shape.	

All hydraulic and structural defects are presented with their corresponding failure modes in Table 3 based on the descriptions presented in Table 2. Many of these defects can be observed through several failure modes. Therefore, several of the described manhole defects appear beside more than one failure mode. The failure mode of "Production failure" defect is not presented in Table 3. This defect represents several different defects that occur as a result of an inadequate manufacturing process. Therefore, it has to be categorized further in order to be able to assign it to a failure mode. This is out of the scope of this thesis.

Table 3: Hydraulic and structural manhole defects with corresponding failure modes.

Failure category: HYDRAULIC FAILURES	
Failure mode	**Defect**
Formation of turbulences in the water flow through the manhole.	Water level, Infiltration
Reduction of the cross-sectional area of the channel.	Roots, Settled deposits, Attached deposits, Obstacles, Deformation of bottom section, Transition during change of construction
Increased roughness of the channel.	Roots, Settled deposits, Attached deposits, Obstacles, Surface damage, Transition during change of construction
Leakage of water	Fissure/fracture in bottom section, Surface damage, Manhole bottom, Exfiltration, Signs of overflow
Altered direction of the flow through the manhole.	Manhole bottom, Transition during change of construction
Infiltration of water	Infiltration, Water level

Insufficient self-cleansing	Manhole bottom, Exfiltration
Traces of wastewater on the benching or bottom section of the manhole	Signs of overflow
Failure category: STRUCTURAL FAILURES	
Failure mode	**Defect**
Reduced bearing capacity	Fissure/fracture, Deformation
Loss of soil support	Fissure/fracture, Deformation, Displaced joint
Chemical attack, biological attack, wear	Surface damage

5.0 Method for classification of manholes

Currently, there is no official Norwegian report for classification of manhole condition. One of the purposes of the work presented in this master's thesis was to develop a framework for a manhole condition assessment report. The report will focus on only one of the required functions of wastewater manholes; the hydraulic reliability. A literature study has been performed in order to establish the possible content of a such report. The proposed framework for the report will be grounded on the principles of IAM. The purpose of the procedure based on such guidelines is to ensure a balance between costs, risk, and desired level of service. It will improve the decision-making regarding the prioritization of future manhole projects and also support the decisions on how to intervene.

Based on the research performed during the literature study it was established that there are several published reports that could be used as a basis for the content and structure of a manhole report dedicated to hydraulic defects. DANVA manhole manual "Brøndmanualen – inspektion og registrering af brønde" is one of such reports. It was published in 2010 by Danish Water and Wastewater Association, also known as DANVA, and was revised in 2016. It contains descriptions of several manhole defects and their severity. All defects are categorized and coded, and their severity is graded on a scale form 1 (not severe) to 4 (crucial) or from 0 to 4 (DANVA, 2010). This system could be adjusted and utilized during inspections of Norwegian manholes. Therefore, it will be used as the basis for the descriptions and grading of the hydraulic defects. The descriptions and types of the defects were additionally based on the literature presented in the CARE-S report D3 "WP2 – Structural condition. Classification systems based on visual inspection". CARE-S stands for Computer Aided Rehabilitation of Sewer Networks and represents a research and technological project of European community. This report is one of several reports developed during this initiative. It presents and compares several national and international standards, guidelines etc. for both wastewater pipes and manholes (Knolmar & Szabo, 2003).

Further assessment of manhole condition will be based on the procedure presented in NORVAR report 150/2007 "Dataflyt – Klassifisering av avløpsledninger" and its revised version published in Norsk Vann report 235:2018 "Dataflyt – Klassifisering av avløpsledninger". These reports were published by Norsk Vann, which is a national association representing Norwegian water industry (Bernhus, et al., 2007). Both reports are based on the principles of IAM and describe the condition assessment of Norwegian wastewater pipes (Haugen, 2018). Procedure for condition assessment of wastewater pipes has also been adjusted and implemented on wastewater manholes in the USA. It has proved to be successful as the workers were already known with the procedure (NASSCO, 2015). DANVA manhole manual and Norwegian condition assessment reports for wastewater pipes were also used as the basis for the classification of Norwegian manholes proposed by Sigurd Malvik in his specialization project "Implementing Asset Management and Inspection Procedures to Wastewater Manholes" (Malvik, 2017). This report was also utilized during the whole development process of the theoretical report presented in this thesis.

Weighting values were determined based on the weighting values for defects observed in Norwegian and Danish wastewater pipes. Norsk Vann report 235:2018 contains weighting values that are utilized for wastewater pipes during CCTV-inspections. These values are based on the Danish weighting values presented in DANVA report number 66 "Fotomanualen – Beregning af fysisk indeks ved TV-inspektion". However, the numbers presented in Norsk Vann report 235:2018 are adjusted to the Norwegian conditions. Both reports were utilized during the determination of weighting values for hydraulic defects observed in wastewater manholes. Table 4 shows the weighting values utilized for Norwegian wastewater pipes (Haugen, 2018), whereas Table 5 shows the weighting values utilized for Danish wastewater pipes (DANVA's Afløbskomité, 2005). English translations of both Norwegian and Danish terms are provided below each term in blue font.

The concept of assigning manholes into condition classes according to pre-defined thresholds of total scores was inspired by the literature presented in Norsk Vann report 235:2018. Whereas, the proposed registration scheme was based on the appendix presented in the DANVA manhole manual.

Table 4: Weighting values utilized for defects observed during CCTV-inspections of Norwegian wastewater pipes. Translated from "Dataflyt – Klassifisering av avløpsledninger", 2018.

Observasjon *Observation*	**Vekt** *Weighting value*				**Enhet** *Unit*
	Grad 1 *Grade 1*	**Grad 2** *Grade 2*	**Grad 3** *Grade 3*	**Grad 4** *Grade 4*	
Deformasjon av fleksible rør og foringer, DF *Deformation of flexible pipes and linings*	0,01	0,02	0,1	0,2	Tverrgående: stk. *Transverse: number* Langsgående: m *Longitudinal: meters*
Sprekk/brudd, SB *Crack/Fracture*	0,01	0,1	2	10	Tverrgående: stk. Langsgående: m
Korrosjon/Slitasje, KS *Corrosion/Wear*	0,02	0,06	0,6	10	m
Produksjonsfeil, PF (Kar: F) *Production failure (Characteristics: F)*	0,02	0,1	0,6	3	Stk.
Produksjonsfeil, PF (Kar: S) *Production failure (Characteristics: S)*	0,02	0,03	0,06	0,1	Stk.
Produksjonsfeil, PF (Kar: I, H, M, D, O, A) *Production failure (Characteristics: I, H, M, D, O, A)*	0,02	0,02	0,1	0,3	Stk.
Innstukket rør, IR *Inserted pipe*	0,01	0,02	0,03	0,6	Stk.
Tilkoblingsfeil, TF *Flawed connection*	0,01	0,02	0,03	0,6	Stk.
Tilkoblingsfeil på foret ledning, TL *Flawed connection on lined pipe*	0	0,02	0,1	0,6	Stk.
Synlig tetningsmateriale, ST *Visible sealing material*	0,01	0,03	0,06	0,1	Stk.
Forskjøvet skjøt, FS *Displaced joint*	0,02	0,1	1	10	Stk.
Defekt overgangsdel eller punktreparasjon, DO *Defective transition part or point repair*	0,01	0,02	0,03	0,6	Stk.
Røtter, RØ *Roots*	0,06	0,2	0,6	2	Stk. (skjøt) *Number (joint)*
Utfelling/Belegg, UB *Precipitation/Coating*	0,02	0,06	0,2	0,6	Punkt: stk. *Point: number* Fortløpende: m *Spread: meters*
Sedimenter, SM *Sediments*	0,02	0,06	0,2	0,6	m
Hindring, HI *Obstacle*	0,02	0,06	0,2	0,6	Stk.
Innsig/Utlekk, IU *Infiltration/Exfiltration*	0,02	0,03	0,06	0,3	Stk. (skjøt) *Number (joint)*

Table 5: Weighting values utilized for defects observed during CCTV-inspections of Danish wastewater pipes. Translated from "Fotomanualen – beregning af fysisk indeks ved TV-inspektion", 2005.

Observation *Observation*	**Point (Vægtning)** *Grade (Weighting value)*					**Enhed** *Unit*
	0.	**1.**	**2.**	**3.**	**4.**	
Vand, VA *Water*	0,00	0,01	0,05	0,20	0,60	Meter *Meters*
Revner/brud, RB *Crack/Fracture*		0,02	2	8	12	Tværgående: stk. *Transverse: number* Langsgående: m *Longitudinal: meters*
Overfladebeskadigelse, OB *Surface damage*		0,05	0,02	3	9	Meter
Produktionsfejl, PF (Type: D, F, I) *Production failure* *(Type: D, F, I)*		0,5	2	4	6	Stk.
Produktionsfejl, PF (Type: A, H, M, R) *Production failure* *(Type: A, H, M, R)*		0,01	0,05	0,1	0,2	Stk.
Deformation, DE *Deformation*		0,10	0,50	1,00	2	Tværgående: stk. *Transverse: number* Langsgående: m *Longitudinal: meters*
Forskudt samling, FS *Displaced joint*		0,05	0,20	5	9	Stk.
Indhængende samlingsmateriale, IS *Intruding sealing material*		0,15	0,20	0,75	3	Stk.
Rødder, RØ *Roots*		0,15	0,75	2	5	Stk. (samling) *Number (joint)*
Indsivning, IN *Infiltration/Exfiltration*		0,05	0,15	0,75	6	Stk. (samling) *Number (joint)*
Aflejring, AF *Deposition*		0,05	0,25	0,50	1,00	Meter
Belægning, BE *Precipitation/Coating*		0,05	0,50	1,50	3	Punkt: stk. *Point: number* Fortløbende: m *Spread: meters*
Forhindring, FO *Obstacle*		0,00	1,00	1,50	3	Stk.
Grenrør, GR *Branch pipe*	0,00	1,00				Stk.
Sadelgrenrør, SG *Pipe fitting*		0,00	0,25	1,00		Stk.
Påhugning, PH *Chiseled*		0,00	0,25	3	6	Stk.
Påboring, PB *Drilled*		0,00	0,25	3	6	Stk.
Opskæring af stik, OS *Cut of connection*		0,00	2	6	12	Stk.
Tilslutning med overgangsprofil, OP *Connection with transitional profile*		0,00	0,50	2	6	Stk.
Overgang ved konstruktionsændring, OK *Transition during change of construction*	0,00	0,00	0,02	3	9	Stk.

6.0 Proposed manhole condition assessment report

6.1 Structure of the proposed manhole report

The proposed framework for manhole condition assessment report will accompany operators in the field from the beginning of an inspection to a finalized assessment of the manhole condition. The framework will help the operators to select codes, grades and weights for the observed defects, and guide them to follow the specified rules of the condition assessment procedure. The proposed manhole report will also provide instructions on how to collect data during inspections. This is suggested here in form of a registration scheme that reflects the rules and tables provided in the proposed framework. The hydraulic reliability of wastewater manholes is in the main focus of the presented manhole report. The content concerning the defects having an impact on this reliability will be presented in the next section of this chapter, together with a corresponding registration scheme. In this section, the structure of the proposed framework will be presented.

In order to present the general layout of the proposed manhole report, it will for now be distinguished between two defect categories; "Hydraulics" and "Structural condition". The first category will comprise of defects that have an impact on the hydraulic reliability of the inspected manhole. These defects will be listed, described, graded and weighted. Total score ranges with corresponding hydraulic condition classes will also be presented. The "Structural condition" category is not in the focus of this study and will not be described as comprehensively as the category "Hydraulics". Theoretical defects from this category will have an impact on the structural reliability of manholes. Some of the structural defects will only be used here as examples to present the structure of the proposed manhole condition assessment report. However, similar procedure of defect description, coding, grading, weighting, total score aggregation and condition class determination should be performed in the future for structural defects.

As mention previously, all defects presented in a defect category should be described, coded and graded. Table 6 presents the structure that will be used for presentation of the defects with corresponding defect codes. The proposed defect codes will comprise of 3 capital letters where the first letter will represent the defect category, as "H" for "Hydraulics" or "S" for "Structural condition". The following two letters are an abbreviation for the defect observation as the codes shown in Table 6. Additionally, each of the defects from "Hydraulics" defect category will be presented with a short description.

Table 6: Example of categorization and coding of manhole defects in category "Structural condition". The table is adjusted from "Implementing Asset Management and Inspection Procedures to Wastewater Manholes", 2017.

Category: Structural condition	**Defect code** (Malvik, 2017)	**Defect code** (Haugen, 2018)
Fissure/rupture	FR	SB
Surface damage	SD	KS
Manufacturing defects	MF	PF
Deformation	DF	DF
Displaced joints	ME	FS
Intruding sealing material	IM	ST

Each of the listed defects will be graded according to their severity. Table 7 presents grading of defect "Fissure/rupture" on a scale from 1 to 4 (DANVA, 2010). Grade 1 represents a not severe defect, while grade 4 represents a crucial observation. Similar grading scale will be utilized for the defects from category "Hydraulics". Additionally, each of the grades will be described in order to indicate which specific observation should be appointed to a grade.

Table 7: Grading of defect "Fissure/rapture" with corresponding description of each grade (DANVA, 2010).

Defect	**Defect code**	**Grade**	**Grade description**
Fissure/ rupture	FR	1	Crack are lines visible.
		2	Crack is open.
		3	A piece of the manhole material is gone, little hole in the manhole structure.
		4	A large piece of the manhole material is gone, the hole is deep and reaches the soil layer.

Each of the defect grades will be assigned a weighting value in order to reflect their criticality in the calculated total score. Table 8 presents weighting values for grades of the defects "Fissure/rupture" and "Surface damage" observed in Norwegian wastewater pipes. Equal setup will be utilized for presentation of the weighting values for the hydraulic defects in wastewater manholes.

Table 8: Weighting values for defects "Fissure/rupture" and "Surface damage" observed in wastewater pipes (Haugen, 2018).

Defect	**Defect code**	**Weight**			
		Grade 1	**Grade 2**	**Grade 3**	**Grade 4**
Fissure/rupture	SB	0,01	0,1	2	10
Surface damage	KS	0,02	0,06	0,6	10

The grade of each observed defect will be multiplied with corresponding weighting value. This will be repeated for all registered defects within a defect category. In order to obtain a total score for the inspected manhole, the products of all multiplications will be summed up into one score for each category. The obtained total score will then be compared against pre-defined thresholds in order to assign manholes into condition classes. A flow chart summarizing the described process is presented in Figure 5.

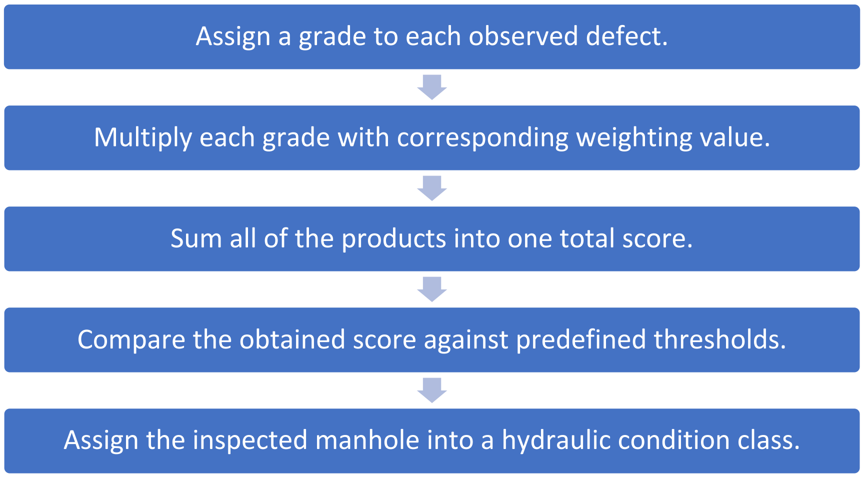


Figure 5: Flow chart summarizing the proposed manhole condition assessment.

Table 9 presents condition classes utilized for wastewater pipes with corresponding thresholds of total scores (Haugen, 2018). The total scores for wastewater pipes comprise of summation of defects from all defect categories. This will not be implemented for wastewater manholes in the report presented here, as the total score ranges will be determined separately for all defect categories. Here, the condition classes and total score ranges will be presented only for defects from category "Hydraulics". Similar table should be obtained in the future for the defects from category "Structural condition" in order to complete all steps of the manhole condition assessment as described in this section. Based on such structure of the assessment, the condition classes will describe the condition of the inspected manhole according to one specific function. This will result in simplified determination of proper maintenance and/or rehabilitation actions.

