2020

# A Systematic Literature Survey of Unmanned Aerial Vehicle Based Structural Health Monitoring

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# A SYSTEMATIC LITERATURE SURVEY OF UNMANNED AERIAL VEHICLE BASED STRUCTURAL HEALTH MONITORING

A thesis submitted to
the Graduate College of
Marshall University
In partial fulfillment of the
requirements for the degree of
Masters
In
Information Systems
by
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Marshall University
December 2020

**APPROVAL OF THESIS**

We, the faculty supervising the work of Sreehari Sreenath, affirm that the thesis, "*A systematic literature survey of unmanned aerial vehicle based structural health monitoring*", meets the high academic standards for original scholarship and creative work established by the Master of Science in Information Systems and the Department of Computer Sciences and Electrical Engineering. This work also conforms to the editorial standards of our discipline and the Graduate College of Marshall University. With our signatures, we approve the manuscript for publication.

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## ACKNOWLEDGMENTS

Completing this thesis was undoubtedly one of the most challenging and grueling things that I have ever done. At this juncture, I would like to take this opportunity to thank all the people who stood by me and without whom none of this would have been possible.

To my professor Dr. Haroon Malik- I cannot thank you enough. Much more than merely a research guide; you were also my teacher, mentor, and one of my biggest inspirations. Thank you for having faith in me even when I doubted myself. Thank you for this excellent opportunity and for helping me achieve this extraordinary milestone in my professional career.

I offer my heartfelt gratitude to Dr. Jamil M Chaudri and Dr. Wael Zatar. It was an excellent learning opportunity to work with such accomplished and eminent personalities and I consider myself greatly privileged to have received your constant guidance.

I also thank my friends Hrishikesh, Kanimozhi, Febin, Asha, Kay, Tosin, Liam, Elizabeth, Precious, Ebuka, and Harshit for all the help and support. You all have made my life in the United States so comfortable. From keeping me focused when I got distracted to pulling me out of my thoughts whenever I desperately needed a break, you have helped me in more ways than anyone could imagine.

To my dad, Sreenath Chettiparambil- I cannot thank you enough for your unparalleled love and care. You are the reason for all the good things and success in my life. I cannot take any credit for it. Dad, you taught me how to dream big and work for it. You believed in me and never gave up on me. You are my superman.

To my mom, Selda Sreenath- I have never seen anyone so kind and compassionate as you, or anyone so committed to and resilient in achieving their goals as you. You are the reason that I believe in hard work. I might not always be the best son, but you are the best mom that anyone could hope for. I love you so much.

I convey my sincere thanks to my sister, Dr. Sreelakshmi Sreenath, and my brother-in-law, Dr. Mithun Rathen. Chechi, I have looked up to you from the day that I can remember. I know I can be annoying at times. Nevertheless, I know you love me and you have been there for me whenever I needed my big sister. You are like a second mom to me- always checking up on me and being a constant source of love and care. To my brother in law- I knew I would be getting a brother when my sister introduced you to me. I appreciate you two for everything you have done during my graduate studies and I could not have asked for more.

I am extremely thankful to my loving fiancée Dr. Swetha Priyadarshan, my partner in crime; I don't know where to begin. For everything from staying up late with me and proofreading my work to being an incredible source of mental strength, thank you for keeping me sane and cared for. Swe, I love everything about you. You are the best thing that has happened to me in my life and I don't know what I did to deserve this remarkable woman, but I am planning to keep this gem for my own.

Finally, I would like to express my gratitude to the frontline essential workers during the Covid-19 pandemic. We all have suffered so much, and many of us lost people we loved and cared for. I am thankful to all the essential workers for working tirelessly to keep everyone including myself safe and helping me finish my thesis study during this pandemic. You are the real heroes. My words will never be enough to show you how much it means to all of us. Thank you!

It was indeed a tough endeavor, but with the support and guidance of God and all these blessed people, I was able to achieve my goals.

**TABLE OF CONTENTS**

## LIST OF FIGURES

## LIST OF TABLES

# ABSTRACT

Unmanned Aerial Vehicles (UAVs) are being employed in a multitude of civil applications owing to their ease of use, low maintenance, affordability, high-mobility, and ability to hover. UAVs are being utilized for real-time monitoring of road traffic, providing wireless coverage, remote sensing, search and rescue operations, delivery of goods, security and surveillance, precision agriculture, and civil infrastructure inspection. They are the next big revolution in technology and civil infrastructure, and it is expected to dominate more than $45 billion market value. The thesis surveys the UAV assisted Structural Health Monitoring or SHM literature over the last decade and categorize UAVs based on their aerodynamics, payload, design of build, and its applications. Further, the thesis presents the payload product line to facilitate the SHM tasks, details the different applications of UAVs exploited in the last decade to support civil structures, and discusses the critical challenges faced in UASHM applications across various domains. Finally, the thesis presents two artificial neural network-based structural damage detection models and conducts a detailed performance evaluation on multiple platforms like edge computing and cloud computing.

# CHAPTER 1

# INTRODUCTION

## 1.1 The Motivation of the Thesis

We as a species are currently in the middle of the greatest surge of advancement this world has seen hitherto. In all fields, in every arena, rapid development is continuously taking place. Skyscrapers and other large-scale civil infrastructures are changing the face of the world as we know it. These civil infrastructures go through various types of loads and impacts, including known effects of aging, and known but unpredictable events of nature as well as those events best described as ‘acts of God’, which adversely affect the usability of the infrastructure as well as its environment.

All these factors take a toll on their health throughout their lifetime and increase the possibility of failure that could, along with the obvious implications, potentially be catastrophic to the life surrounding them. Therefore, scheduled monitoring and inspections are often mandated. Structural Health Monitoring (SHM) addresses the above concerns. Unfortunately, the task of effectively monitoring structural health is becoming increasingly challenging due to the sheer quantity and scale of the infrastructures.

ASCE (American Society of Civil Engineers) provided an infrastructure report card of The United States of America for the year 2017 with an overall score of “D+”. Table 1 provides insights into various types of civil infrastructures and their respective scores. As is evident by the overall and aggregated scores as shown in Table 1, huge improvements and periodical monitoring techniques are in serious need. The sheer quantities of the infrastructures suggest that conventional SHM techniques are inefficient and obsolete.

**Table 1: ASCE infrastructure report of 2017**

| Infrastructure | Quantity | Aggregated Score |
|---|---|---|
| Bridges | 614,387 | C+ |
| Dams | 90,580 | D |
| Roads | 4000000+ miles | D |
| Airports | 19000+ | D |
| Electric transmission lines | 640000 miles | D+ |

Referenced from the ASCE infrastructure report card [61].

### 1.1.1 Structural Health Monitoring (SHM)

Structural Health Monitoring (SHM) incorporates a set of techniques for implementing a damage detection and characterization for engineering structures. SHM is now widely used on infrastructures as a periodical inspection routine for tracking structural changes and estimate structural reliability. However, Conventional SHM techniques involve various professional equipment and tools which make them an expensive process.

### 1.1.2 Risk Factors

The primary means to inspect a structure is visual inspection. Visual inspections are conducted on-site with the help of specialized domain experts who provide qualitative assessment feedback. Nevertheless, current practice suffers from severe drawbacks such as follows.

a) Time-consuming

b) Require on the spot visual inspections by human experts

c) High cost of site preparation and machinery required for assessment of areas inaccessible to human experts

d) The significant risk involved to human life in inspecting certain structures by virtue of size, location etc.

e) Disruption of essential services during the process of inspection of the structures that provide it.

### 1.1.3 Unmanned Aerial Vehicle Assisted Structural Health Monitoring (UASHM)

To overcome the challenges of the current practice of SHM, there is a need for a robust SHM method that can successfully cover all the difficult to access locations during the inspection. UAV Assisted Structural Health Monitoring (UASHM) has emerged as a viable and promising option to overcome the challenges of conventional Visual Inspection techniques.

An Unmanned Aerial Vehicle (UAV) is defined by the Federal Aviation Authority) FAA as an aircraft flown with no pilot on board. UAVs are sometimes referred to as drones. In the thesis, these terms are used interchangeably. The vehicle is controlled either through programmed-agency or through live-remote-control by a pilot from the ground and can carry a wide range of technology and devices (also referred to as payloads), including still, video, infrared, and other types of sensors [49]. UAVs are an emerging technology with many potential applications in the field of civil engineering. Efficient and adequate visual inspection of a wide variety of structured types in challenging locations is a fundamental concern frequently voiced in civil engineering platforms and relevant SHM literature [2], [4]. To overcome the limitations of the visual inspection, the use of the UASHM is an option. The UASHM of Civil infrastructure is expected to dominate the more than $45 Billion UAV market due to its many advantages, such as the following:

1. *Navigational Ease* – The utilization of the sensor varies from one structure to another. UAV could navigate automatically as a mobile data collector. It is free from the mobility limitations of ground transportation and can be used in regions that human beings would not normally be able to approach.

2. *Quicker Data Collection* — Compared to ground data collection, aerial data collection uses a controllable aerial vehicle, that has a greater facility of movement. It could increase the speed of searching and eliminates the time otherwise consumed in visiting the nodes on the structures and bridges. Using UAV, the data collection life cycle of large WSN (e.g., encompassing large bridges and highways), spanning over many miles, can be significantly reduced.
3. *Performance* — UASHM has a lower latency and higher bandwidth. The aerial data collection often has fewer obstacles and, more extensive coverage of wireless signals that could lower the communication latency and increase the bandwidth.
4. *Heterogeneity* — Most of the available UAVs in the market, allow for attaching external sensors, and relaying the data back to a ground station using telemetry communication links. Moreover, the UAVs can (a) lift a certain payload and (b) have (or can be easily fitted with) an expandable interface for attaching custom sensors, thus overcoming the limitation of single-purpose platforms, which are costly to cover for other tasks.
5. *Risk Factor* — Adoption of UASHM helps to reduce a risk to safety. Since the UAV can be controlled from the ground it avoids the need for putting people on cranes or constructing a partial-exoskeleton (scaffolding) that would permit eye-inspection, taking material samples, videos, and photos for analysis.
6. *Versatile Data analysis Methods* — UAVs collect real-time, high-resolution, information-rich images, and versatile data. The data acquired from UAVs can be directly examined by a domain specialist to identify damages or data that can be used as an input for the damage detection machine learning model to detect and identify various damages. Also, the collected

data by UAV can be reused multiple times to perform by various data analysis methods to achieve different objectives.

### 1.2 Problem Statement

In the past decade, the deployment of UASHM has gained momentum and caught the eye of many leading researchers in industry, as the advantages of UASHM have proven to have significant implications over time. There have been many research studies that propose various kinds of strategies aimed towards integrating UAVs in the SHM cycle.

Although technologists accept the advantages of deploying UASHM for the purpose of determining structural integrity, the technology has remained under-used by commercial organizations involved in the construction and maintenance of intricate, complex, or massive structures. Research that has been published in the last decade contains a lot of information that can positively affect the development of UASHM. Due to the diversity in research approaches and its sheer volume, there is a need to consolidate these studies in the field of UASHM in a systematic manner. To date, there is no comprehensive study other than on the application of UAV assisted SHM for civil infrastructure. This thesis aims to conduct a systematic literature survey that documents key contributions made to the field of UASHM in the past decade. Also, the thesis focuses on finding the research trends for UAV uses and future insights.

### 1.3 Scope of the Thesis

The research papers that have been studied for the thesis are limited to the timeframe of 2012-2019. All the included papers are picked from the Google Scholar database only. Due to time constraints, the search pool was restricted to the top 10 articles for each year and the literature papers were manually picked among them by reading through the abstract. Upon completion of the filtering process, 50 have successfully been selected for the systematic literature survey.

# CHAPTER 2

# BACKGROUND

This chapter provides background information about Unmanned Aerial Vehicle assisted Structural Health Monitoring for civil structures. This chapter concentrates on a specific case and technologies employed by UAVs for structural health monitoring (SHM) of civil structures.

## 2.1 Unmanned Aerial Vehicle

Few sectors in the technology industry have boomed the way Unmanned Aerial Vehicles, conveniently called drones, have. Their history dates back centuries to 1848 when Austrians launched the first air raids in history on the city of Venice with the help of unmanned balloons that were carrying explosives. Previously considered an expensive asset with limited applicability, UAVs have come a long way. It was only after 1982, when Israel successfully and cost-effectively used UAVs to destroy a Syrian missile, drawing the world's attention to these devices for the first time, that many nations started investing money into developing them. Advancements in the industry brought down the cost of manufacturing drastically. The introduction of micro UAVs broke through into the consumer industry and opened the world of newly found opportunities for UAVs. A notable mention is Jeff Bezos, the founder, CEO, and president of Amazon.com, expressing his vision to establish a UAV delivery method, highlighting the potential of the consumer-grade UAV industry.

The main attraction of UAVs for SHM is their data capturing abilities. The visual data generated by UAVs have proven to be beneficial in many respects and applied in research and industries for various purposes. The evolution of computer vision techniques has made UAVs capable of running on autopilot, object detection, and identification, reading warning signs and symbols, and working with other wireless IoT (Internet of Things) devices. The abovementioned improvements of UAVs positively impacted the UASHM techniques. Autopilot capabilities opened doors for autonomous flight features during periodical infrastructure inspection. Object detection and identification techniques led to improved damage detection systems. Also, recent developments in communication and connectivity resulted in efficient merging with IoT (Internet of Things) devices.

**2.2 Structural Health Monitoring**

Structural Health Monitoring (SHM) is the process of building a system for damage detection in engineering structures. It is one of the emerging fields where UAVs are showing great potential. In the last decade, there has been significant growth in the number of relevant research publications related to UASHM.

Eschmann et al. [10] explored the feasibility of UAVs in Structural Health Monitoring and suggested the idea of including features like crack detection in the framework. Later after two years, Eschmann et al. [60] continued their research study and observed that capturing high-resolution images using UAVs could improve crack and defect detection in civil structures.

Hallerman and Morgenthal [15], two pioneers in the UASHM community, examined existing civil structures and demonstrated the use of computer vision to extract 3D geometry of the structures. In continuation of their research, Hallerman and Morgenthal [16] performed displacement analysis on civil structures using UAV based data collection. The early attempts in UAV assisted SHM was limited to the collection of images and 3D model extractions so that the image data became available to domain specialists at a low cost. This trend started to change when practitioners began to apply computer vision algorithms and filtering tools in images.