Table 9: Condition classes for wastewater pipes presented in Norsk Vann report 235:2018 (Haugen, 2018).

Condition class	Total score thresholds	Condition description
S1	0-5	Very good
S2	6-10	Good
S3	11-20	Questionable
S4	21-50	Bad
S5	>50	Very Bad

When manhole condition classes for both "Hydraulics" and "Structural condition" defect categories are obtained, they should be compared. A comparison of both condition classes should result in an idea of needed preventive action as it will be clear what is the dominant malfunction of the assessed manhole. Figure 6 and 7 present visualizations of such comparisons together with some guidelines on the type of needed preventive measure. The first figure presents a case where the obtained hydraulic class is H1, which represents a very good hydraulic condition, is paired together with different structural condition classes. The second figure presents another case where the obtained hydraulic class is changed to H5, which represents a very bad hydraulic condition.

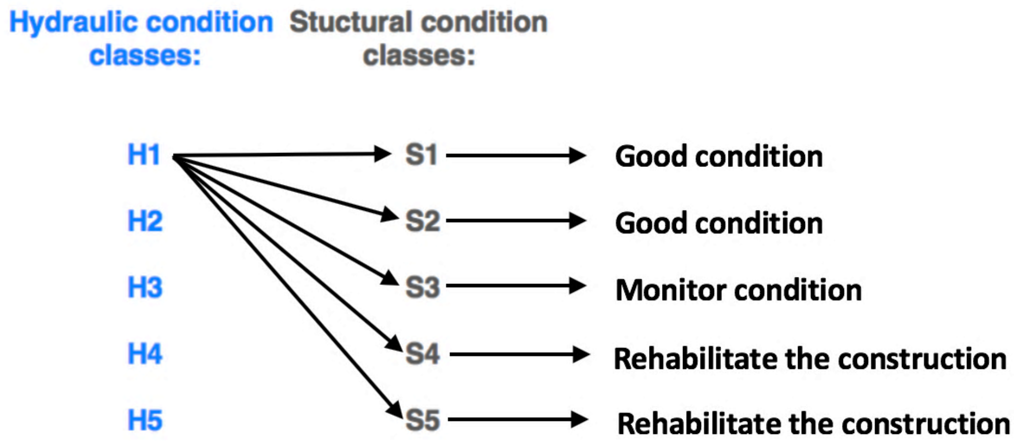


Figure 6: Hydraulic condition class H1 paired with different structural condition classes resulting in different types of desirable preventive actions.

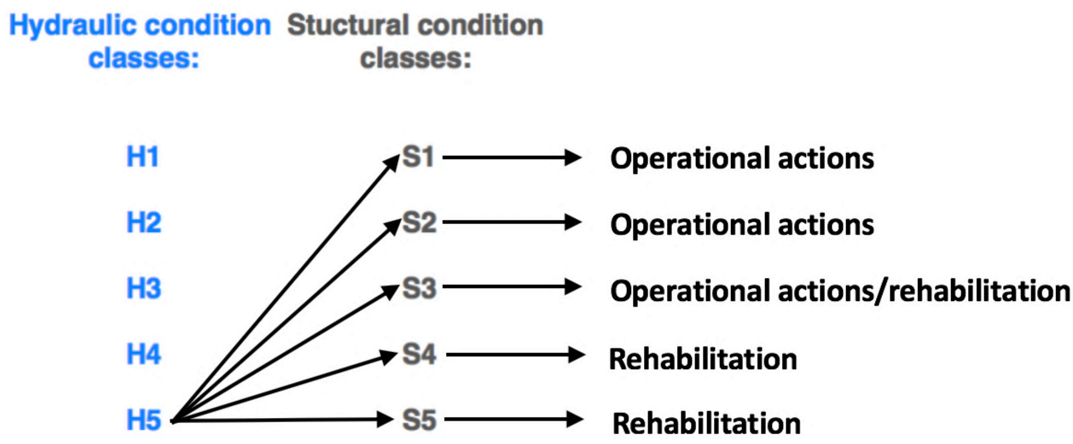


Figure 7: Hydraulic condition class H5 paired together with different structural condition classes resulting in different types of desirable preventive actions.

According to the figures presented above, it can be assumed that wastewater manholes within condition classes H1/S1 or H1/S2 do not require any actions in form of rehabilitation. Condition class H3/S3 might require improved monitoring of the condition with additional consideration of precautionary operational or structural interventions. Manholes within condition classes H4/S4 and H5/S5 will require immediate actions either in form of maintenance, rehabilitation or replacement. It should be noted that if any defect with grade 4 (most severe) is observed in any of the condition classes above, the manhole should be maintained or rehabilitated immediately.

The last section of the proposed manhole condition assessment procedure will present a suggestion for a registration scheme that should be utilized out in the field during inspections. The purpose of this scheme is to ensure that all necessary information is registered and available for the person performing the assessment of the manhole condition. The proposed registration scheme includes only the template for defect registration in order to use the proposed condition assessment approach.

6.2 Assessment of the hydraulic reliability of wastewater manholes

6.2.1 Defects with potential to affect the hydraulic reliability

There are several defects that have a potential to affect negatively the hydraulic reliability of wastewater manholes. The most common defects with high potential to reduce this reliability are presented in Table 10. The selected defects are listed with corresponding defect code, description and types. In addition, some of the defects presented in Table 10 are visualized through a picture example in the first part of Table 2 in section *4.4 Wastewater manhole defects*. The descriptions of defects and types were determined based on the descriptions presented in DANVA manhole manual and the CARE-S report D3.

Table 10: Description of the defects from defect category "Hydraulics" with corresponding defect codes and types.

Defect	**Defect code**	**Description**	**Type**
Water level	HWL	The observed level of water inside the manhole.	D: Drinking water S: Stormwater W: Wastewater
Roots	HRO	Roots of trees or other plants are growing into the manhole through joints, defects or connections.	F: Independent fine roots M: Complex mass of roots T: Tap root
Infiltration	HIN	Ingress of water through the wall of the manhole, joints or defects in the wall, benching or invert channels of the manhole.	S: Sweating; slow ingress of water, no visible drips. D: Dripping; water is dripping in, not continuous flow. F: Flowing; a continuous flow of water. G: Gushing; water is entering under pressure.
Settled deposits	HSD	Deposited material such as sediments or other bottom deposits are observed in the invert channels, water line or on the benching.	O: Other F: Fine (e.g. sand, silt) C: Coarse (e.g. gravel, rubble) H: Hard or compacted material (e.g. concrete) P: Paper/faeces
Attached deposits	HAD	Materials that stick to the invert channel.	O: Other G: Grease F: Fouling (e.g. organic material) P: Precipitated inorganic materials (e.g. iron, lime, ochre)

Obstacles	HOB	Foreign objects in the bottom section of the manhole.	O: Other objects D: Dislodged brick or masonry unit P: Pieces of broken pipe
Deformation of bottom section	HDB	The cross-sectional shape of the manhole bottom has been deformed from its original cross-section shape.	G: General deformation; affects a large portion of the wall of the manhole. P: Point deformation; affects a relatively small portion of the wall.
Surface damage	HSF	Inner side of the manhole is affected by aggressive media (corrosion) or wear (erosion).	O: Other A: Visible/missing aggregate C: Corrosion V: Visible reinforcement
Fissure/ fracture in bottom section	HFF	A fracture occurs in the material of the bottom section of the manhole.	S: Spalling B: Break/fracture C: Circular – crack extends perpendicular to the manhole axis. L: Longitudinal – crack extends along the manhole axis. M: Composite – combination of both circular and longitudinal cracks.
Manhole bottom	HMB	Condition assessment of the bottom section including benching and invert channels.	B: Defective benching C: Defective channel S: Sand trap
Transition during change of construction	HTC	Transition during change of material, dimension, direction or cross-section.	D: Change in dimension. M: Change in material. T: Change in direction. C: Change in cross-section.
Signs of overflow	HOV	Visible signs of overflow inside the manhole.	S: Stormwater W: Wastewater
Exfiltration	HEX	Visible leakage of flow out of the manhole.	D: Drinking water S: Stormwater W: Wastewater

6.2.2 Grading of the hydraulic defects

Grades and corresponding grade descriptions of all hydraulic defects described in section *6.2.1 Defects with potential to affect the hydraulic reliability* are presented in Table 11. Majority of the defects is graded on a scale from 1 to 4, where grade 1 represents a not severe observation, while grade 4 represents a crucial observation. Thus, grade 4 is assigned to the defect observations that have the most negative effect on the hydraulic reliability of the inspected manhole. However, defects such as “Water level”, “Manhole bottom”, “Transition during change of construction”, “Signs of overflow” and “Exfiltration” have an additional grade 0. Both grade scales and grade descriptions were based on the ones presented in the DANVA manhole manual. The descriptions presented in this report were occasionally rewritten in order to focus more on the potential impact on the hydraulic reliability of wastewater manholes.

The grades of defects such as “Roots”, “Settled deposits”, “Attached deposits”, “Obstacles”, and “Deformation of bottom section” are described through the percentage reduction of the cross-sectional area of the invert channels. The “Water level” defect was graded based on the different water heights that could be observed in a manhole, while the “Infiltration” defect was graded based on the nature of the water penetrating the manhole construction. The grades of the defect “Surface damage” were based on the observed condition of the surface and corresponding roughness of the channel, while the “Manhole bottom” defect was graded based on the observed slope of the benching and bottom section of the manhole. The grades of the defect “Fissure/fracture in bottom section” were described based on the nature of the observed fissure. “Transition during change of construction” defect was graded based on the percentage change of the manhole shape.

The grading of the defects “Signs of overflow” and “Exfiltration” required implementation of a smaller grade scale, where the first defect was graded on a scale from 0 to 2 and the second defect was graded on a scale from 0 to 1. For these two defects the grade 0 stands simply for none visible observation of either defect. The grades 1 and 2 for “Signs of overflow” defect stand for visible observations of the defect, where the grade 1 reflects the observation of stormwater overflow and grade 2 reflects the observation of wastewater overflow. Grade 1 of defect “Exfiltration” stands for visible observation of leakage. Both “Signs of overflow” and “Exfiltration” defects were not graded in the DANVA manhole manual.

Table 11: Grades of hydraulic defects with corresponding description of each grade.

Defect	Defect code	Grading
Water level	HWL	0: Water is not observed inside the manhole. 1: Water is observed in the invert channels. The observed water level is below the level of benching. 2: Observed water level is on the benching, above the highest point of the main invert channel, but below the highest point of the benching. 3: Observed water level is above the highest point of the main invert channel, but below the adjusting construction and cover frame. 4: Observed water level reaches the manhole taper, adjusting construction or cover frame.
Roots	HRO	1: Roots represent up to 10% of the cross-sectional area of the channel. The reduction is observed either from the bottom or top section of the channel. 2: Roots represent from 10% and up to 50% of the cross-sectional area of the channel. The reduction is observed either from the bottom or top section of the channel. 3: Roots represent from 50% and up to 90% of the cross-sectional area of the channel. The reduction is observed either from the bottom or top section of the channel. 4: Roots represent over 90% of the cross-sectional area of the channel. The reduction is observed either from the bottom or top section of the channel.
Infiltration	HIN	1: Manhole element is humid which is an indication of infiltration. No visible signs of penetrating or dripping water. Can often be observed as "shiny spots" on the manhole wall. 2: Water is penetrating the manhole construction, dripping inside the manhole. 3: Water penetrates continuously though the manhole wall or joints as pressurized flow in a thin water jet. 4: Water penetrates tremendously though the manhole wall or joints as pressurized flow in a thick water jet.

Settled deposits	HSD	1: Settled deposition represents up to 10% of the cross-sectional area of the channel. 2: Settled deposition represents from 10% and up to 50% of the cross-sectional area of the channel. 3: Settled deposition represents from 50% and up to 90% of the cross-sectional area of the channel. 4: Settled deposition represents over 90% of the cross-sectional area of the channel.
Attached deposits	HAD	1: Attached deposits represents up to 10% of the cross-sectional area of the channel. 2: Attached deposits represents from 10% and up to 50% of the cross-sectional area of the channel. 3: Attached deposits represents from 50% and up to 90% of the cross-sectional area of the channel. 4: Attached deposits represents over 90% of the cross-sectional area of the channel.
Obstacles	HOB	1: Obstacle represents up to 10% of the cross-sectional area of the channel. 2: Obstacle represents from 10% and up to 50% of the cross-sectional area of the channel. 3: Obstacle represents from 50% and up to 90% of the cross-sectional area of the channel. 4: Obstacle represents over 90% of the cross-sectional area of the channel.
Deformation of bottom section	HDB	1: The invert channels overlap well with the pipe inlet/connected pipe. Deformation represents up to 10% of the cross-sectional area of the channel. 2: The transition between the inlet pipe and invert channels is displaced. Deformation represents from 10% and up to 50% of the cross-sectional area of the channel. 3: The invert channels overlap poorly with the inlet pipe. Deformation represents from 50% and up to 90% of the cross-sectional area of the channel. 4: The invert channels do not overlap with the inlet pipe. Deformation represents over 90% of the cross-sectional area of the channel.

Surface damage	HSF	1: The roughness of the manhole element is increased. The inspector can observe starting exposure of stones in concrete manholes. 2: The roughness of the manhole element is visibly increased. The stone material is visibly exposed. The surface of the bricks is attacked, or grout is partially removed in brick manholes. 3: The roughness of the manhole element is increased considerably. Parts of the stone material are missing, or the reinforcement is exposed to the environment. 4: Parts of the manhole elements' inner side are corroded or eroded away. Soil and/or holes are visible.
Fissure/fracture in bottom section	HFF	1: Fissure lines are visible on the bottom section. 2: Fissure is open in the bottom section. 3: A piece of the manhole bottom material is gone or displaced (range: under clock position 4). 4: A piece of the manhole bottom material is gone or displaced (range: clock position 4 or more). Masonry is collapsed, or the bottom section has sat down in relation to the masonry.
Manhole bottom	HMB	0: Cross-section of the bottom is uniform with slope towards outlet. The slope of the benching is towards outlet. The bottom is a sand trap. 1: Cross-section of the bottom can contribute to operational disturbances (expansions/narrowing). 2: The bottom section does not have a slope. Benching is installed without slope. 3: The bottom section has a reverse slope. Benching is partially gone. 4: Bottom or benching is gone.

Transition during change of construction	HTC	0: The transition is carried out with prefabricated transition piece without any imperfections and without change in the shape of the manhole cross-section. 1: The transition is smooth and close to the manhole wall, without imperfections. The change in the shape of the manhole cross-section is less then 10% of the cross-sectional area. 2: Seemingly tight transition with minor imperfections. The change in the shape of the manhole cross-section is from 10% and up to 50% of the cross-sectional area over the highest point of the main channel. 3: Seemingly tight transition with minor imperfections. The change in the shape of the manhole cross-section is from 10% and up to 50% of the cross-sectional area under the highest point of the main channel. 4: Over 50% change in the shape of the cross-section in the transition. The soil is visible.
Signs of overflow	HOV	0: None visible signs of either stormwater or wastewater overflow. 1: Yes, visible signs of stormwater overflow. 2: Yes, visible signs of wastewater overflow.
Exfiltration	HEX	0: None visible signs of exfiltration. 1: Yes, visible signs of exfiltration.

6.2.3 Weighting values for hydraulic defects

Weighting values for the defect grades described in section *6.2.2 Grading of the hydraulic defects* are presented in Table 12. The proposed weighting values were based primarily on the values presented in the Norsk Vann report 235:2018. Numbers proposed in this report were based on the values from the DANVA report number 66. However, they were additionally adjusted to the Norwegian conditions. Weighting values for Norwegian wastewater pipes were presented in Table 4, while the Danish values were presented in Table 5. Not all defect grades from Table 12 were weighted in the Norsk Vann report 235:2018, therefore the DANVA report number 66 was also utilized.

The weighting values presented in Table 12 are higher than the values given to defects observed in Norwegian pipes. During calculation of the total score for wastewater pipes, the sum of all defects multiplied by the weighting value is divided by the length of the pipe in order to distribute the defects throughout the whole pipe length. This will not be performed during calculation of the total score for manholes since manholes represents nodal points in the system. Therefore, higher weighting values for manhole defects will ensure total score ranges that are easier to work with.

Weighting values for defects “Roots”, “Settles deposits”, “Attached deposits”, “Obstacle”, “Deformation of the bottom section” and “Transition during change of construction” were decided to be equal. The definitions of grades for these defects are all based on the same scale of percentage reduction of the cross-sectional area of the invert channel due to presence of these defects. The weighting values for the defect “Water level” were based on the values presented in the DANVA report number 66. These values are lower than the values assigned to previously mentioned defects since the theoretical consequences of the defect “Water level” are assumed to be less crucial for the hydraulic reliability. Defects “Signs of overflow” and “Manhole bottom” were not weighted in both Norsk Vann and DANVA reports. However, the weighting values for these defects were determined based on an assessment of theoretical consequences and already established values for other defects. Defect “Manhole bottom” was assigned equal weighting values as the defects defined by the cross-sectional reduction of the invert channel since it was difficult to assess the extent of consequences of “Manhole bottom” defect in relation to the other defects.

The weighing values of defect “Infiltration” were decided to be lower than the values for defects such as “Settled deposits” and “Obstacles”. The problem of infiltration is well known in Norway and represents smaller issues than defects that contribute to the buildup of deposits in the invert channels. The values for grades 3 and 4 of defects “Surface damage” and “Fissure/fracture in bottom section” are equal to the ones given to defects such as “Roots” and “Obstacles”. However, for grades 1 and 2 the values are lower as the impacts of these defects according to their grade descriptions are theoretically less significant.

Table 12: Weighting values for hydraulic defect grades.

Observation	**Weight**				
	Grade 0	**Grade 1**	**Grade 2**	**Grade 3**	**Grade 4**
Water level	0	0	0,1	1	2
Roots		0,5	2	4	6
Infiltration		0,1	0,3	0,5	2
Settled deposits		0,5	2	4	6
Attached deposits		0,5	2	4	6
Other obstacles		0,5	2	4	6
Deformation of the bottom section		0,5	2	4	6
Surface damage		0,5	1	4	6

Fissure/ fracture in bottom section		0,1	0,5	4	6
Manhole bottom	0	0,5	2	4	6
Transition during change of construction	0	0,5	2	4	6
Signs of overflow	0	2	4		
Exfiltration	0	3			

6.2.4 Hydraulic condition classes with corresponding total score thresholds

Total score for an inspected manhole will be calculated by multiplying the grades of the observed defects with their corresponding weighting values and summarizing all of the resulting products. The formula for the calculation of the total score is presented in Equation 2. In addition, the defect grades that are observed several times in a manhole should be multiplied with the number of the observations.

Equation 2: Proposed calculation of the total score.

$$\boldsymbol{TS} = (\boldsymbol{G_1} * \boldsymbol{W_1}) + (\boldsymbol{G_2} * \boldsymbol{W_2}) + \cdots + (\boldsymbol{G_n} * \boldsymbol{W_n})$$

where

$\mathrm{TS} =$ Total score for the inscpected manhole

$G_n =$ Grade of the $\mathrm{n^{th}}$ observed defect

$W_n =$ Corresponding weighting value for the grade of the $\mathrm{n^{th}}$ observed defect

After the calculation of the total score, the score must be compared against the pre-defined thresholds presented in Table 13. The comparison will result in allocation of the inspected manhole into a hydraulic condition class. The manholes can be assigned into one of five proposed condition classes, where the hydraulic condition class "H1" represents a very good hydraulic condition while class "H5" represents a very bad hydraulic condition. The letter "H" stands for "Hydraulics" which is the name of the defect category that is being assessed. The total score thresholds shown in Table 13 are proposed as a first attempt. They are obtained by simulating multiple combinations of defects with different grades. Only the availability of a large amount of inspection data can verify and eventually adjust the proposed thresholds. This has been attempted here through assessment of a small number of wastewater manhole images. However, these images do not represent enough variation in order to fairly state whether the proposed thresholds are accurate and thus do not require further adjustments. Two of the assessed images are presented in Appendix 1.

Table 13: Hydraulic condition classes with corresponding total score thresholds.

Hydraulic condition class	Condition class description	Total score thresholds
H1	Very good	0 – 6,7
H2	Good	6,8 – 20,4
H3	Questionable	20,5 – 48,7
H4	Bad	48,8 – 66
H5	Very bad	> 66

6.2.5 Registration scheme

Completion of the whole assessment of the hydraulic condition of a manhole depends on a proper registration of data out in the field. Table 15 present a suggestion for the layout of the registration scheme. However, the full report should include requirement for registration of additional information. Such data should include records of the address and/or ID-number of the inspected manhole, reason for the inspection, date of the inspection, method by which the inspection was conducted, name of the inspector etc. In addition, the official registration scheme should include a requirement of proper picture documentation of the inspected manhole. It should underline that the images must be of a good quality and represent accurately the current state of the manhole condition.

The registration scheme presented in Table 15 includes only the template for defect registration in order to use the proposed condition assessment approach. It consists of seven columns where the first four focus on the registration of the defect, defect code, defect type and defect grade. The following column is dedicated to the registration of the location of the observed defect. The location will be specified by numbers as presented in Figure 8. The proposed numbers are defined in Table 14.

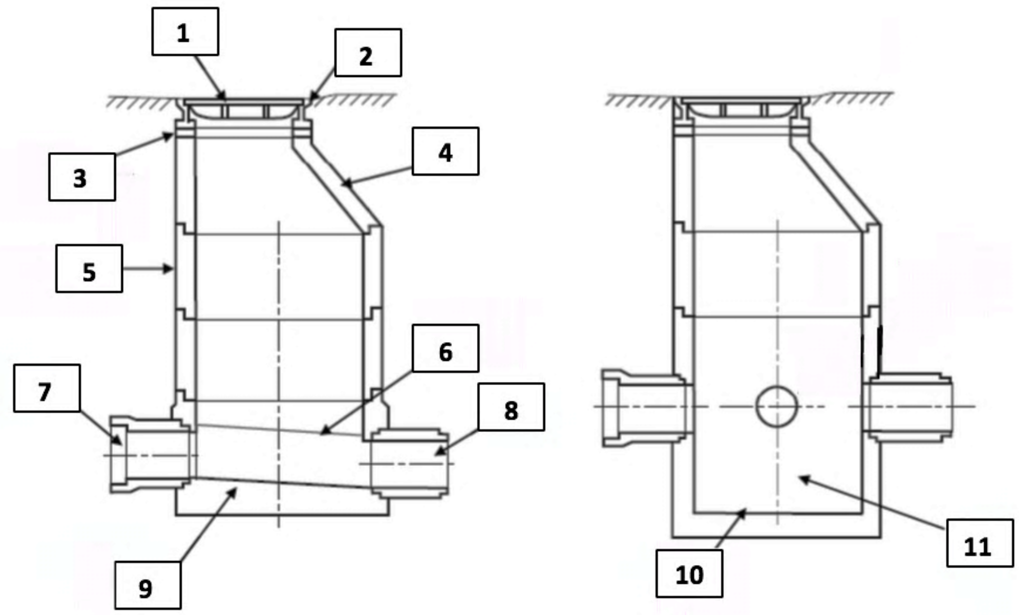


Figure 8: Possible locations of defects observed in a manhole labeled by numbers. The illustration is adjusted from DANVA manhole manual (DANVA, 2010).

Table 14: Definitions of the locations labeled by numbers.

Location number	Definition of the location
1	Cover
2	Frame
3	Adjusting construction
4	Taper
5	Chamber
6	Benching
7	Inlet
8	Outlet
9	Channel
10	Bottom section
11	Silt pit

The subsequent column is dedicated to the registration of the circumferential location of the observed defects. This location should be registered for all defects, whenever it is possible. The position around the circumference of the manhole should be recorded using the clockface references. A defect distribution of 1 hour corresponds to 30 degrees measured in relation to the manhole center (DANVA, 2010), as presented in Figure 9. Circumferential location is named "CF location" in Table 15.

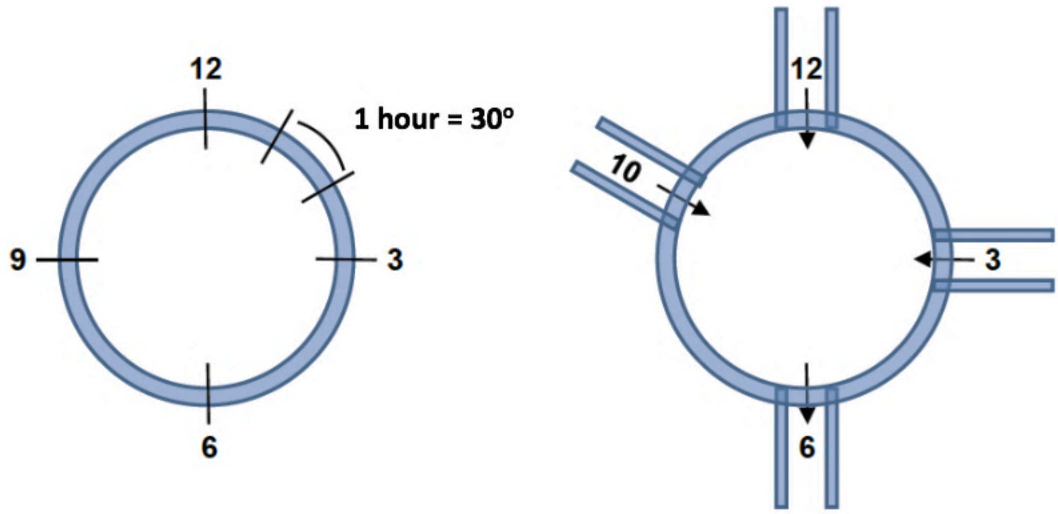


Figure 9: Clockface references for circumferential location of manhole defects (DANVA, 2010).

The last column is dedicated to additional remarks related to each observed defect, whereas the last row of the scheme is dedicated to the remarks related to the overall observed condition of the manhole. This row should be utilized when the condition of the inspected manhole is visibly bad or very bad. The person performing the assessment will then know that the condition is not satisfying and should be improved even if the calculated total score would suggest otherwise.

Table 15: Registration scheme.

Defect	**Code**	**Type**	**Grade**	**Location (1-11)**	**CF location**	**Remarks**
Water level	HWL	D S W	0 1 2 3 4			The height of the observed water level should be recorded.
Roots	HRO	F M T	1 2 3 4			
Infiltration	HIN	S D F G	1 2 3 4			The means of entry of the infiltration should be recorded with circumferential location.
Settled deposits	HSD	O F C H P	1 2 3 4			If type O; further details should be recorded.
Attached deposits	HAD	O G F P	1 2 3 4			If type O; further details should be recorded.
Other obstacles	HOB	O D P	1 2 3 4			If type O; further details of the observed obstacle should be recorded.
Deformation of the bottom section	HDB	G P	1 2 3 4			If type P: additional record of circumferential location is required.

Surface damage	HSF	O A C V	1 2 3 4			The cause of the damage should be recorded: K: chemical damage (e.g. corrosion of reinforcement) B: biochemical attack due to sulfuric acid (e.g. damage above the water) M: mechanical damage A: attack by wastewater (e.g. damage below the water level) E: cause not evident
Fissure/ fracture in bottom section	HFF	S B C L M	1 2 3 4			
Manhole bottom	HMB	B C S	0 1 2 3 4			This observation must be recorded in all manholes where the bottom section is visible.
Transition during change of construction	HTC	D M T C	0 1 2 3 4			If possible, circumferential location should be recorded.
Signs of overflow	HOV	S W	0 1			
Exfiltration	HEX	D S W	0 1			The means of leakage should be recorded with circumferential location.
Additional overall remarks regarding the manhole	*Short description of the overall condition of the manhole if it is visibly bad or very bad.*					

7.0 Discussion of the proposed manhole condition assessment report and recommendations for future research

The research work presented in this master's thesis deals with the development of a framework for condition assessment of wastewater manholes. It covers the first two steps of the development process of an official manhole report as shown in Figure 10. Despite the availability of other reports that can be used as a basis for the Norwegian manhole condition assessment report, its development will not be an easy task as it is starting from scratch. As indicated in Figure 10, the path, starting from the work presented here and ending with an official manhole report, is long and will require coordination, research and more inspections of wastewater manholes. The framework for the condition assessment of wastewater manholes has been described in this thesis. However, it will require validation. The process of defect description, grading and weighting has been performed for the defects that have an impact onto the hydraulic reliability of wastewater manholes. As shown in the figure below, the presented research has to be continued by including the structural defects into the condition assessment. In addition, a decision has to be made whether the hydraulic and structural defect categories cover all defects that can be observed in a manhole or if the number of defect categories should be expanded. When the previously mentioned factors are dealt with, the work can continue with adjustments of all weighting values and total score thresholds for determined condition classes, respectively. Only when this process is completed, an official condition assessment report can be formulated and published.

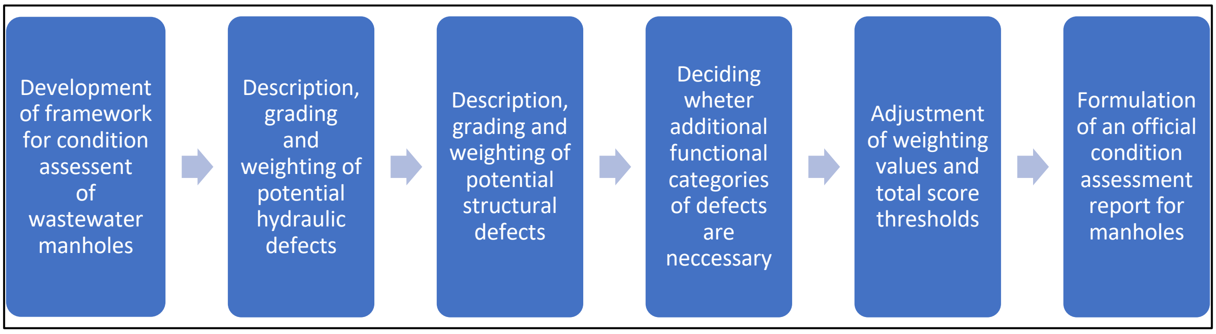


Figure 10: Flow chart for development of an official condition assessment report for Norwegian wastewater manholes.

The development of a manhole condition assessment report that includes both inspection and classification guidelines for manholes will result in several benefits for the Norwegian water utilities. It will increase the focus on condition monitoring of manholes and data availability, and consequently ensure that the water utilities dedicate more time and resources to manholes. The report will highlight the importance of well-functioning manholes as they have a significant impact on the whole system. Therefore, they should be evaluated and maintained in a similar manner as wastewater pipes, with aim to ensure proper condition and performance throughout their lifecycle. The report will provide the means to execute appropriate inspection and assessment of manhole condition. Nowadays, the inspection of manholes is performed visually by qualified personnel in the water utilities. However, the execution of inspection varies, and the interpretation of observations might often be subjective. Guidelines will ensure proper collection of desired data and will subsequently objectify the registration of information.

It will also guarantee that employees within water utilities inspect and assess wastewater manholes equally. As a result, the collected data will become more reliable and accurate as the report will consist of proper descriptions of defects and their severity, leading to a more knowledge-based approach in the decision-making concerning the maintenance. Manholes are buried assets, thus both visual inspection and assessment of manholes are time demanding and expensive. Guidelines on how they should be performed will optimize and simplify both procedures. As a result, proper manhole condition assessment report will help Norwegian water utilities to accurately identify, register and assess the condition of these assets. Extensive condition monitoring and assessment of manholes will result in large databases. The report system will ensure that all manholes are classified, photographed and described in a way that reflects the accurate condition of each manhole class. With data describing the current condition and existing defects, appropriate preventive measures can be properly planned and implemented. Based on this information the infrastructure owners can make proper decisions in order to optimize the utility of the manholes over their lifecycle. Knowledge of the condition and performance will support decision-makers in implementation of adequate actions such as maintenance and rehabilitation. Establishment of plans for proper maintenance and repair can be optimized further as the database will get more comprehensive with time.