Ellenberg et al. [52] emphasized the importance of applying filters like Prewitt edge detection to the images so that cracks and defects could be identified easily. Ellenberg et al. [52] suggested that the GPS location and the angle at which the image is captured are crucial to analyze the data. GPS sensors are weak when they are exposed closely to structures, therefore taking pictures by keeping the UAV relatively away from the structure would be ideal [52].

Sánchez et al. [54] implemented a hybrid cloud-based detection method. The authors combined the point cloud system with the LIDAR sensors to increase the accuracy and tried classifying the civil structures [54].

By the year 2015, the entire industry made headway as technology giants such as Amazon, Intel, and Google identified UAVs as the way to the future. The impetus led to the development of assistive sensors and devices which can be mounted on the UAVs.

Yeum and Dyke [32] identified the dangers of fatigue cracks in metal components and worked on building a computer vision model for detecting them. The Frangi filer and Canny edge detector algorithms are used to process images and detect defects in the proposed model [32].

Sankarasrinivasan et al. [26] examined the drawbacks in the system proposed by Yeum and Dyke [32] and suggested the idea of combining Hat transform and HSV threshold to better identify defects. A percentage index of surface degradation was calculated using the ‘Greyscale Thresholding’ method to integrate surface degradation information into the model. The proposed model was tested in real-life and results were published in the paper.

Pereira and Pereira [55] introduced their version of embedded image processing models for detecting defects in the civil structures, with the highlight being their combination of aerial-based and ground-based detection approaches to maximize the efficiency of the system. The crack detection was done in Raspberry-Pi mounted on the UAV, and selected images were stored for detailed analysis. Post-data capture analysis contained a Sobel operation filter to maximize the accuracy of the detection model [55].

Na and Baek [22] proposed the idea of adding vibration-based NDT (Nondestructive Testing) sensors to improve the data input qualities of UAVs. Even though the results were promising, the complexity of the proposed model made the research unsuccessful in UASHM. [22].

Phung and Hoang [24] used sensor fusion techniques to integrate laser sensors with image data to increase the accuracy of the model. They used peak detection algorithms to uncover cracks and defects [24].

The emergence of efficient Machine Learning algorithms helped researchers build models with improved accuracy. Following the drastic progress in Convolutional Neural Networks (CNN) since the introduction of AlexNet in 2012, many researchers started using CNN as their primary computer vision algorithm in UAV assisted Structural Health Monitoring.

Bar et al. [56] developed their damage detection model by adopting the transfer learning approach, which refers to using pre-trained machine learning models to train on related tasks for achieving rapid progress and optimization. It is very common to see practitioners using fully connected layers, which are trained in ImageNet and modified by training on datasets that serve a specific use case [56]. By doing so, practitioners can avoid prolonged waiting time for training and the need for huge computing hardware resources as a usual experience when DCNN models are developed from scratch [56].

Shin et al. [57] also recommended a transfer-learning approach for defect detection using UASHM . Shin et al. [57] also recommended the use of pre-trained neural networks like VGG-16, AlexNet, and GoogLeNet, and then training them on the datasets that contain images of cracks and damages in civil structures or even publicly available datasets like ImageNet [57].

According to Sarkar et al. [58], although Deep Learning showed promise, the lack of well-labeled datasets for damage detection for civil structures prevented researchers from building models and achieving maximum accuracy. A solution to this issue was to build a large dataset for damage detection and manually label the images in it. Nevertheless, it is painstaking to label all the images for such large datasets.

Yang et al. [31] put forth a great effort to act on the lack of well-labeled datasets for crack detection by building an extensive database of concrete cracks to train Machine Learning networks. A VGG-16 based Convolutional Neural Network was selected as the model and trained with new datasets to achieve the desired accuracy [31].

Gopalakrishnan et al. [13] opted for a pre-trained VGG-16 computer vision model as a damage detection system for UASHM. The model never used any preprocessing or augmentation and achieved around 90% accuracy in testing [13]. The proposed model accuracy was compared with other Machine Learning algorithms such as Support Vector machines (SVM) and Random Forest (RF), and the comparison showed the superiority of the Gopalakrishnan method. [13].

Kang and Cha [19] proposed an autonomous UASHM method where they used an ultrasonic beacon system with geo-tagging functionality. Instead of opting for a pre-trained model, they developed a defect detection model based on classical Convolutional Neural Networks and trained them from scratch. The authors claimed that the proposed model was ideal for situations where the GPS network was lacking [19].

Cha et al. [5] brought forward the Faster R-CNN model to detect damages in civil structures using UAVs. Faster R-CNN is a performance-tuned computer vision algorithm that uses region-based detection to maximize efficiency and performance [5]. The authors claimed that the quasi-real-time detection model could identify multiple types of damages with 87.8% of average precision (AP) [5].

Dorafshan and Maguire [7] conducted a research study to compare UASHM and conventional SHM methods. The research showed that UASHM is becoming crucial owing to its ease of use, inexpensive and faster-monitoring capability, and potential to reach places where conventional methods struggle to go [5]. UAV assisted Structural Health Monitoring was found to be 37% faster than the conventional approach while also being 66% cheaper [7].

While Crack detection remains the mainstream, Ellenberg et al. [9] used IR (Infrared) sensors to detect delamination defects in civil structures. Bridges were chosen as a real-life representative sample, and results were compared with a different IR camera on a rolling platform [9].

Corrosion is a major defect seen in civil structures. Yeum and Dyke [32] brought up the issue in UASHM. Unfortunately, they were not successful in implementing a system for their detection. Similarly, Henrickson et al. [18] have also studied the need for corrosion detection in UASHM.

Ellenberg et al. [47] in 2016, came up with a model that could pick up corrosion in civil structures. The research was partially successful in implementing the system in MatLab and utilized the K-means algorithm to find the area covered by corrosion [47].

Even though a lot of research has been conducted and new methods with varying success have been introduced, Deep Learning based damage detection is still in its early stages, and there is room for improvement.

## 2.3 Computer Vision

The field of Unmanned Aerial Vehicles is exploding, with these ingenious devices being deployed in various areas such as surveillance and civil infrastructure inspections. The evolution of capable Computer Vison has paved the way for the development of damage detection techniques such as crack, corrosion, and delamination detection.

By definition, Computer Vision is a field of Artificial Intelligence and computer science, which enables computers to achieve the vision, identification, and processing capabilities like humans to give out meaningful information. Nowadays, computer vision is being used in applications ranging from autonomous vehicles, monitor and security systems, and facial recognition, all the way to the healthcare industry where more than 90% of the data are images. The possibilities are limitless.

The evolution of Computer Vision was gradual, beginning its growth in the early 1960s. The primary milestone took place in 1959 when Hubel and Wiesel [59] published a paper titled "Receptive fields of single neurons in the cat's striate cortex" describing how a cat's cerebral cortical neurons respond to various images. This ground-breaking research built the foundation of Deep Learning techniques in Computer Vision. The field gained momentum in the 1970s when building 3D structure extraction techniques, and edge detection algorithms had evolved. For the following two decades, researchers were committed to more complex mathematical analysis on visuals and the invention of contours and object detections.