The main features of the proposed assessment approach will result in additional benefits for the water utilities as:

- <u>It is reliability-based</u>: the proposed manhole condition assessment is based on reliability. This means that the proposed condition classes are defined according to the effect or the impact of the possible defects on to a specific functional requirement of wastewater manholes; this research work has been focused on the hydraulic reliability. In order to ensure correct functionality of the proposed assessment system, further research should focus on defects that have an impact on the structural reliability. This must be done in order to perform the last step of the assessment which is the comparison and analysis of both hydraulic and structural condition classes together, see section *6.1 Structure of the proposed manhole report*. Such structure of the manhole condition assessment procedure will make the obtained total scores, for both hydraulic and structural functional requirements, easier to understand as they will reflect the current state of the inspected manhole much clearer considering the assessed function. The condition assessment procedure proposed here represents also an improvement of the approach currently used to assess condition of pipelines from inspections, since the current approach in use for pipes mixes the different defects in a score regardless the effect to specific functional requirements. The overview and evaluation of the effect of a given defect onto one or another function is relevant and helpful when selecting the type of intervention needed. The proposed assessment process will indeed simplify the understanding of the required interventions as it does not allow to lose the information concerning the reason for the obtained condition of the inspected manhole. This is mainly due to the fact that the defects are separated according to either hydraulic or structural functional requirements. As a result, the person performing the assessment will know better whether the improvement of the manhole condition requires an operational intervention such as flushing, a structural intervention such as reconstruction of manhole components, or a combination of both.

- It supports operators from condition monitoring to condition assessment: the proposed approach covers all the aspects from defect definitions, grading, weighting and class assessment. However, several simplifications had to be made in order to attempt to validate and exemplify the proposed report. Consequently, the results presented here will require further analysis in future studies. The explanations of the defects, grading, weighting and calculation of the total score represent a good starting point for the development of an official manhole condition assessment report. However, as mentioned previously, the proposed report must be expanded with at least one additional defect category considering structural defects.

- It provides a coding system for unique identification of defects: the design based on abbreviations and numbers will ensure good collaboration with software programs. The coding and grading of the defects will provide good basis for the labelling of manhole images, which can be further used in image recognition software. A such system provides also a good basis for development of a software that can assess the manholes and assign them automatically into condition classes.

7.1 Suggestions for future work

The work presented here is far from being finished since the field is new from both a theoretical point of view (the reliability-based condition assessment approach) and the operative point of view (the machine learning approach presented further on). Therefore, suggestions for further research concerning the theoretical point are here presented as guidance for the future studies on this field. Suggestions concerning the operative point will be discussed in chapter *11.0 Discussion of the Custom Vision performance*.

It is suggested that in the future work:

- The defects that have an impact on the hydraulic reliability and are here described, will also be assessed in terms of their eventual impact on the structural reliability. Therefore, defects impacting both reliabilities will have to appear in both defect categories. However, their description, grading and weighting should be defined separately according to the potential impact they have onto each defect category, i.e. a defect can impact both types of reliability, but the effect can be very different in terms of severity and thus cannot be analyzed with regards to a combined effect. Consequently, this will require the assessment of one defect in two separate ways; one from the hydraulic point of view, and the other from the structural point of view. Performance of a manhole inspection in the proposed way will be more time demanding and thus expensive in the beginning of the application as the qualified personnel of the water utilities will get familiar with the process. However, the possible benefits of the more precise inspection and assessment of manholes should out weight these additional expenses since they will result in better decisions on how to rehabilitate and maintain manholes.

- The proposed descriptions of the defects and defect grades will be validated by a qualified group of people with long experience with wastewater manholes. These descriptions were based mainly on the descriptions provided in the DANVA manhole manual and the CARE-S report D3. As a result, they might require additional adjustments, to the ones done here, in order to reflect the Norwegian conditions even more accurately. In addition, the grading of defects such as "Signs of overflow" and "Exfiltration" might be done in a way that imitate their severity more precisely. Here, they are graded with simple visible or none visible signs of the defect. However, experienced professionals might have an improved approach to grade these defects. Similar concerns apply to the proposed weighting of the hydraulic defects. The proposed weighting values were based primarily on the values utilized for the defects observed in wastewater pipes. As a result, the weighting values proposed here cannot be directly applied onto the hydraulic defects out in the field as they require thorough analysis. In the future research work, the official weighting values should be obtained by carrying out a sensitivity analysis.

- The proposed formula for the calculation of the total score will be analyzed. During the calculation of the total score for a wastewater pipe, the person assessing the pipe multiplies the defect grade with its corresponding unit. For defects such as surface damage, the grade is multiplied with the number of meters that the observed defect spreads over. In addition, the formula for the total score for wastewater pipes includes also a division by the length of the inspected pipe. This is not incorporated in the formula proposed here (see *Equation 2*), mainly due to the fact that the manholes simply represent nodal points joining the incoming sewer or sewers with the outgoing sewer. Therefore, a such distribution of the manhole defects over a manhole length should not be necessary theoretically. However, analyses confirming or denying a such assumption should be performed in order to validate it.

- The total score thresholds must be validated as the thresholds presented here were obtained based on a simulation performed in Excel. Several combinations of different defect grades were multiplied with their corresponding weighting values and summed up together in order to obtain the proposed thresholds. As a result, these ranges of total scores are not reliable and thus will require adjustments. This work will demand execution of several inspections of wastewater manholes in order to test the performance of the proposed assessment procedure. The experiences from the inspections together with the obtained total scores will represent a good basis for the adjustment process. These observations will help to obtain total score thresholds that reflect accurately the state of the condition classes that the inspected manholes are supposed to be assigned into.

- Norwegian water utilities are a part of the previously described processes as they have most experience with manholes and thus can provide lots of valuable input. In addition, external factors that could have an impact on the condition of manholes cannot be neglected and should also be included into the assessment process. Factors such as soil type and traffic load have an influence on the state of the manhole condition as they are related to the infiltration problems and loads that a manhole is subjected to (Malvik, 2017). This additional data is also important in order to understand the failure modes occurring in manholes.

- The development of IAM tools used for modeling of deterioration is researched and attempted for manholes. Execution of proper inspections will result in comprehensive databases containing massive amounts of information concerning the state of the manhole condition. Theoretically, this data could be used for modelling of the evolution with time of the manhole condition classes. Recently, this type of modeling is performed for wastewater pipes by utilization of Markovian models (Myrans, et al., 2018). Theoretically, the same type of modelling could be performed for manholes. Markovian models will predict the probability of transition from one manhole condition class to a worse condition class (Ugarelli, 2018). Future database can also be utilized for development of deterioration curves through identification of trends in the obtained dataset. These curves are determined based on the current state of the manhole condition. Deterioration curves will use this data to predict the expected end of life of the manhole (Ugarelli, 2018). Such information will optimize further the planning of maintenance and rehabilitation. In addition, registered information together with labelled images might be used for Long-Term Planning (LTP) of manhole rehabilitation. Images and information about the construction year, manhole type and material could be utilized to decide criteria for cohorts or groups of manholes with similar features.

7.2 Position of this work with regards to other national initiatives

As mentioned, several times throughout this thesis, the focus of Norwegian water utilities and the wastewater industry has always been primarily dedicated to the wastewater pipes. This point of view has to change as the work regarding the assessment and rehabilitation of pipes is constantly being improved. It is now time to place part of this focus onto manholes and their condition. The work regarding the structure and content of the report proposed in this thesis is pioneer in the field of Norwegian wastewater systems. However, it is only a start of the process regarding the development of an official manhole condition assessment report. Norsk Vann, the Norwegian national interest organization for water and wastewater industry, has already started the development of a manhole report. However, the extent to which they plan to cover the actual assessment procedure is unknown. Anyhow, the work presented here should inspire the developers to formulate an assessment procedure that is at least equally comprehensive. They should analyze the procedure proposed here and try to include something similar in their version of the report. Several of water utilities that provided information for this thesis, have expressed a request for an assessment procedure for manholes. This demand cannot be neglected and should be addressed in the official report as it will have an impact not only on the manhole condition, but also on the condition of the whole wastewater system.

8.0 Artificial Intelligence, Machine Learning and Deep Learning

Artificial Intelligence (AI) is an academic discipline with a goal "to create smart machines that think and act like humans, with the ability to simulate intelligence and produce decisions through processes in a similar manner to human reasoning" (Salvaris, et al., 2018). The study field of AI focuses on development of algorithms for tasks previously performed only by intelligent beings in order to enable machines to learn, respond to feedback and engage in abstract thought (Salvaris, et al., 2018). Several practical applications and active research topics have made AI to a well-established and prosperous field (Goodfellow, et al., 2016). Continuous progress within AI has contributed to development of areas where computers already outperform humans, as for instance the execution of a vast amount of computations in a relatively short amount of time (Wolfgang, 2012). However, there are still several areas where the human remains superior due to the adaptivity of human intelligence. Still, over the years the AI research has contributed to automatization of routine labor through intelligent software, understanding of images and speech, determination of medical diagnoses, and support of other scientific research (Goodfellow, et al., 2016).

Machine learning (ML) is a central subfield of AI where computers are learned to process information and make decisions based on this information (Varone, et al., 2018). The term refers to automated recognition of meaningful patterns in data (Shalev-Shwartz & Ben-David, 2014). ML enables the systems to learn automatically from the data without human assistance (Varone, et al., 2018), where the "learning" of the system refers to the procedure of transforming the experience into expertise or knowledge (Shalev-Shwartz & Ben-David, 2014). The process of learning is often called training. Based on the learned patterns, the system will make data driven decisions without being explicitly programmed to carry out a certain task (Varone, et al., 2018). Machine learning tools are concerned with providing programs the ability to learn and adapt (Shalev-Shwartz & Ben-David, 2014). Typical ML tasks include classification, object detection, regression, recommendations, ranking and clustering (Salvaris, et al., 2018). Recently, ML has become a common tool in almost any task that requires information withdrawal from large datasets (Shalev-Shwartz & Ben-David, 2014). Technology based on machine learning has become a large part of the society as it represents the basis for search engines, anti-spam software, smart phones etc. ML is also broadly utilized in scientific fields such as biology, medicine and astronomy (Shalev-Shwartz & Ben-David, 2014).

Machine learning uses a variety of algorithms which utilize statistical techniques to give computer systems ability to learn from input, describe it and predict outcomes (Rouse & Burns, 2018). The algorithms are trained by using great amount of data, and the understanding is improved over time as new data become available. As the model is constantly fed with new input, the predicted output is constantly updated (Rouse & Burns, 2018). Based on these algorithms, machines learn how to model the relationships among several sets of input features and the outcome they are supposed to predict (Salvaris, et al., 2018). Machine learning algorithms are classified as supervised or unsupervised. The class of supervised algorithms is the most common type of ML and require a data specialist to provide the algorithm with the input and desired output. The specialist will also decide which factors should be analyzed and used to develop predictions (Rouse & Burns, 2018). A model with such features will have labels that represent the outcome against which the model is learned (Salvaris, et al., 2018).

Desired outcome data is not required for training of the unsupervised algorithms. In order to analyze data and derive conclusions computers utilize an iterative approach called "Deep Learning". These algorithms are used for more complex applications such as processing speech, languages and images (Rouse & Burns, 2018).

Deep Learning is another subfield of both AI and ML (Salvaris, et al., 2018). A relationship between the Artificial Intelligence, Machine Learning and Deep Learning is presented in Figure 11. Deep Learning is broadly utilized in applications where the data does not comprise of easily extractable features (Goodfellow, et al., 2016). Such data include text, audio and images. Utilization of deep learning algorithms allow computers to not require human assistance to specify all the knowledge that they need to perform a certain task. The computer is able to learn complex concepts by creating them out of simpler concepts. This is possible through a hierarchy of concepts embedded in the deep learning algorithms (Goodfellow, et al., 2016). As a result, a deep learning model based on such algorithms has the goal to map from an input to an output, e.g. audio to text, pixels in a picture to a predefined classification of this picture (Salvaris, et al., 2018). Approaches featuring deep learning involve application of a multilayer deep neutral network (DNN) to massive quantities of data. DNN models include many layers that allow the automatic learning of high-level abstractions through the hierarchy of patterns embedded in these layers (Salvaris, et al., 2018). As the deep learning models normally have millions of parameters, they require vast training sets to avoid overfitting (Salvaris, et al., 2018).

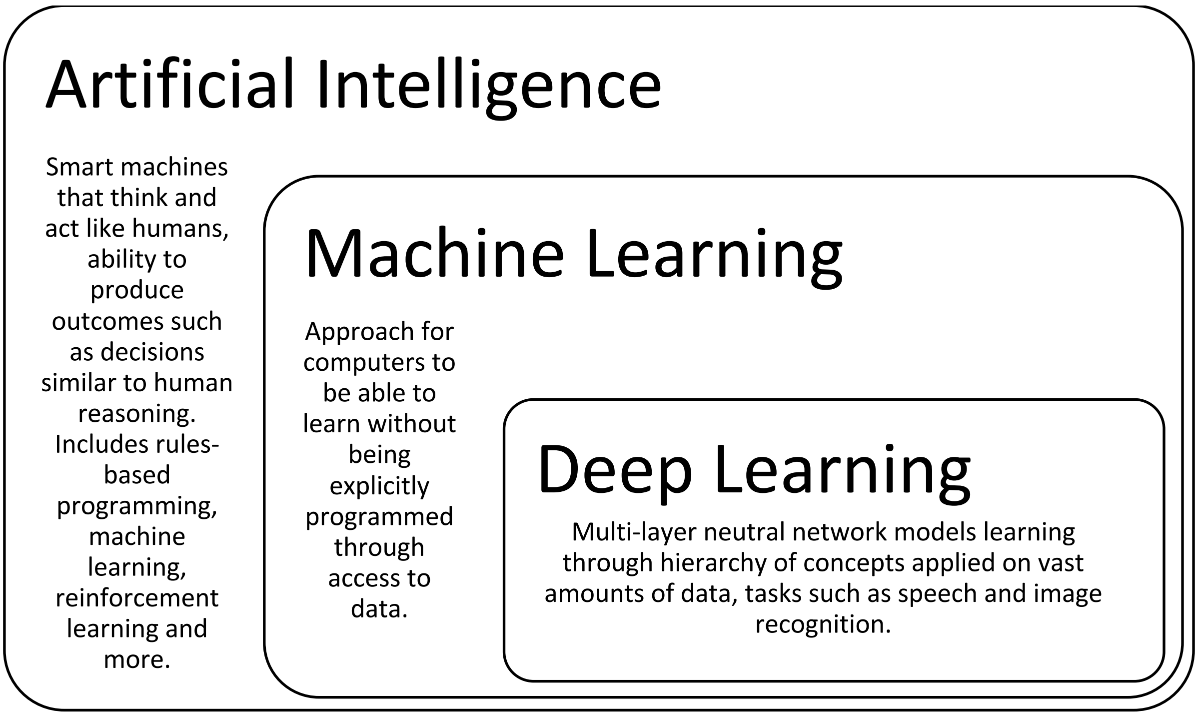


Figure 11: Representation of relationship between Artificial Intelligence, Machine Learning and Deep Learning (Salvaris, et al., 2018).

8.1 Microsoft Azure Cognitive Services and Custom Vision

Microsoft Azure Cognitive Services are a collection of ML algorithms, deep learning models and application programming interfaces (APIs) developed by Microsoft in order to solve problems in the field of AI (Windows App Team, 2017). An API allows an application to correspond with another application or a database, network or operating system, etc. (Conrad, et al., 2016). The Cognitive Services are easily available online for people to use in their own applications. They are divided into two main types; pretrained models available as REST APIs and bring-your-own-data services. The first type does not require any customization in order to consume in end applications (Salvaris, et al., 2018). Custom Vision is an example of a bring-your-own-data service. The application allows the user to develop a customized image classification model without any background in AI (Salvaris, et al., 2018). The development of the model is done by simple upload of images and clicking a button to train the model. There are five categories of the Cognitive Services APIs available today:

- Vision – image and video analysis
- Speech – speech recognition and identification of the speaker
- Language – understanding of sentences and intent
- Knowledge – tracking of scientific knowledge
- Search – application of ML to web searches

Custom Vision is one of the Vision Cognitive Services. The main page of the application is presented in Figure 12. This application allows the users to customize, deploy and improve their own state-of-the-art computer vision models based of a prebuild model developed by Microsoft (Microsoft Azure, 2018). The development of a customized Custom Vision model requires a relatively small set of labelled images. The provided background model has been trained with thousands of images. As a result, it is already familiar with the concepts of images, pixels, edges, color etc. Custom Vision utilizes transfer learning and data augmentation techniques to train the customized model for chosen scenario (Salvaris, et al., 2018).

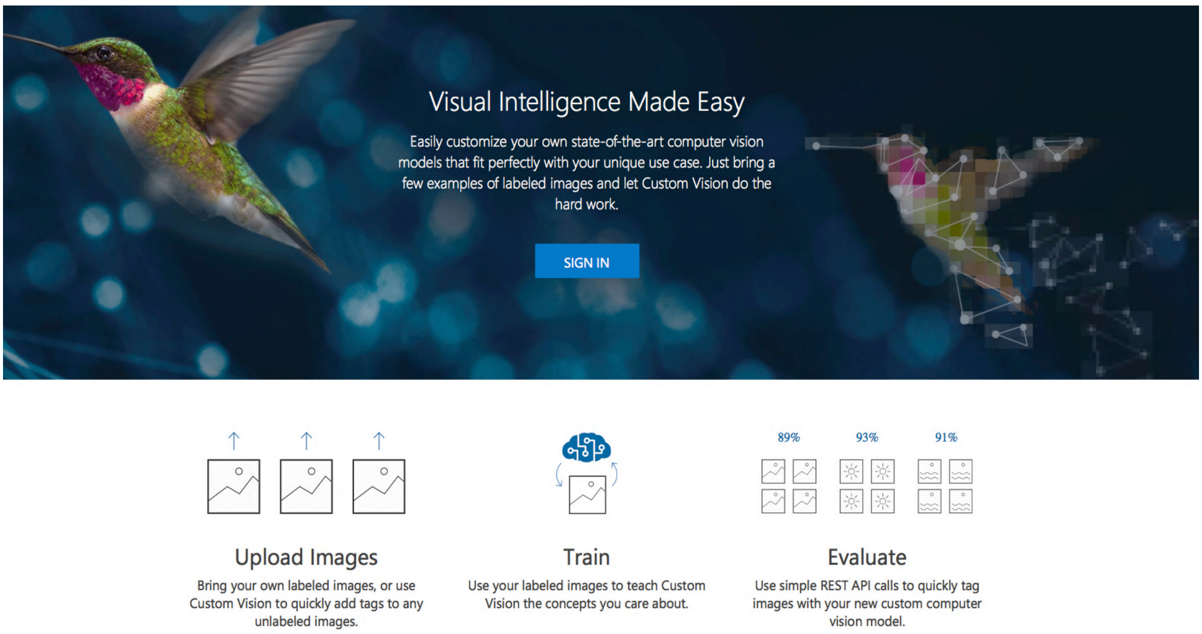


Figure 12: Custom Vision main page (www.customvision.ai).

An image classifier is an artificial intelligence service that classifies the images according to some defined characteristics. Classifiers developed in Custom Vision can be based on one of two types of features; image classification or object detection (Microsoft Azure, 2018). Image classification tags whole images, while object detection finds the location of content within the image. In image classification classifiers, the user can also choose between two types of classifications. These include multilabel and multiclass classification. Multilabel classification allows to assign one or several tags to each image, while in multiclass each image is assigned one single tag. Both image classification and object detection classifiers must be assigned a domain, which is an algorithm optimized for different subject material (Microsoft Azure, 2018). The domains enable the user to customize the background model that is most relevant for the chosen scenario (Salvaris, et al., 2018). The available domains for both image classification and object detection are presented in Table 16. Compact domains allow the model to be exported to run locally on mobile devices such as iPhones, iPads or Android tablets (Microsoft Azure, 2018). Embedment of compact domains into the model will provide the user with a prediction URL which is used further for the development of the application that allows the model to be utilized on mobile devices (Salvaris, et al., 2018).

Table 16: Available domains for image classification and object detection classifiers accessible in Custom Vision (Microsoft Azure, 2018).

Image classification domains	Object detection domains
General	General
Food	Logo
Landmarks	
Retail	
Adult	
General (compact)	
Landmarks (compact)	
Retail (compact)	

After the described features are decided, the user can upload the images used for training of the model. Each uploaded image must be given a single tag or multiple tags, depending on the type of classification. Tags are defined by the user according to the purpose of the developed classifier. The model must be trained with several pictures in order to learn the characteristics of each used tag. Generally, 50 images per each tag can give good results (Microsoft Azure, 2018). However, the number of images per tag depends strongly on the complexity of the image feature to be classified or detected. After sufficient number of images has been uploaded and tagged in each category, the model must be trained. The training of the model is obtained through a click on a button labelled "Train". During this process, the algorithm in the model will split the tagged dataset in two. One part is utilized for the training of the model, while the other part is used for cross-validation of the trained model (Microsoft Azure, 2018). The accomplished performance of the trained model based on object detection is given by three values; precision, recall and mAP (Microsoft Azure, 2018). The last value is not obtained for image classification projects. The precision value shows the likelihood that the tags are predicted correctly. The recall value presents the percentage of how many tags the model identified correctly out of the tags that should have been predicted correctly. mAP value is defined by Microsoft Azure as "the mean average precision which is the overall object detector performance across all of the tags" (Microsoft Azure, 2018). The model can be retrained until the desired values of precision, recall and mAP are obtained.

The model can be tested after finished training. The testing of the model is performed by uploading several pictures that have not been used during the training process. The model will run the uploaded image through the trained model and return the suspected tag/tags with a confidence score for each predicted tag. The score is given on a scale from 1 to 100% certainty (Microsoft Azure, 2018). The user can also set a threshold for displayed predictions, also called probability threshold. Predictions with confidence score below this value will not be presented for the user. In object detection classifiers, the location of the object to be detected must be marked in the image with a bounding box during the training. Several areas can be marked and tagged in a single picture. As a result, a trained classifier with features of object detection will predict the suspected tag with additional location in the tested image (Microsoft Azure, 2018).

9.0 Training and testing process of the Custom Vision model

The selection of image recognition software has been based on results obtained in the specialization project "Image recognition applied to condition assessment of wastewater manholes". This project was written by the writer of this thesis and represented the foundation for the work presented here. The performed categorization with Custom Vision model was a simple binary categorization, where the images were divided into two categories; "Invert channel" and "No invert channel". The model obtained promising results by predicting correctly 13 out of 14 testing images with considerably high certainty (Makuszewska, 2018). Based on these results, it was decided to continue the training of Custom Vision to recognize grades of manhole defects. Custom Vision model was described in section *8.1 Microsoft Azure Cognitive Services and Custom Vision*.

One of the main benefits of Custom Vision is the fact that it already has been trained with thousands of pictures. Therefore, it is already familiar with the concept of images, pixels, edges, color etc. As a result, the model requires less pictures for training of the last layer, which will here represent the concept of recognizing different grades of "Settled deposit" defect in the wastewater manholes.

The Custom Vision trial performed during this study was a supervised classification where the user provided the features that should be associated with each tag category. Therefore, the model was trained on a set of manhole pictures with easily recognizable features. The areas in training images uploaded to the model were tagged by the user into one of four separate categories that they visualized. The categories represented the four grades that the "Settled deposits" defect may be assigned into during an inspection of wastewater manholes. The description of the grades was presented in section *6.2.2 Grading of the hydraulic defects*. Based on these descriptions, the areas in the training images showing settled deposits could be tagged into one of the following categories; "HSD 0-10%", "HSD 10-50%", "HSD 50-90%" and "HSD over 90%". HSD is the defect code for the hydraulic defect "Settled deposits", while the percentages represent the cross-sectional reduction of the invert channel which is associated with the four grades. The project type was set to object detection. Therefore, areas representing the settled deposits had to be marked manually with a boundary box in all of the images used for the training of the model. Picture set in all four categories had to represent enough variation in order to achieve better predictions. Therefore, pictures showing different cases of deposition have been used in all categories.

After the completed training process, the model was tested on an additional set of images. This set was not a part of the image set used for the training and contained images representing all four categories of settled deposits. The set with testing images was analyzed manually before they were uploaded to the model. The areas that were expected to be recognized by the model were marked by the user. The expected tag was also noted. These images are presented in Appendix 2. Afterwards, the images were uploaded into the model and resulting prediction of which category each area represented was quickly obtained. After testing and prediction of all images was completed, the results and further use of Custom Vision was evaluated.

9.1 Case: The municipality of Trondheim

The images used for the training and testing of the Custom Vision model were provided by the water utility of Trondheim. The database owned by the water utility consists of nearly 7 000 images of wastewater manholes (Makuszewska, 2018). The images within this database are of varying quality. Therefore, the images had to be carefully analyzed in order to be selected by the user of the Custom Vision model. Out of nearly 4 000 analyzed images, only 386 pictures were selected for the Custom Vision trial performed here. An additional visual analysis of these images resulted in a database with a total of 356 images suitable for the Custom Vision model. 344 images were used for the training and the remaining 12 images were used for testing of the model.

The majority of the images in the database of the Trondheim water utility showed clear and good representation of the condition of photographed wastewater manholes. However, not all of the manholes had settled deposits within the manhole invert channels. In addition, some of the images showing settled deposits included some additional elements such as CCTV-robot, pointing arrows, ladder and gaskets. The use of these images was reduced to a minimum as such additional elements might have an impact on the performance of the model. Images that were blurry and of poor quality were excluded from the image sets used for training and testing of the Custom Vision. Some of the images had to be re-sized to a size under 6 MB in order to be able to upload them to the Custom Vision model.

10.0 Custom Vision results

The purpose of this trial was to train the Custom Vision model to recognize all four grades of the defect "Settled deposits". The project type performed in this trial was set to object detection with general domain. This allows the model to detect objects inside an image with their locations, instead of just being a simple classifier. The model was trained with 344 images. Regions that showed the objects to be detected have been tagged and marked with a boundary box in all images. The majority of training images showed several grades of settled deposits within one image. All of the grades shown in a picture were tagged into the corresponding categories as shown in Figure 13. Therefore, the image count in all categories together was higher than 344 images. The areas were tagged into one of four possible categories. The category "HSD 0-10%" consisted of 238 tagged images, category "HSD 10-50%" consisted of 147 tagged images, category "HSD 50-90%" consisted of 79 images, while category "HSD over 90%" consisted of 45 images.

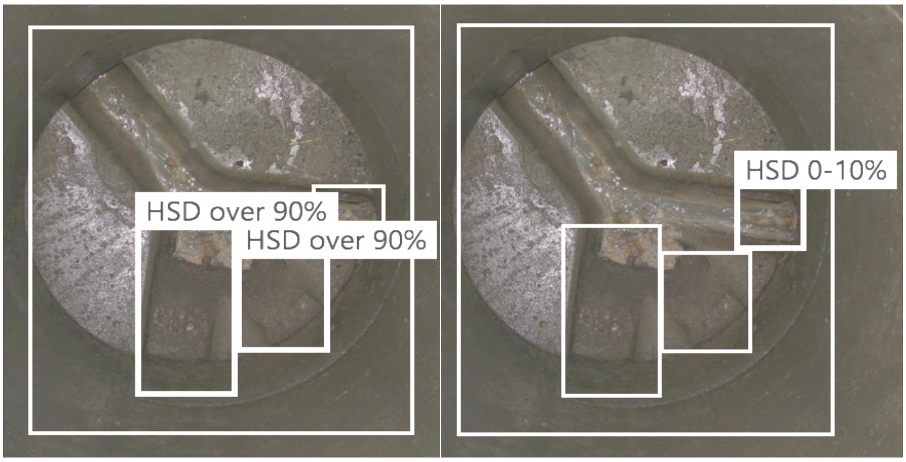


Figure 13: Training image tagged into category "HSD over 90%" and "HSD 0-10%".

After the images were tagged into correct category, the model was trained. During the training process the image set is divided in two, where one of them is used for training and other for the validation of the trained model. After completed training, the model obtained overall precision value of 87,0%, recall value of 37,8% and mAP value of 38,1% as shown in Figure 14. For the explanation of each value, see section *8.1 Microsoft Azure Cognitive Services and Custom Vision*. The performance of the model per category is shown in Table 17.

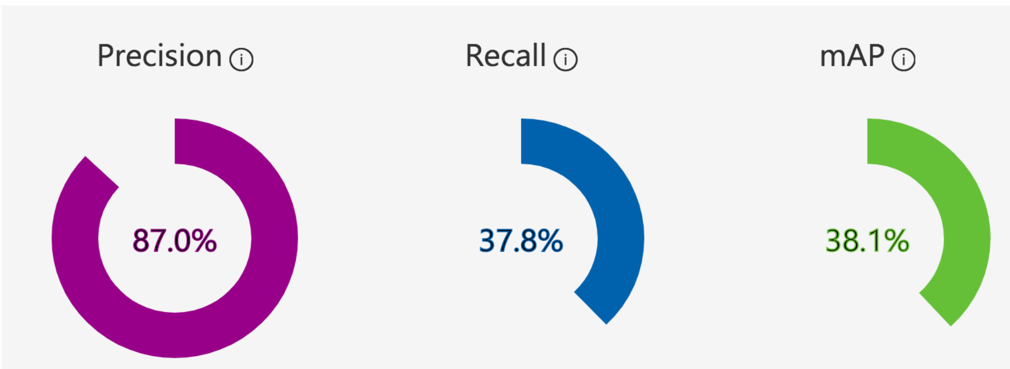


Figure 14: Overall performance of the trained Custom Vision model.

Table 17: Performance per category.

Category	Precision	Recall	Average precision	Image count
HSD 0-10%	82.4 %	16.9 %	46.6 %	238
HSD 10-50%	27.3 %	8.6 %	13.3 %	147
HSD 50-90%	75.0 %	12.5 %	22.8 %	79
HSD 90% and more	75.0 %	25.0 %	46.5 %	45

The trained model was tested with 12 images that showed manhole invert channels with all four grades of "Settled deposits" defect. The probability threshold was set to 50% for all predictions. Predictions obtained both above and below this threshold will be discussed in the next chapter. As for the training images, the majority of images selected for testing included several grades of the settled deposits within one image. All 12 images showed a total of 39 separate areas representing different grades of the selected defect. These areas were expected to be detected by the model and are shown in Appendix 2 together with the expected tag. Out of 39 areas, 38 were predicted correctly with varying tag certainty. However, 1 area was not predicted at all. Appendix 3 present all testing images together with the obtained predictions. A summary of all predictions and the corresponding probability range is presented in the Table 18. The results from the testing have been divided into three categories, where each represent different probability range. The total number of images assigned within each probability range is also presented. As shown in the table below, 23 out of 39 areas were predicted correctly with a probability over 50%. The distribution of predicted areas within the probability range of 50-100% is presented in Figure 15.

Table 18: Summary of all predictions with corresponding probability ranges.

Prediction	Number of areas
Predicted correctly above probability threshold of 50%	23
Predicted correctly with probability between 10-50%	12
Predicted correctly with probability value below 10%	3
Not predicted	1

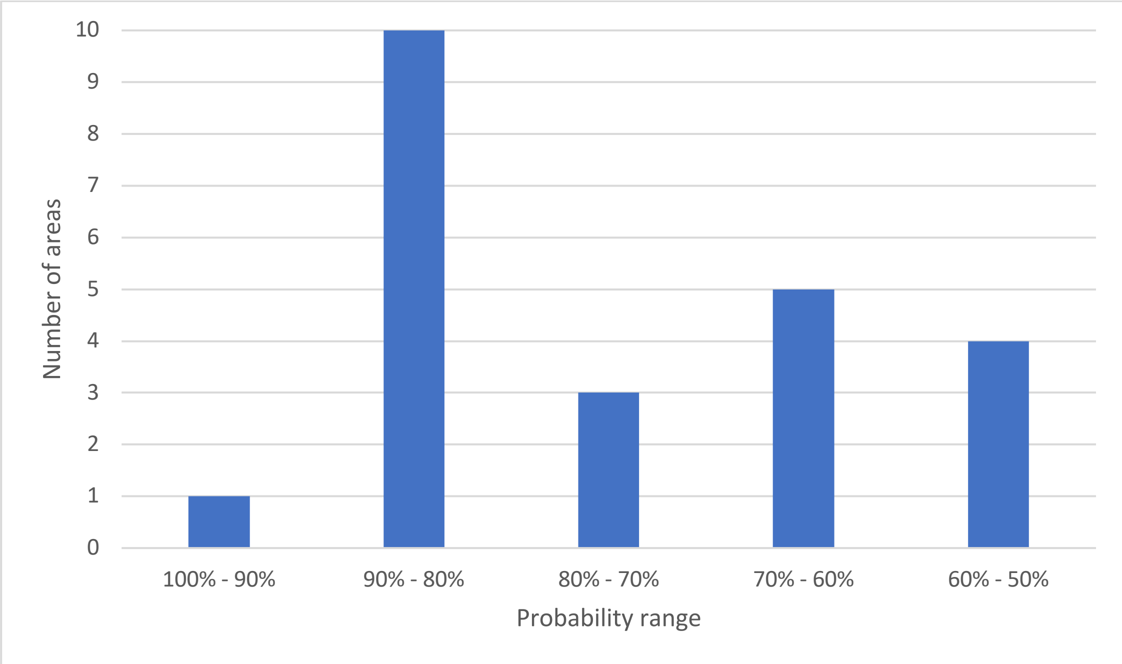


Figure 15: Distribution of areas with prediction above probability threshold of 50%.