The growth of Machine Learning and Deep Neural Networks influenced Computer Vision to be more mature and reliant as the present world experiences. One of the downsides of using Deep Neural Networks is that it consists of several layers of complex mathematical analysis, which requires a great deal of computing horsepower. The downside has held back the expansion of computer vision and artificial intelligence in general for some time. Not so long ago in 2012, even IT industry giants such as IBM had admitted their struggles in efficiently utilizing Deep Learning frameworks to real-world use cases [60]. Conventional CPU (Central Processing Unit) based architectures were not designed to handle the kind of parallel processing that Deep Learning frameworks required. The breakthrough came in the early 2010s when the industry switched to using GPU architecture due to its parallel computing capabilities. The opportunities skyrocketed and there has been no looking back since.

# CHAPTER 3

# REVIEW ANALYSIS

## 3.1 Infrastructure Categories

***RQ. 1 What are the different categories of civil structures for which UAVs have been used to monitor structural health?***

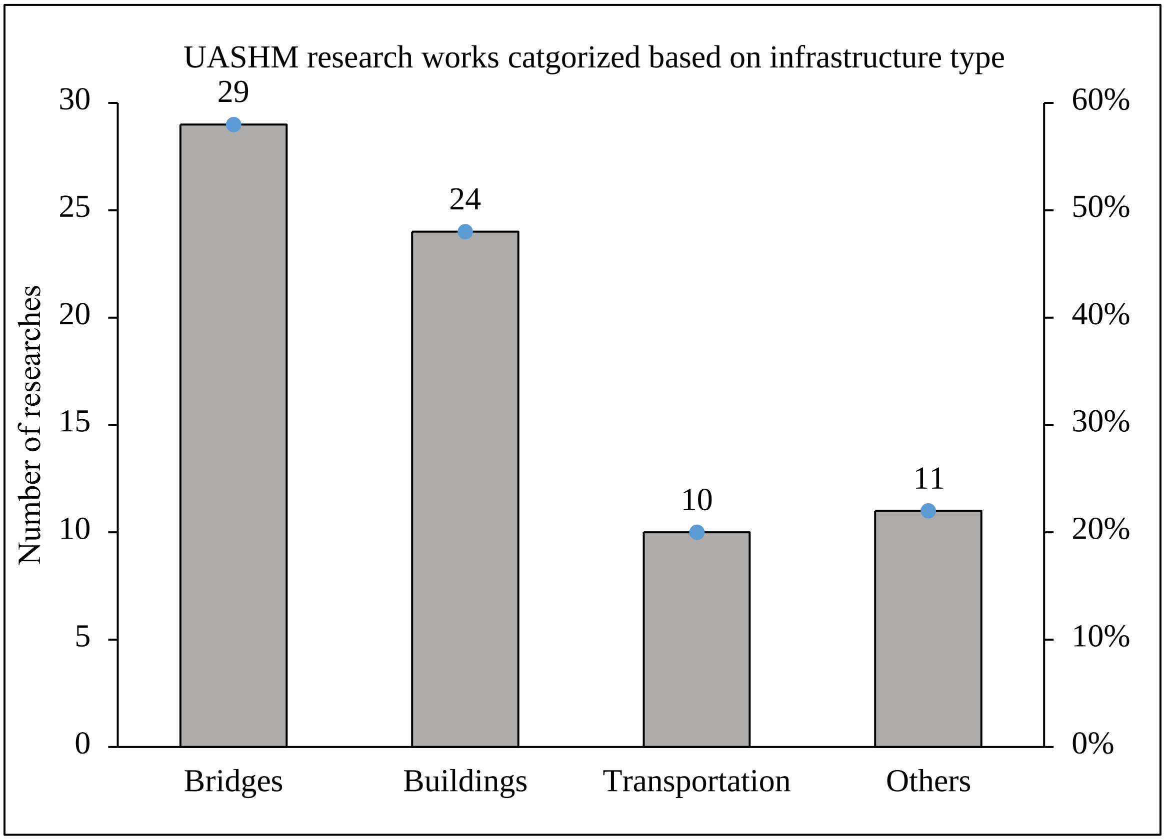



**Figure 1: UASHM research works categorized based on civil infrastructure** types

This review question aims to identify civil structure categories for which UAVs have been employed for health monitoring. Figure 1 shows the main categories of the civil structure, observed in the research works, for which either UAV are used for SHM or a technique/methodology is proposed to support UASHM. So, the civil structure can be categorized into four major categories: bridges, buildings, transportation, and others. This thesis detail each of the categories. The details of the categories help to better understand the adoption mechanism of UASHM for each of them. Also, it provides important insight into the improvements that the UAV industry should take into consideration to facilitate the SHM.

### 3.1.1 Bridge Infrastructure

Bridges have a lifespan of about 50 years. According to the American Society of Civil Engineers (ASCE), there are a total of 614,387 bridges in the United States [61]. Among them, approximately one-fourth are classified as functionally obsolete and about 9.1% of them are classified as structurally deficient [61].

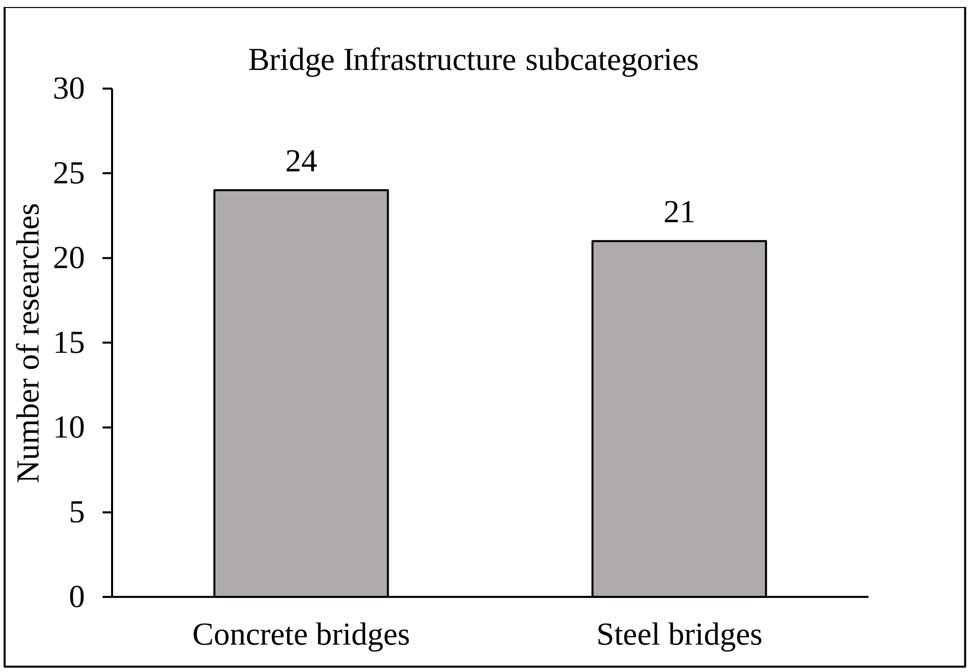



**Figure 2: UASHM bridge infrastructure subcategories**

Out of the 50 research studies which are the basis of the current report 30 papers have discussed structural health monitoring of bridge infrastructure. Among the thirty papers, Further categorization led to two subcategories; Steel bridges and Concrete ridges. The categorization is taken into consideration by analyzing the major difference in the material and design of the built. As shown in Figure 2, there are 24 research works out of 30 research papers discussed the SHM of concrete bridges, while 21 of them covered steel bridges. The simplified finding is that the researchers prefer to study both steel and concrete bridge infrastructures together whenever the researches focused on bridges.