11.0 Discussion of the Custom Vision performance

The results obtained from the trained Custom Vision model are promising. The model managed to recognize correctly 38 of 39 areas in the testing images, where 23 areas were predicted with a certainty above 50%. Only one area was never detected. However, this case of deposition was very small. It is assumed that the model did not detect this area because there were not enough of similar areas within the training images. Therefore, the model was not trained properly to detect all areas with similar cases of insignificant deposition.

The presented results show that an image recognition software is indeed able to detect different grades of manhole defects. Therefore, it is encouraged to continue the training of the model to recognize not only the "Settled deposits" defect grades, but also the rest of the defects from the future hydraulic and structural defect categories. The process of development of an application for image recognition of manhole defects should be performed by IT-companies that provide current IT-systems for Norwegian water utilities. The development of an application that is able to recognize all manhole defects by grade will not be an easy task. It will be time and resource demanding as it will require a massive amount of training images. The image recognition software on its own is only able to optimize the inspection of the manholes as it only can grade the observed defects. Therefore, it could be reasonable to integrate manhole assessment into the image recognition software and thus additionally optimize the assessment procedure. The digitalization of the manhole assessment will require development of an additional software that can utilize the results from image recognition software, weight them, calculate a score for the inspected manhole and assign it into a condition class. However, this will require expertise from several data scientists that are able to transform the image recognition software and assessment procedure from the manhole report into an application for mobile devices. Such digitalization of both inspection and assessment of manholes will make both processes less time demanding, cheaper to perform, more objective and executed equally out in the field by the personnel within Norwegian water utilities. Flow chart of the development process of an application that inspects and assesses the condition of manholes is presented in Figure 16.

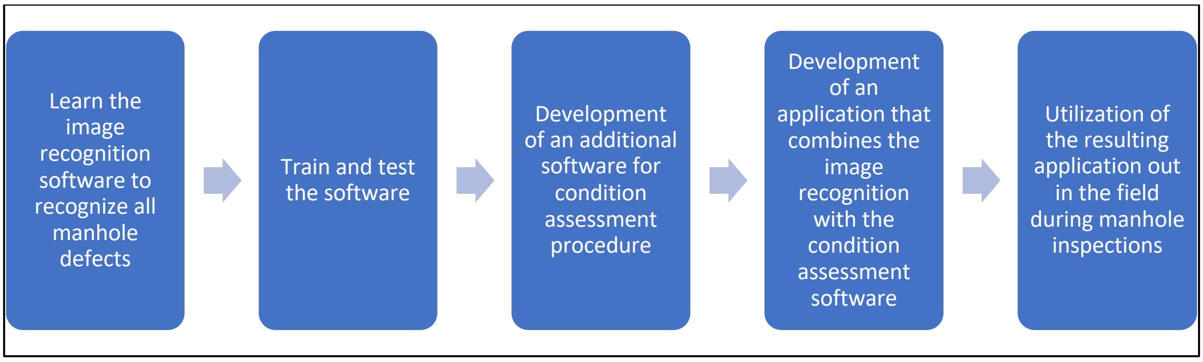


Figure 16: Flow chart of the development of an application that can inspect and assess the condition of manholes.

Despite the great detection of the areas showing the settled deposits, the certainty of these predictions varied greatly. The main reason for this variation is differing image count between the categories. These differences resulted in a considerably low overall performance of the trained model and low performance per each category. Overall performance is shown in Figure 14, while the performance per category and corresponding image count in each category is shown in Table 17. However, these values can be improved by increasing significantly the number of images used for the training of the model. The training process requires high quality images that show defect grades in a way that makes them easily recognizable. Finding such images will not be an easy task as the quality of pictures is varying in the current databases. Therefore, the process will demand merging of several databases from different water utilities in order to acquire an adequate number of images showing different grades of manhole defects. It is assumed that at least 400-500 images in each category should be enough for the model to learn the complexity of each grade, and thus achieve sufficient training and a good model performance. The water utility of Trondheim provided images for the training and testing performed here. Out of nearly 4000 images only 344 were considered adequate for the purpose of this training. This relationship between the available and acceptable images underlines the importance of coordination among the Norwegian water utilities in sharing their image databases. In addition, a proper picture documentation during future manhole inspections should be encouraged by the Norwegian manhole report as the implementation of image recognition software on good quality images will optimize the inspections of manholes. Theoretically, the trained software could also be used for sorting and classification of the images in the current databases.

The low overall performance of the model resulted in multiple tagging of the same areas in the images used for testing. During testing, the probability threshold was set to 50% for all predictions. This means that for a tag to be shown, the model had to be very certain that the predicted tag is really present in the image. The probability threshold was set to 0% at the end of the testing process in order to acquire all of the predicted tags for each tested image. The image on the right side of Figure 17 shows one of the images with several tag predictions when probability threshold was set to 0%. The same image is shown on the left side of the Figure 17 when the probability threshold was set to 40%.

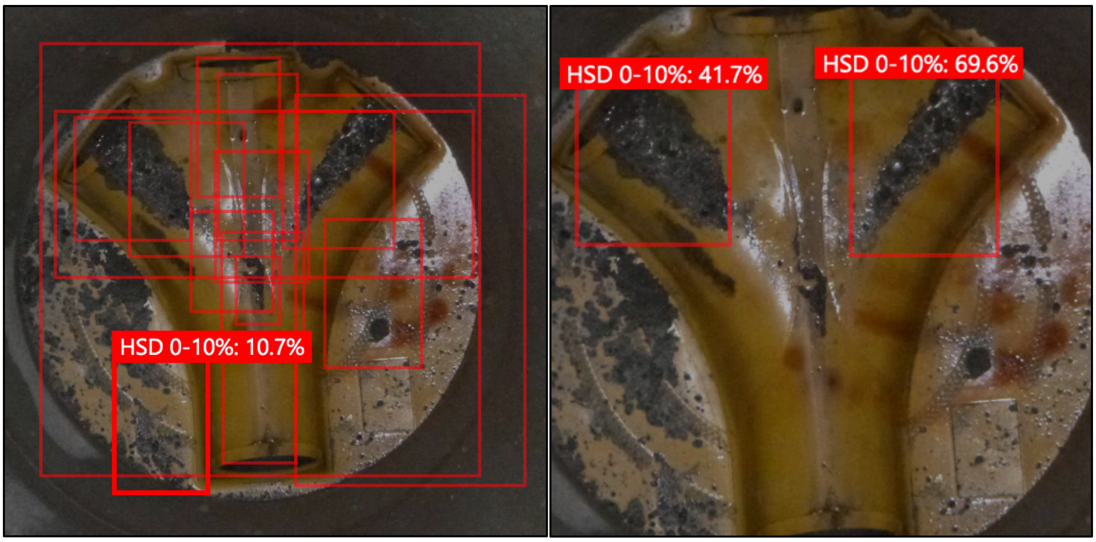


Figure 17: One of the manhole images used for testing. Predictions above the probability threshold of 0% are shown on the image to the left, while predictions above probability threshold of 40% are shown in the image to the right.

In the left image in Figure 17, the model tags all of the areas where it detects presence of settled deposits. It ignores the fact that it is supposed to focus on the areas within the invert channels and ends up with also tagging the deposits present on the benching. However, the probability of these additional tags was very low. It was enough to increase the threshold to 40% in order to acquire two out of three predictions for the areas the model was supposed to detect, as shown in right image in Figure 17. The third area, which is the smaller area showing the deposition in the middle of the invert channels, was also detected and assigned to correct defect category. However, the certainty of this prediction was 1,6 % and thus very low. Beside the low model performance, another reason for the multiple tagging of images might be the additional elements present in both training and testing image sets. Objects such as ladders, gaskets, CCTV-robots and pointing arrows will confuse the model when the distribution of training images that include these elements is uneven between the defect categories. As a result, the model is then trained to think that these elements are a part of the feature to be detected. During future applications of Custom Vision, this problem must be avoided through additional training of the model to recognize these elements into their own categories. The model will then distinguish correctly between the four original defect categories without being disrupted by unknown or unspecified elements.

Prior to the future training of the model, it is encouraged to develop criteria that guide the user on which training image or areas within the images should be assigned to a distinctive defect grade. The tagging process of training images has proven to be difficult as it was often hard to distinguish between the tag categories. Here, the person performing the tagging had no previous knowledge on the real cross-sectional reduction of the invert channel displayed in the training images. Therefore, the decision concerning the assignment of tags was indeed subjective as it was based only on the users' interpretation of the settled deposits state visualized in the images. As a result, it was often hard to decide whether an area showing settled deposits should be categorized as "10-50% reduction" or "50-90% reduction". The endpoints such as "0-10% reduction" or "over 90% reduction" were somehow easier to determine as they differed more in relationship to the two previously mentioned categories that are in the middle spectrum of the classification. Based on these experiences, it is encouraged to analyze images prior to the training in order to decide some criteria that describe how the users should distinguish between the defect grades. For the case of settled deposits recognition performed here, the descriptions of the grades provided by the proposed manhole report were simply not enough as they barely related to the two-dimensional representation of settled deposits displayed by the images.

12.0 Conclusion

As of today, there is no Norwegian manhole report for inspection and classification of wastewater manholes. Lack of guidelines has resulted in limited evaluation and rehabilitation of manholes. However, the focus on manhole assessment is increasing and the need of a report has been expressed by several municipalities. The theoretical content and structure of a such report has been proposed in this master's thesis, and covers all the aspects from defect definitions, grading, weighting and class assessment. The evaluation method proposed here is a reliability-based condition assessment of manholes, where the proposed condition classes were defined according to the effects of the possible manhole defects on to the functional requirements of wastewater manholes. This research work focused on the hydraulic reliability of manholes. However, the importance of future addition of structural reliability into the assessment procedure has also been discussed and encouraged. An assessment procedure based on the proposed features will allow for a transparent decision-making on the way of rehabilitation or maintenance based on the nature of the worst type of the condition class. Such structure of the manhole condition assessment procedure will make the obtained total scores, for both hydraulic and structural functional requirements, easier to understand as they will reflect the current state of the inspected manhole much clearer considering the assessed function. The overview and evaluation of the effect of a given defect onto one or another function is relevant and helpful when selecting the type of needed intervention. The proposed assessment procedure will indeed simplify the understanding of the required interventions as it does not allow to lose the information concerning the reason for the obtained condition of the inspected manhole. As a result, the person performing the assessment will know better whether the improvement of the manhole condition requires an operational intervention such as flushing, a structural intervention such as reconstruction of manhole components, or a combination of both.

Based on the presented research, the official manhole report should consist of guidelines on how to inspect the manholes, register the necessary information and utilize it further for assessment of the manhole condition. Inspection guidelines are needed in order to ensure objective collection of all desired information. The procedure should be presented with examples of how defects with varying severity should be registered in order to minimize human subjectivity and misunderstandings. The assessment procedure for wastewater manholes should be grounded on the principles of IAM, as proposed here. This procedure is already known for the workers as it is also utilized for the condition assessment of wastewater pipes. As the maintenance and rehabilitation of manholes have been limited in the recent years, the future investments in upgrading the current state of manholes might be high. Classification approach based on IAM will optimize the prioritization of such interventions through integration of a risk assessment procedure.

An attempt on implementation of image recognition software on manhole images has also been performed during the study conducted for this thesis. Custom Vision was the utilized model. A set of 344 images was uploaded to Custom Vision in order to train the model to recognize the four distinguished grades of the "Settled deposits" defect. As a result, the training images were divided into four categories where each category represented one of the four possible grades. After completed training, the model obtained overall precision value of 87,0 %, recall value of 37,8% and mAP value of 38,1%. It was tested with 12 images with several areas showing settled deposits in manhole invert channels. The model was able to predict correctly 38 out of 39 areas, where 23 of these were predicted with a certainty above the probability threshold of 50%. These results are promising as they show that the software is able to recognize correctly different defect grades. Based on these results, it is encouraged to continue the training of the software with other defects and their corresponding grades. Despite the correct recognition of the defects, the certainty of these predictions varied significantly. This can be improved in the future through increased number of training images, enhanced image manipulation, tagging of additional elements present in the images and labelling of all training images. Further training of the Custom Vision model to recognize manhole defects will be challenging, but achievable as several municipalities showed interest in providing images for the development of a such application. The image recognition software on its own is only able to optimize the inspection of the manholes as it only can grade the observed defects. However, it could be reasonable to attempt to integrate manhole assessment into the image recognition software and thus additionally optimize the assessment procedure. The digitalization of the manhole assessment will require development of an additional software that can utilize the results from image recognition software, weight them, calculate a score for the inspected manhole and assign it into a condition class. This will require expertise from data scientists that are able to transform the image recognition software and assessment procedure from the manhole report into an application for mobile devices. Such digitalization of both inspection and assessment of manholes will optimize and simplify both processes as it will make them less time demanding, cheaper to perform, more objective and executed equally out in the field by the personnel within Norwegian water utilities.

The research presented here is pioneer in the field of Norwegian wastewater systems. However, it is only the starting point of development of both an official manhole report and a digital application that can inspect and assess manholes. Several suggestions for the future research have been presented in this thesis. The purpose of these suggestions is the validation and further improvement of the concepts presented here. Continuation of this research is important as it will result in an improvement of the condition and performance of manholes, and consequently contribute to enhanced condition of the whole wastewater system.

13.0 References

Alegre, H. & Coelho, S. T., 2012. Infrastructure Asset Management of Urban Water Systems. In: A. Ostfeld, ed. *Water Supply System Analysis - Selected Topics .* s.l.:IntechOpen.

Alegre, H. et al., 2012. An integrated approach for infrastructure asset management of urban water systems. *Water Asset Management International*, June, pp. 10-14.

AMWA, NACWA and WEF, 2007. *Implementing Asset Management: A Practical Guide ,* N/A: Association of Metropolitan Water Agencies (AMWA), National Association of Clean Water Agencies (NACWA) and Water Environment Federation (WEF).

AWARE-P, 2011. *The AWARE-P approach to infrastucture asset management.* [Online] Available at: http://aware-p.org/np4/approach/
[Accessed 22nd May 2019].

Bernhus, C., Nilssen, O., Mosevoll, G. & Hansen, A., 2007. *Dataflyt - Klassifisering av avløpsledninger,* Hamar: Norsk Vann.

Birolini, A., 2007. *Reliability Engineering: Theory and Practice.* 5. edition ed. Berlin: Springer.

Bruaset, S., 2018. *Strategic rehabilitation planning of urban water systems.* Trondheim: TVM 4141: Vannforsynings- og avløpssystemer, videregående kurs (2018 HØST), NTNU.

Buttler, D. & Davies, J. W., 2011. *Urban Drainage.* 3. edition ed. Abingdon, Oxon: Spon Press.

Conrad, E., Misenar, S. & Feldman, J., 2016. *CISSP Study Guide.* 3rd edition ed. Waltham, MA, USA: Syngress.

DANVA, 2010. *Brøndmanualen - Inspektion og registrering af brønde,* Aalborg: Dansk Vand- og Spildevandsforening (DANVA) .

DANVA's Afløbskomité, 2005. *Fotomanualen - Beregning af fysisk indeks ved TV-inspektion,* Skanderborg: DANVA Sekretariatet.

Federtion of Canadian Municipalities and National Research Council, 2002. *Deterioration and Inspection of Water Distribution Systems,* Canada: Federation of Canadian Municipalities and National Research Council.