Considering the statistical figures provided by ASCE as mentioned earlier, it has become evident that the need for Structural Health inspection of bridges is necessary. One of the most widely used methods of the SHM is the visual inspection. Visual inspection is commonly performed bi-annually, involves checking the general condition of the bridge, assessing materials and elements, and identifying repairs needed. Inspectors primarily use their own eyes as well as cameras to access the defective areas in the bridges. Considering the infrastructure, it is needless to say that bridges are very difficult to conduct visual inspections due to their complex shape of architecture. Conventional visual inspection is costly, time-consuming, requires complete human intervention, and is in some cases difficult to conduct, especially for hard to reach areas such as in the areas beneath the bridges.

Bridge architecture demands a novel SHM method where visuals of the infrastructure can be captured remotely (other than SHM domain experts directly assessing all the difficult areas with the help of a crane etc.). Considering the infrastructure-build and safety factors, even minute cracks and damages are supposed to go through inspection. Such detailed visuals can be achieved provided when the data capturing devices such as high-pixel density cameras are put under close-proximity to the infrastructure-surfaces.

To overcome these challenges, UAV Assisted Structural Health Monitoring (UASHM) has emerged as a viable and promising alternative. UAVs' ability to access locations that are difficult to get into for bridge inspectors makes it a must-have tool in SHM.

### 3.1.2 Building Infrastructure

The building infrastructure category consists of factories, massive civic Buildings, aging historical buildings, monuments, churches, etc. as shown in Figure 3. The main stand-out characteristic of this infrastructure is that its sheer size and its need for close-proximity inspection. Buildings that are tall and old raise potential safety issues. Tall buildings in old metropolitan areas often are crowded together, leaving inadequate space between structures to allow for safe inspection and maintenance.

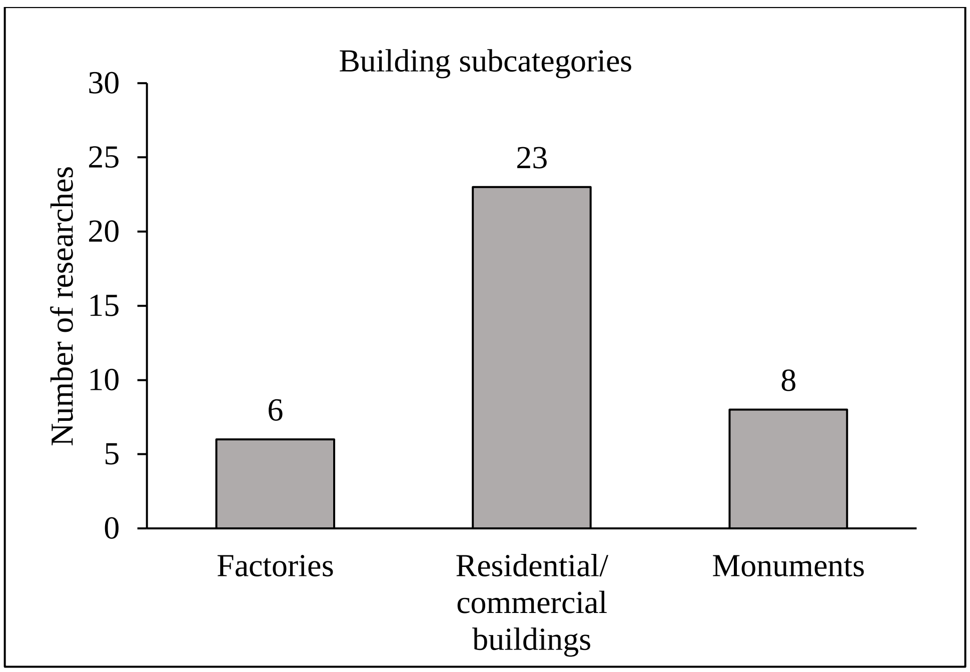



**Figure 3: Building subcategories**

The most efficient way to study the characteristics of building infrastructure is to categorize them according to their nature of built. Factories and tall chimneys are a unique type of architecture due to their specific design and utility and therefore they are considered as one of the infrastructure sub-categories.

UAVs can be a very helpful tool in assessing tall buildings since they are remotely controlled, and a few types of UAVs possess vertical and hover features. The hover feature can become very handy when the gap between buildings is minimal.

UASHM was first exercised on buildings Eschmann et al. [10] mentioned the concern of aging infrastructures.  Eschmann et al. [10] continued to point out the difficulties with a traditional man-driven visual inspection as the choice of SHM methods.

### 3.1.3 Transportation Infrastructure

This category comprises roads, pavements, and railway-tracks.  This type of infrastructure covers wide areas and covering such areas in a limited time is a challenging task for conventional SHM methods. So, the preferred method of SHM demands fast-paced inspections in a limited time.

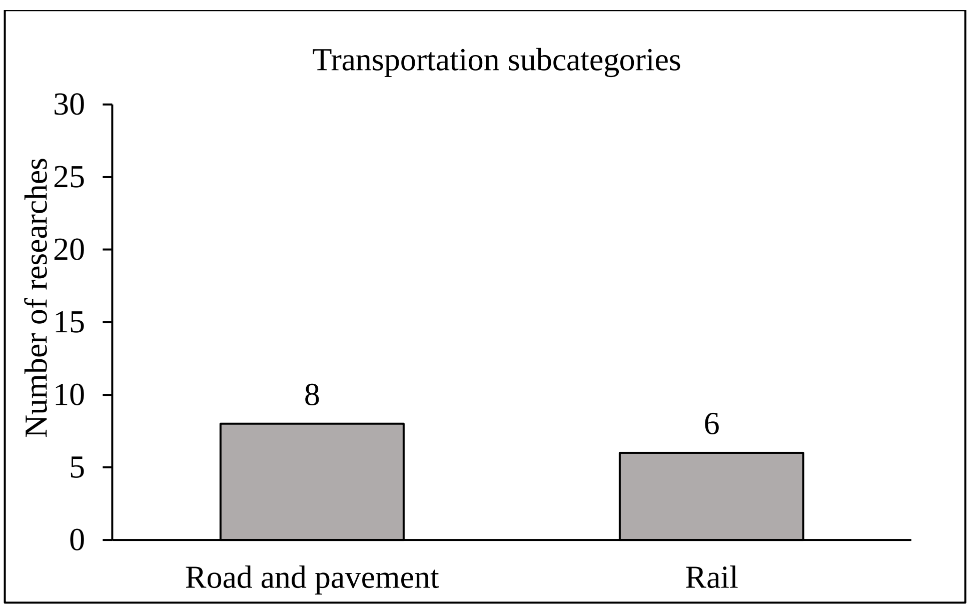



**Figure 4: Transportation subcategories**

One of the main benefits of UASHM is its ability to cover wide areas in lesser time compared to conventional SHM methods. This ability of UASHM makes it ideal for monitoring transportation infrastructure. Modern railway security systems used in infrastructure protection applications include a set of different sensing technologies integrated by appropriate management systems. Such systems are still highly dependent on human operators for supervision and intervention. One of the challenging goals of the research community in UASHM is the automatic detection of both natural and malicious threats scenarios. Flammini et al. [11] have illustrated the possibility of monitoring railway infrastructure using UAVs. The author pointed out that the recent innovations in the field of UAVs would enable UASHM in railway infrastructure to include wireless charging with RF energy, and wireless interaction between IoT (Internet of Things) devices associated with railway infrastructure [11].The wireless charging and RF energy features could be used in combination to allocate wireless charging spots across the infrastructure. These charging spots can be utilized by the UAVs for quick wireless recharges since one of the concerns about UAVs are their low battery life and endurance.

Unpaved roads constitute approximately 40% of the U.S. road network and are the lifeline in rural areas. Thus, it is important for timely identification and rectification of deformation on such roads. To support the SHM of roads, especially in rural areas, an innovative Unmanned Aerial Vehicle (UAV)-based digital imaging system focusing on efficient collection of surface condition data has been proposed [34].

### 3.1.4 Other Infrastructures

Apart from the mainstream civil structures, some other categories stand out. Some examples are dams, tunnels, retaining walls, and wind turbines. They are unique in their design of build, and most often, traditional SHM methods are difficult to perform. For large-scale structures like retaining walls or dams, due to their immense size, a detailed all-embracing investigation is technically complex and time-consuming. Specially trained inspection engineers are needed to assess structural stability. This complexity leads to very high costs, which often result in longer inspection periods causing deficits in detailed inspections and lacks of safety. For the detection of global as well as small local displacements of retaining walls, Hallerman and Morgethal [51] combined a new fast UAV-based data acquisition technology with computer vision methods for an automatic displacement detection of retaining walls. Their approach would compensate for the deficit in structural monitoring of retaining walls, especially of fine structured anchored retaining walls. This technique was tested on one of the biggest anchored retaining walls in Germany along the highways.

### 3.2 An investigation of the distribution of UASHM-Projects over Time

***RQ. 2 What is the distribution of research work over the last decade for UASHM?***

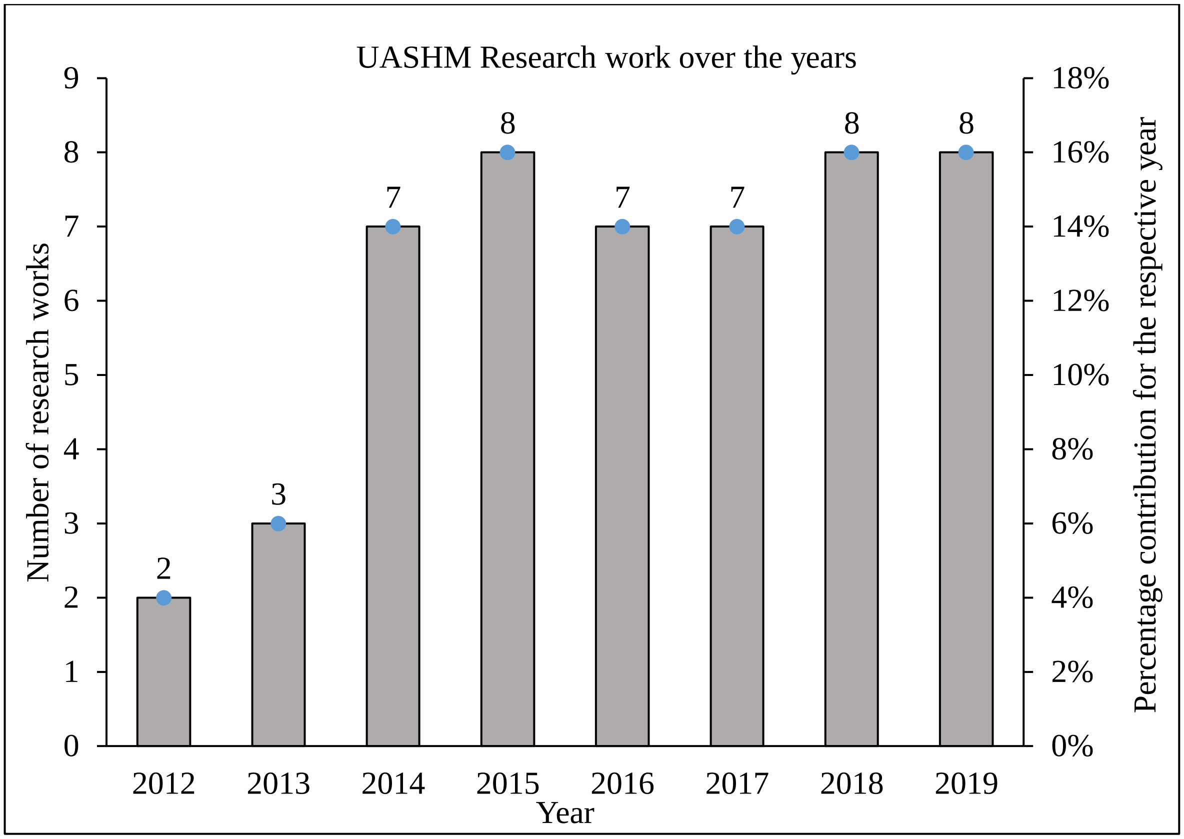



**Figure 5: Distribution of UASHM works through the years**

Figure 5 shows the relatively non-uniform distribution of relevant literature papers during the span of the past 8 years (2012-2019). There has been a overall growth in the availability of relevant researches. The year 2019 does not show a rise in the number of researches in comparison to the year 2018. This trend is due to the fact that the survey is conducted in the middle of 2019. More relevant literature would fill up space in the graph as the year proceeds.

Categorizing the UASHM research works according to the type of infrastructure and plotting them against the time unveiled more in-depth details as shown in Figure 6.