Goodfellow, I., Bengio, Y. & Courville, A., 2016. *Deep Learning.* 1. edition ed. Cambrigde, MA : MIT Press.

Gulati, R. & Smith, R., 2009. *Maintenance and Reliability Best Practices.* 1. edition ed. New York : Industrial Press.

Hafskjold, L. S., 2009. *Trykktap i avløpsnett ,* Hamar : Norsk Vann.

Hager, W. H., 1999. *Wastewater Hydraulics: Theory and Practice.* Berlin: Springer.

Haugen, H. J., 2018. *Dataflyt - Klassifisering av avløpsledninger ,* Hamar: Norsk Vann.

International Electrotechnical Commission, 1990. *IEC 60050-191:1990 International Electrotechnical Vocabulary. Chapter 191: Dependability and quality of service,* Genéve: International Electrotechnical Commission.

International Organization for Standardization, 2014. *ISO 55000:2014,* N/A: International Organization for Standardization.

Keseler, K. L., Urke, I. J. & Hauge, P., 2018. *Veiledning for bruk av betongrør og kummer ,* Hamar: Norsk Vann.

Knolmar, M. & Szabo, G. C., 2003. *Report D3: Classification systems based on visual inspection,* Budapest : CARE-S: Computer Aided Rehabilitation of Sewer Networks, Research and Technological Development Project of European Community.

Larvik kommune, 2018. *VA-norm Larvik kommune.* [Online]
Available at: https://www.larvik.kommune.no/media/1211/vanorm.pdf
[Accessed 17 November 2018].

Lindholm, O., Endersen, S., Smith, B. T. & Thorolfsson, S., 2012. *Veiledning i dimensjonering og utforming av VA-transportsystem,* Hamar: Norsk Vann.

Loe Rørprodukter AS, 2017. *Loe-kummer generelt.* [Online]
Available at: http://loe-ror.no/filer/Loe-Kummer_generelt.pdf
[Accessed 31 Januar 2019].

Makuszewska, K., 2018. *Implementing image recognition to condition assessment of wastewater manholes,* Trondheim: Kamila Makuszewska.

Malvik, S., 2017. *Implementing Asset Managament and Inspection Procedures to Wastewater Manholes,* Trondheim: Sigurd Malvik .

Microsoft Azure, 2018. *How to build a classifier with Custom Vision.* [Online]
Available at: https://docs.microsoft.com/nb-no/azure/cognitive-services/Custom-Vision-Service/getting-started-build-a-classifier
[Accessed 4 October 2018].

Microsoft Azure, 2018. *What is Custom Vision?.* [Online]
Available at: https://docs.microsoft.com/en-us/azure/cognitive-services/custom-vision-service/home
[Accessed 3 October 2018].

Mosevoll, G., 2008. *Kampen om grøfta - VA-entrepenørene setter dagsorden.* Skien: Gunnar Mosevoll.

Myrans, J., Everson, R. & Kapelan, Z., 2018. Automated detection of faults in sewers using CCTV image sequences. *Automation in Construction*, 16 August, pp. 64-71.

NASSCO, 2015. *Manhole Assessment (MACP).* [Online]
Available at: https://www.nassco.org/manhole-assessment-macp
[Accessed 16 November 2018].

Rokstad, M. M., 2018. *Water as critical infrastructure: challenges, transition trends and modelling approaches.* Trondheim: TVM 4141: Vannforsynings- og avløpssystemer, videregående kurs (2018 HØST), NTNU.

Rouse, M. & Burns, E., 2018. *Definition of Machine Learning (ML).* [Online]
Available at: https://searchenterpriseai.techtarget.com/definition/machine-learning-ML
[Accessed 13 Desember 2018].

Salvaris, M., Dean, D. & Tok, W. H., 2018. *Deep Learning with Azure.* 1. edition ed. Berkeley, CA: Apress.

Shalev-Shwartz, S. & Ben-David, S., 2014. *Understanding Machine Learning - From theory to algoritms.* 1. edition ed. New York : Cambridge University Press.

Stiftelsen VA/Miljø-blad, 2018. *VA/Miljø-blad Nr.2 - Renovering av kum ,* Drammen: Stiftelsen VA/Miljø-blad.

Too, E. & Tay, L., 2008. *Infrastructure Asset Management (IAM): Evolution and Evaluation.* [Online]
Available at: http://www.irbnet.de/daten/iconda/CIB11465.pdf
[Accessed 2 November 2018].

Ugarelli, R., 2018. *Condition assessment of water and wastewater pipes.* Trondheim: TVM 4141: Vannforsynings- og avløpssystemer, videregående kurs (2018 HØST), NTNU.

Ugarelli, R., 2018. *Infrastructure Asset Management (IAM).* Trondheim: TVM 4141: Vannforsynings- og avløpssystemer, videregående kurs (2018 HØST), NTNU.

Ugarelli, R., 2018. *Reliability analysis of urban water systems and LCC.* Trondheim: TVM 4141: Vannforsynings- og avløpssystemer, videregående kurs (2018 HØST), NTNU.

Varone, M., Mayer, D. & Melegari, A., 2018. *Expert system - What is Machine Learning? A definition.* [Online]
Available at: https://www.expertsystem.com/machine-learning-definition/
[Accessed 26 October 2018].

Windows App Team, 2017. *Windows Blogs, Cognitive Sevices API: Vision.* [Online]
Available at: https://blogs.windows.com/buildingapps/2017/02/13/cognitive-services-apis-vision/
[Accessed 3 October 2018].

Wolfgang, E., 2012. *Introduction to Artificial Intelligence.* 2. edition ed. Cham, Switzerland : Springer International Publishing .

Appendix

Appendix 1: Condition assessment of two wastewater manholes visualized through images provided by the water utility of Trondheim

Appendix 2: Images used for testing of the Custom Vision model with marked areas that were expected to be detected

Appendix 3: Custom Vision predictions of the testing images

Appendix 1: Condition assessment of two wastewater manholes visualized through images provided by the water utility of Trondheim

This appendix contains two examples of condition assessment of wastewater manhole images. The condition of these manholes was evaluated based on the assessment procedure presented in the proposed manhole condition assessment report. The observed defects were graded and weighted, the total score was calculated and used for the assignment of each manhole into a hydraulic condition class. The pictures were provided by the water utility of Trondheim.

Example 1

Observed failures with corresponding grades, weights and calculation of the total score:

Observation		**Grade**	**Weight**	**Grade*Weight**
Type	**Code**			
Water level	HWL	1	0	0
Infiltration	HIN	1	0,1	0,1
Settled deposits	HSD	2	2	4
Surface damage	HSF	2	2	4
Manhole bottom	HMB	1	0,5	0,5
			TOTAL	**8,6**

Total score of 8,6 places this wastewater manhole into hydraulic condition class H2.

Example 2

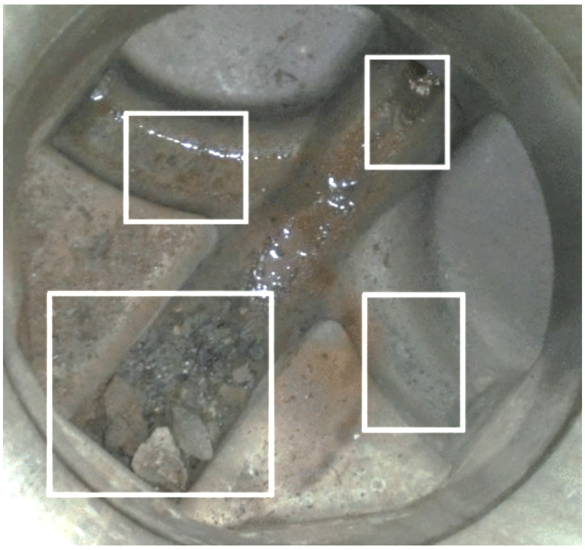
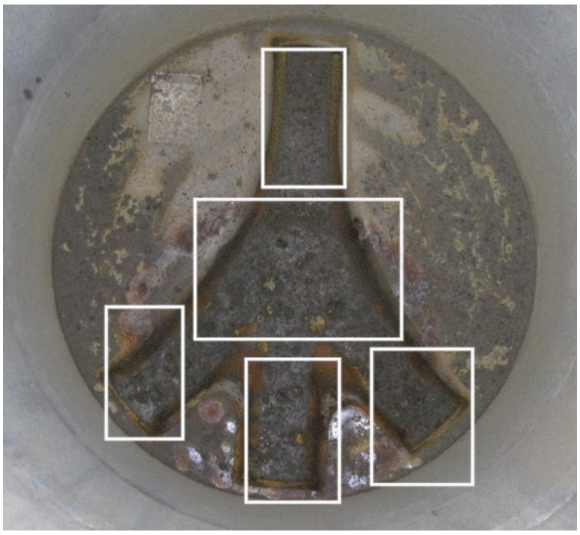
Observed failures with corresponding grades, weights and calculation of the total score:

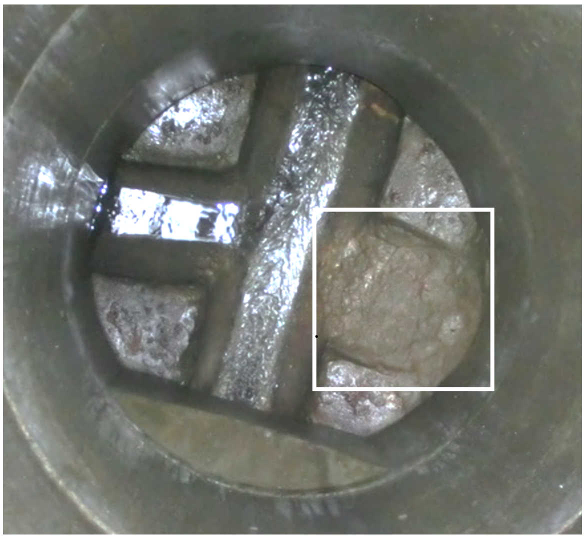
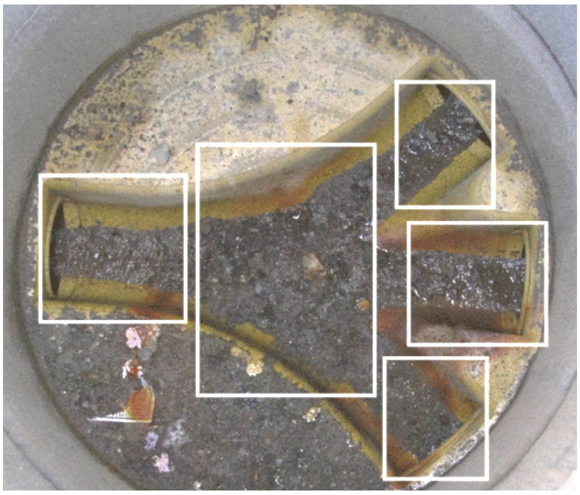
Observation		Grade	Weight	Grade*Weight
Type	**Code**			
Water level	HWL	1	0	0
Settled deposits	HSD	3	4	12
Attached deposits	HAD	1	0,5	0,5
Surface damage	HSF	2	2	4
Manhole bottom	HMB	1	0,5	0,5
			TOTAL	**17**

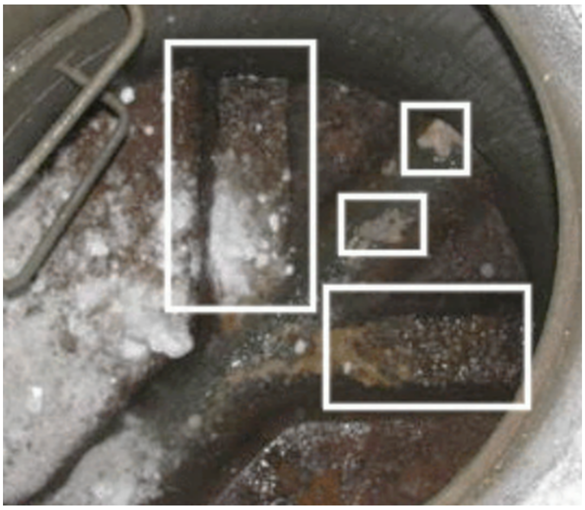
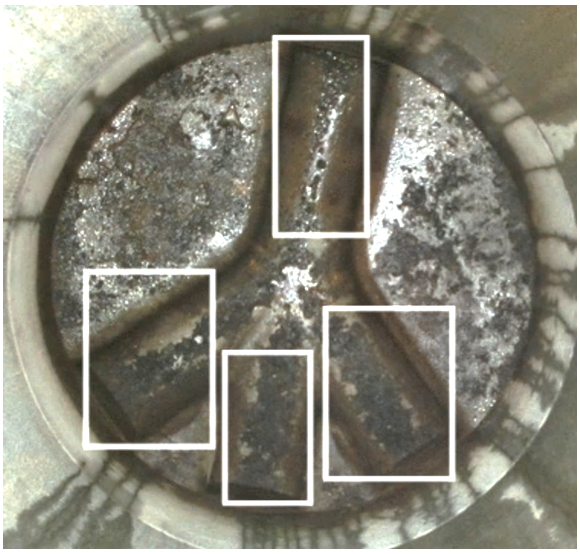
Total score of 17 places this wastewater manhole into hydraulic condition class H2.

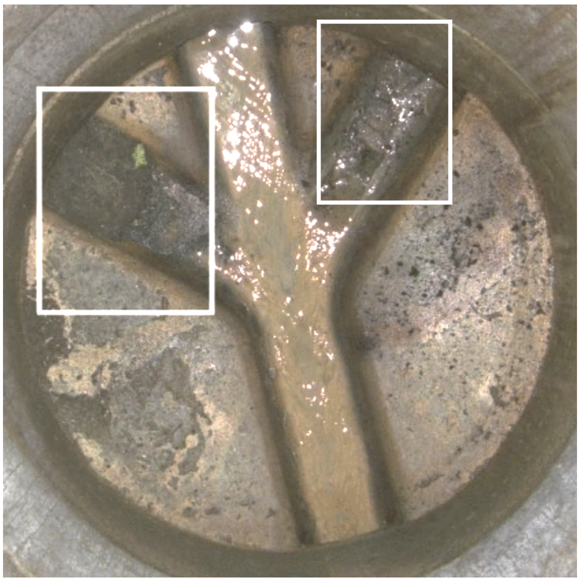
Appendix 2: Images used for testing of the Custom Vision model with marked areas that were expected to be detected

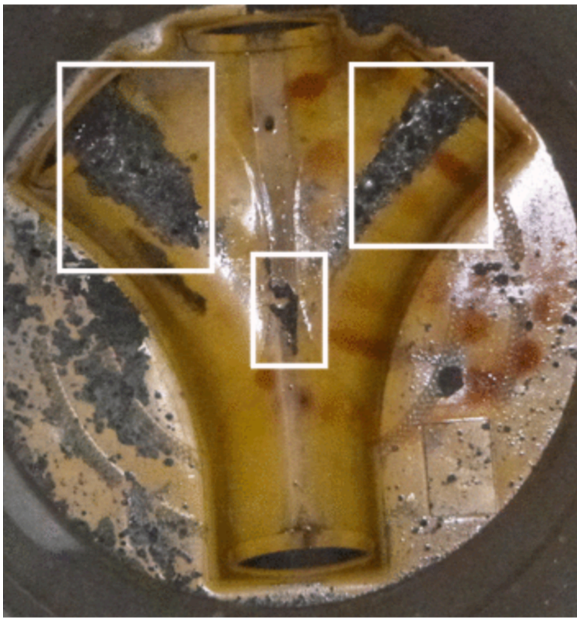
The images presented in this appendix were used for the testing of the trained Custom Vision model. All images were analyzed prior to the upload to the model. The areas that were expected to be detected by the model were marked separately by the user of the model. They were also assigned a tag that the model should predict for these areas. This was done in order to track the performance of the model and simplify its evaluation.

Image	Description
	Four areas to be detected. Three smaller areas are expected to be predicted as "HSD 0-10%", while the largest area should be predicted as "HSD over 90%".
	Five areas to be detected. All five are expected to be predicted as "HSD 10-50%".

	Four areas to be detected. Three smaller areas are expected to be predicted as "HSD 0-10%", while the largest area on the top of the image should be predicted as "HSD over 10-50%".
	One area to be detected. This area is expected to be predicted as "HSD over 90%".
	Five areas to be detected. The largest area in the middle is expected to be predicted as "HSD 10-50%", while the four other areas are expected to be predicted as "HSD 0-10%".