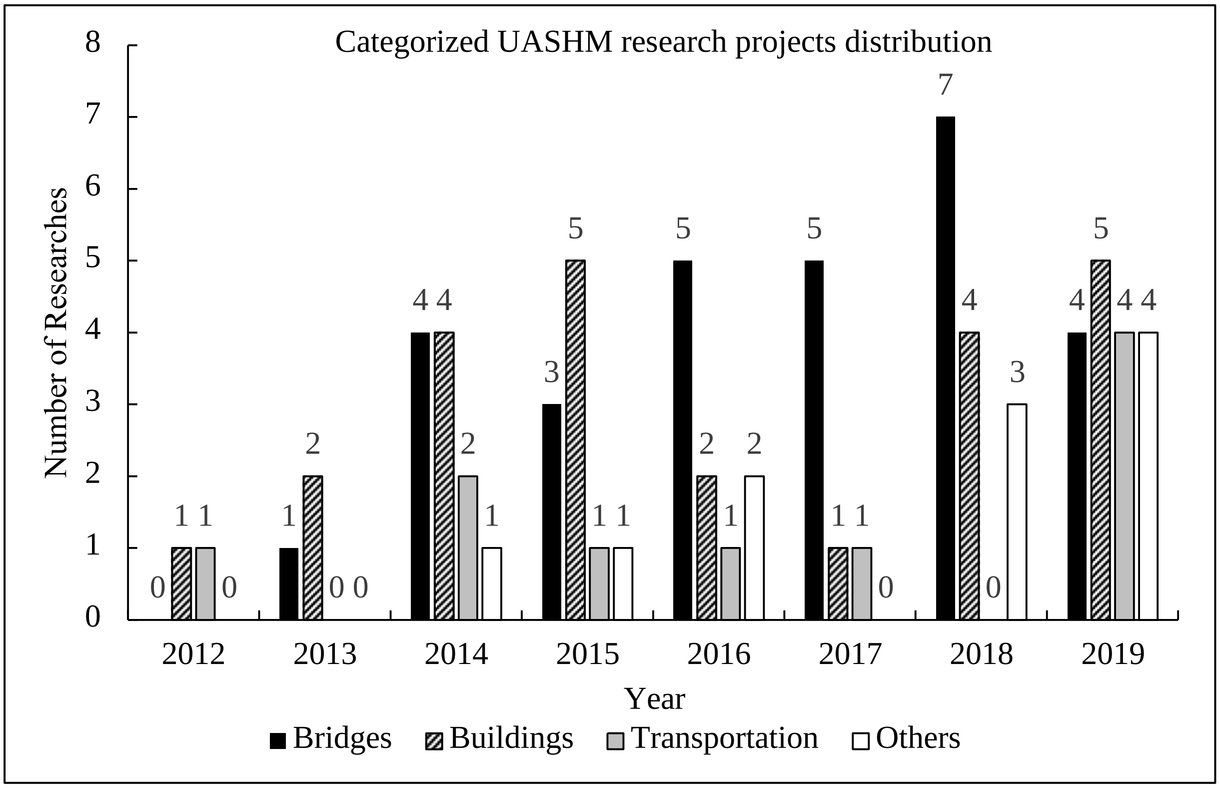



**Figure 6: Distribution of categorized UASHM works through years**

### 3.3 Types of UAVs

***RQ. 3 What are the various types of UAVs employed for SHM?***

In the UASHM field, UAVs can be classified into four categories based on their aerodynamics and design of built. The categories are *Multi-rotor*, *Fixed-wing*, *Single-rotor helicopter*, and *Hybrid fixed-wing UAVs*. Figure 7 gives an overall idea of how Multi-rotor is the mainstream UAV used for SHM. Others are also being used due to their specific advantages over Multi-rotors. In the literature reviewed, we did not encounter report on Hybrid-Fixed Wing.

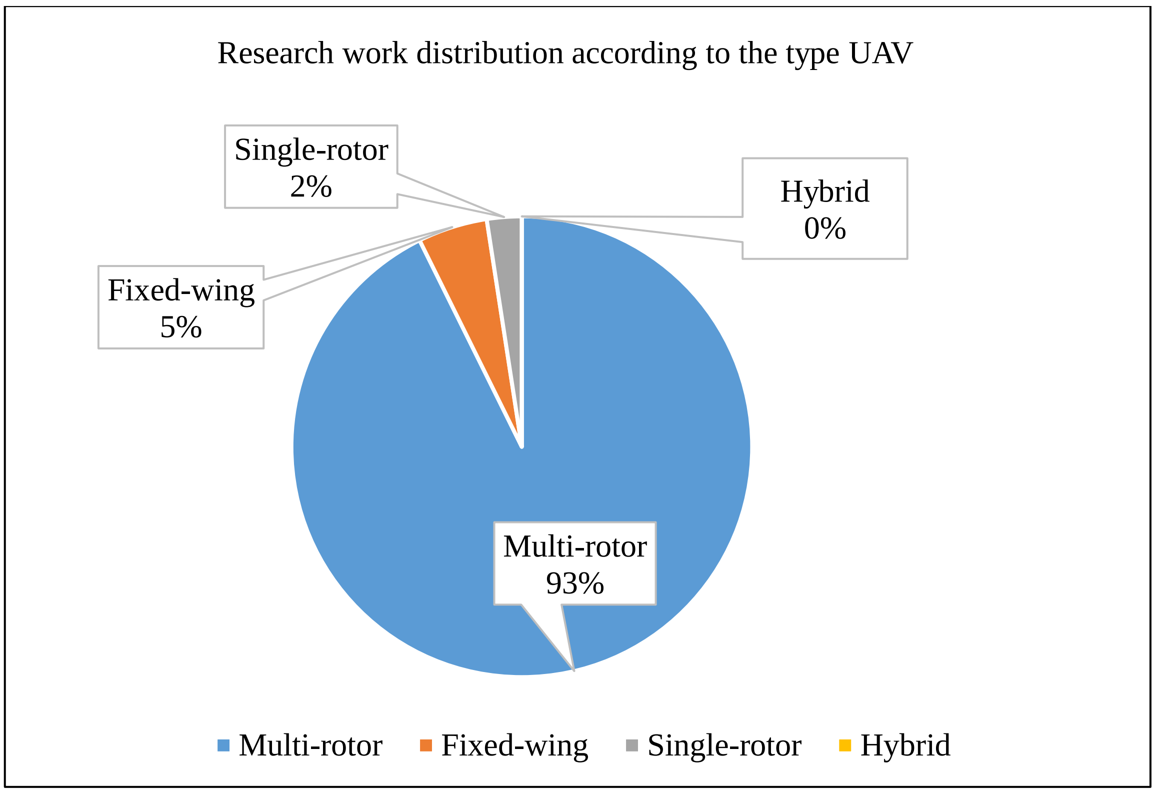



**Figure 7: Types of UAVs employed in UASHM.**

#### 3.3.1 Multi-Rotor UAV

Here, two or more rotors are used for uplift and horizontal movement. Most common versions use four to eight rotors. A visual illustration of a multi-rotor UAV is shown in Figure 8.

They are the most commonly used type of UAV in the industry, especially for SHM, at the moment, owing to the fact that they are relatively low priced, with easy flight mechanism and handling.  Smaller versions of multi-rotors are used in areas offering limited maneuverability.and they possess incredible image stability- a clear win for image processing when the purpose is to find cracks and other noticeable visual defects. Multi-rotors also support hover flight and VTOL (vertical take-off and landing), which is an added advantage.

**Figure 8: Example of a multi-rotor UAV**
The figure is referenced from Yoon et al. [33]

As far as usage goes, multi-rotors are preferred mainly for bridges and buildings, which require the steady image capture modes that multi-rotors excel at. Their relative diminutive size gives them access to difficult places such as areas underneath bridges and for tall buildings, etc. VTOL capabilities offer ease of operation.

The main downside of the multi-rotor type is their energy inefficiency. They tend to consume a huge amount of energy simply to remain airborne, and due to this disadvantage, their battery life takes a toll usually, and they end up results in short flight times.

### 3.3.2 Fixed-Wing UAV

Fixed-wing UAVs use their fixed wings to provide an uplift using predetermined airfoil and forward velocity. The velocity thrust is created by a propeller powered by an IC engine or electric motors. Figure 9 shows an example of what fixed UAVs typically look like. Fixed wings are preferred where a large amount of geographical area must be covered, such as roads and highway bridges. They are faster as compared to multi-rotors. Designed for greater efficiency, fixed wings tend to have superior battery lifetime thus high endurance [35]. This feature helps them travel long-range and stay in the air for a significant amount of time without requiring a recharge. On account of all these advantages, fixed-wing UAVs are favored where aerial triangulation and digital elevation techniques are performed.