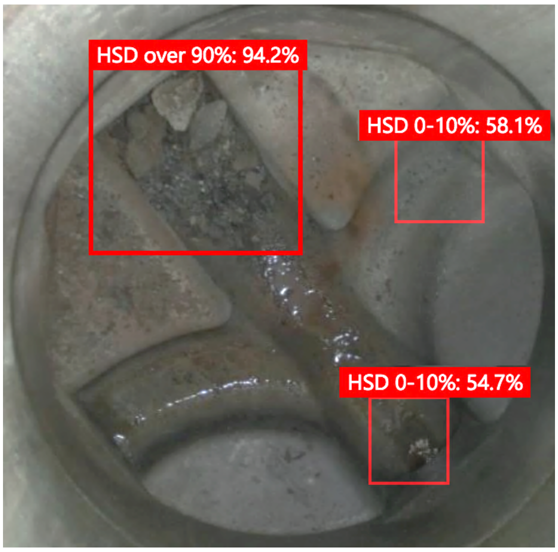
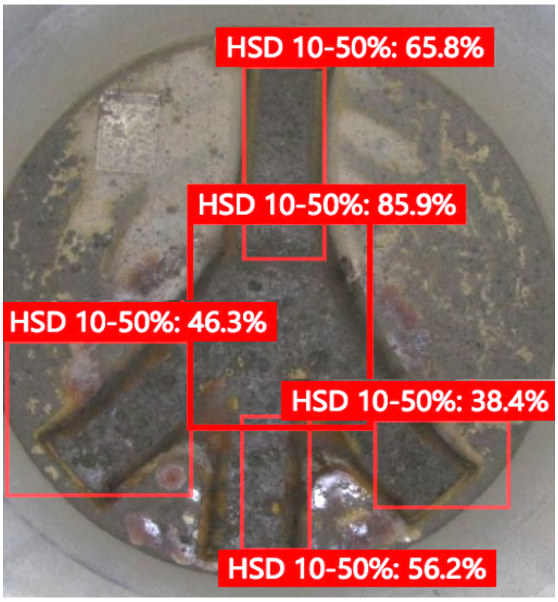
<table>
<tr><td></td><td>Four areas to be detected. The two smaller areas are expected to be detected as “HSD 0-10%”, the area on the left/top is expected to be detected as “HSD 50-90%”, while the area to the right/bottom is expected to be tagged as “HSD 10-50%”.</td></tr>
<tr><td></td><td>Four areas to be detected. All four are expected to be predicted as “HSD 0-10%”.</td></tr>
<tr><td></td><td>Two areas to be detected. The area to the left is expected to be detected as “HSD 10-50%”, while the area to the right is expected to be detected as “HSD 0-10%”.</td></tr>
</table>

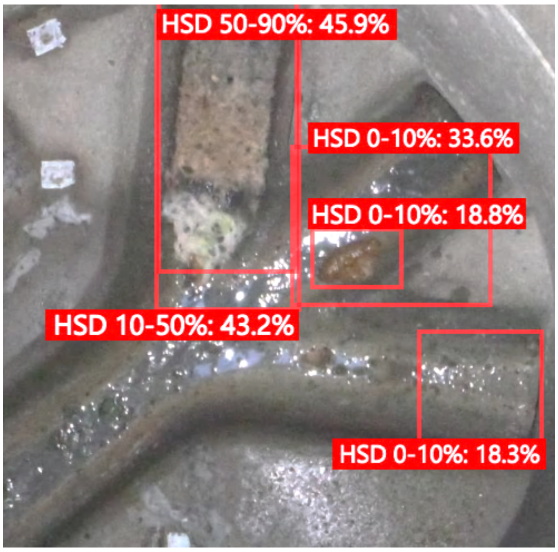
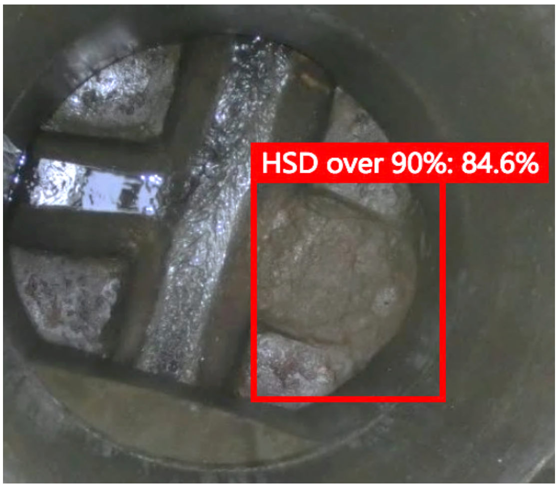
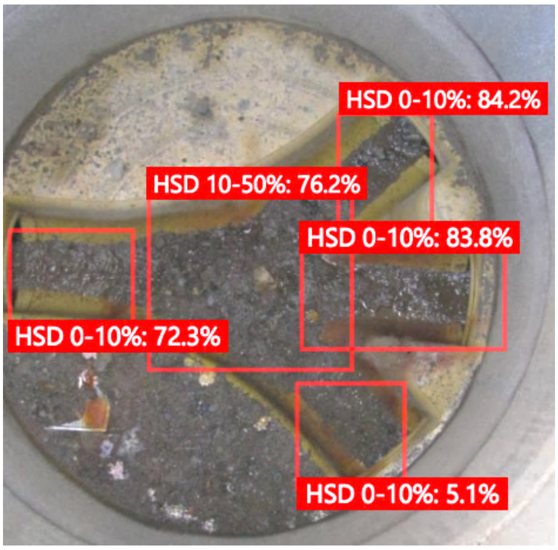
	Two areas to be detected. The area on the top of the image is expected to be tagged as “HSD 0-10%”, while the area on the bottom of the image is expected to be tagged as “HSD 10-50%”.
	Three areas to be detected. All are expected to be tagged as “HSD 10-50%”.
	Two areas to be detected. The area to the left is expected to be predicted as “HSD over 90%”, while the area to the right should be predicted as “HSD 10-50%”.

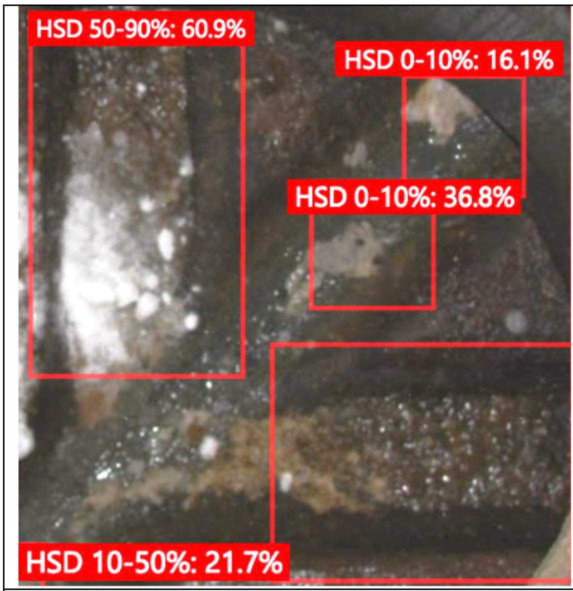
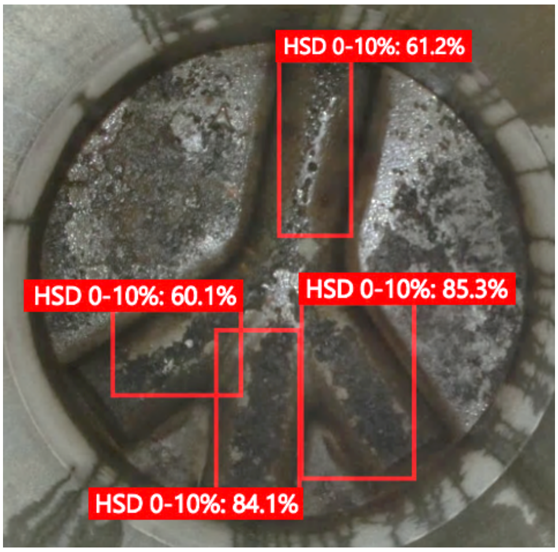
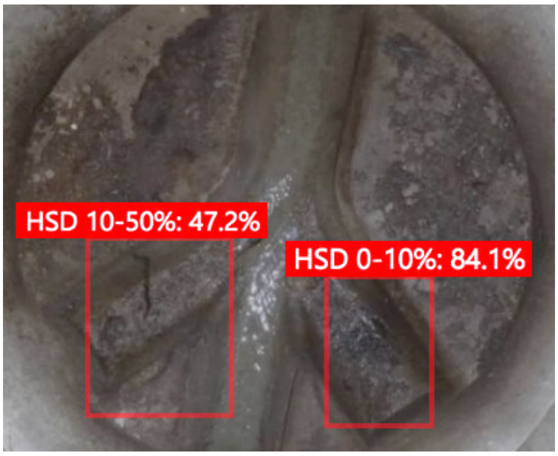
	Three areas to be detected. All of the areas are expected to be predicted as “HSD 0-10%”.

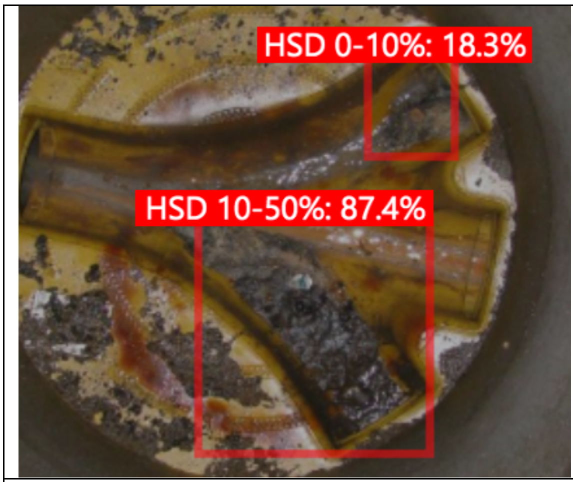
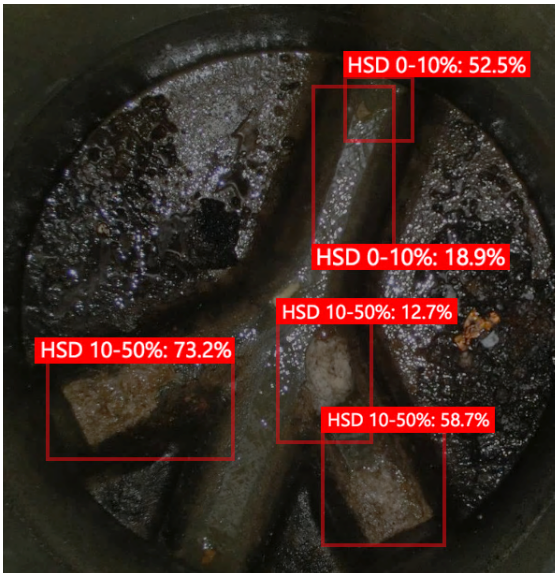
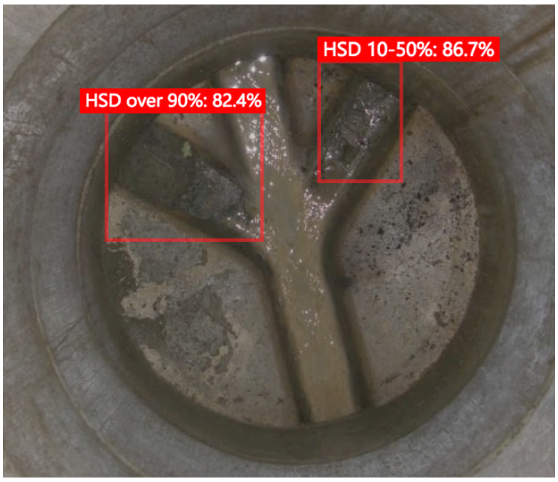
Appendix 3: Custom Vision predictions of the testing images

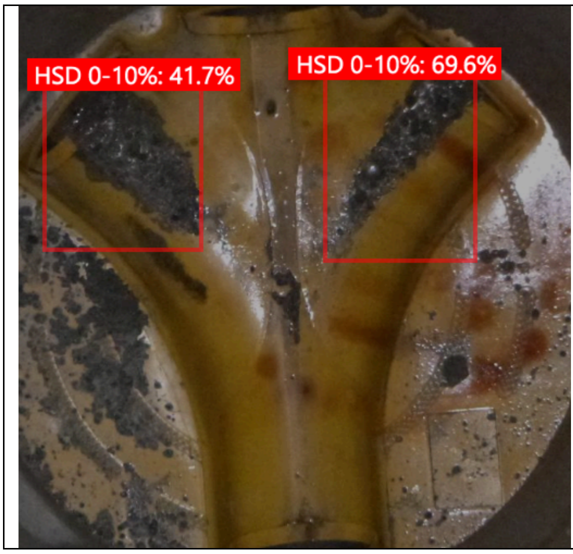
The images presented in this appendix show the predictions obtained during the testing of the trained Custom Vision model. Each image is presented with a short description of the displayed predictions.

Manhole image with predicted tags	Description of predictions
	Three out of four areas were recognized and tagged correctly. The "HSD over 90%" defect grade was predicted with 94.2% certainty, which is the highest obtained among all predictions. The two other "HSD 0-10%" tags received 58.1% and 54.7% certainty, respectively. However, one additional area of type "HSD 0-10%" in the other side channel, was not recognized by the model.
	Five out of five areas were predicted correctly. All of the tags represent the "HSD 10-50%" defect grade. Starting from the prediction on the top of the image, the tags received following percentages of certainty; 65.8%, 85.9%, 46.3%, 38.4% and 56.2%.

	All of the areas were recognized and tagged into correct defect categories. However, some of the areas were also tagged several times when the probability threshold was decreased in order to obtain all of the expected predictions. As shown here, the tag "HSD 0-10%" was predicted twice in the same area with 33.6% and 18.8% certainty. In addition, another area is also tagged twice but with different defect grades, "HSD 50-90%" and "HSD 10-50%", where the last tag is the correct one. The fourth area that was expected to be predicted received "HSD 0-10%" tag with 2.9% certainty and is not shown in the image.
	The area was predicted correctly with "HSD over 90%" tag and a high certainty of 84.6%.
	Five out of five areas were predicted correctly. Four of the tags represented the "HSD 0-10%" defect grade. The certainty of these tags varied, where three of the tags received high certainty (84.2%, 83.8% and 72.3%) and one received very low certainty (only 5.1%). The area in the middle of the invert channels was predicted with "HSD 10-50%" with a certainty of 76.2%.

	Four out of four areas were predicted correctly. Two of the tags represented the "HSD 0-10%" defect grade. The obtained certainty of these tags was 16.1% and 36.8%, respectively. The area tagged into "HSD 50-90%" received 60.9% certainty and the "HSD 10-50%" tag received 21.7% certainty.
	Four out of four areas were predicted correctly. All of the tags represent the "HSD 0-10%" defect grade. Starting from the prediction on the top of the image, the tags received following percentages of certainty; 61.2%, 85.3%, 60.1% and 84.1%.
	Both areas were predicted and assigned into correct defect grade. The tags have been predicted with varying certainty. One of the tags received 47,2% certainty, which is slightly below probability threshold of 50%, while the other tag received 84,1%.

	Both areas were predicted correctly. However, the certainty of predictions varied greatly. One tag has been predicted with high certainty of 87,4%, where the other tag received only 18,3 % certainty.
	Areas with tags "HSD 0-10%: 52.5%" and "HSD 0-10%: 18.9%" are additional areas that the model tagged during testing. The first area is correct because it tagged a rock. However, the second area tagged parts of the rock and wastewater as deposits, which is wrong. The three other areas were expected to be detected by the model. All three are tagged into correct grade category "HSD 10-50%" with 73.2%, 12.7% and 58.7%, respectively.
	Both areas were predicted correctly. Both tags have been predicted with high certainty of 82.4% and 86.7%, respectively.

	Both areas were predicted correctly. The tags have been predicted with varying certainty of 41.7% and 69.6%, respectively. The deposition in the middle of the invert channels was also predicted with tag "HSD 0-10%". However, the certainty of this prediction was very low (1.6%).

NTNU
Norwegian University of
Science and Technology