**Figure 9: Example of a fixed-wing UAV.**
The figure is referenced from Henrickson et al. [18]

In the field of SHM, fixed-wing UAVs make the best candidate for transportation infrastructures such as roads, pavements, and railways. Considering that they arecan cover large areas, fixed-wing UAVs fit the bill perfectly. Unfortunately, the higher efficiency and faster speed come with a price. Fixed-wing UAVs require some type of runway for takeoff and landing. Also, they are usually found to be more on the expensive side, and they require professional skills to operate. Another huge downside is their inability to remain stationary while airborne. Fixed-wing UAVs do not possess hover or VTOL (vertical take-off and landing). Steady image capture is of utmost importance for the defect detection system. Since hovering is thus unachievable, fixed-wing UAVs are seriously handicapped for detailed close-range inspection.

### 3.3.3 Single-Rotor Helicopter UAV

Single rotor helicopters are the type of UAVs where, although it has two rotors, it is different from the multi-rotor ones in that it has one main rotor and an auxiliary rotor, used only for control of direction of flight. Although they are very popular in the manned aerial vehicle category, they take up a relatively miniature share in the UAV market.

Single-rotor helicopters are more energy-efficient than multi-rotors, mainly because of their larger rotor- efficiency increase being directly proportional to the length of the rotor blades. They also possess the VTOL and hover capabilities that multi-rotors do. Single rotors can also lift more than fixed-wing UAVs and therefore come in handy where heavy lifting is required. Elaksher et al. [34] have demonstrated how single rotors can be deployed in UASHM techniques and Figure 10 shows the model they picked for the experiment. There are many reasons why single rotors are generally not preferred over multi-rotors and fixed wings. Single rotors are expensive, and the design is too complex. Their long rotor blades are hazardous to anyone close to them. Consequently, although theoretically single rotors can be utilized for building and bridge inspection, the evolution of multi-rotors has displaced them to the sidelines and taken over the industry. Despite these limitations, thanks to their flexibility and hover features, they have been preferred over the others in certain instances.

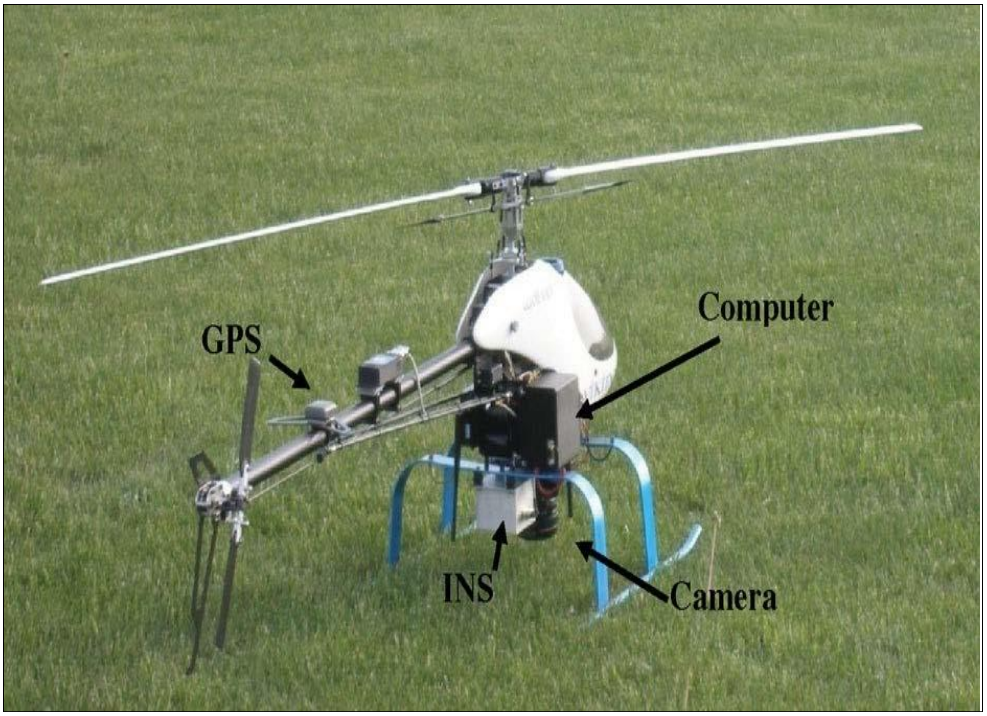



**Figure 10: Example of a single rotor UAV**
The figure is referenced from Zhang and Elaksher et al. [34]

### 3.3.4 Fixed-Wing Hybrid VTOL

These UAVs consist of fixed-wing and rotor mechanisms attached for uplift and forward movement. Combining the benefits of multi-rotors and fixed wings, hybrids are the new breakthrough innovation in UAVs. Their VTOL and hover features complement their ease of use and high definition image capture capabilities. They have better battery life and can perform a larger area inspection in one stretch.

**Figure 11: Example of a Hybrid fixed-wing VTOL.**
The figure is referenced from Li and Liu [48]

Hybrid UAVs have the potential to effectively take over the field of SHM from its counterparts and have the potential to disrupt the industry and market share. They are, however, still under development and have many prototypes that are yet to hit the market. The few products which are already in the market must undergo a few iterations in order to meet the industrial standards and be ready for high scale adoption.

### 3.4 Payload Information

***RQ. 4 What are the different payloads that are useful for SHM?***

The payload can be explained as the weight of goods that can be carried by the UAV during flight. The goods in context to SHM could be data capturing devices, navigators, sensors, or any specific type of equipment the user wants the UAV to carry to facilitate the SHM task. Applicability of UAVs is rewarded by their payload capacity. Higher payload capacity implies that they can carry more devices/attachments. Nowadays, the lack of lightweight high definition cameras and sensors pose a significant challenge for UASHM. The demand of lightweight devices has created an impetus for downstream manufacturers to find solution to the device-weight problem

#### 3.4.1 Payload Capacity

Following a careful analysis study on the shortlisted research works, the payload capacity of UAVs is categorized into three sections as given below.

##### 3.4.1.1 Payload up to 1Kgs

This category comes under micro UAVs, also known as micro UAVs. They are generally less expensive than their larger UAV counterparts. They usually come inbuilt with only the most necessary devices like cameras, navigation, and communication sensors. Their poor payload capacity limits consumers to using only the onboard devices and sensors. Since High-definition FPS (Frames Per Second) cameras and other sensors outweigh their capacity, these UAVs are relatively less favored.

#### 3.4.1.2 Payload Between 2-5Kgs

The UAVs included in this category successfully hit the sweet spot between cost and payload capacity. The fact that most of the UAVs which have been mentioned in literature fall under this category highlight their popularity in the SHM field. They come with respectable image capturing capabilities and a wide array of navigation and communication sensors. As a bonus, an additional payload can be attached if required.

#### 3.4.1.3 Payload Above 5Kgs

These heavy lifting UAVs are designed with an eye of being the carrier of heavy data capturing devices and other payloads. They are pricey in comparison to the above two categories and according to regulations, require a special license and pilot certification to operate. As a result, they remain unfavorable for SHM. Health inspection demands extreme mobility and smaller UAVs so that SHM personnel and inspectors are able to access areas that are difficult to reach.

### 3.4.2 Payload Types

Information-driven insights from the literature suggest that payload can be categorized into four types, in general, based on their application in SHM. They are data acquisition devices, navigation and control devices, Communication devices, and custom payloads for specific use cases.

#### 3.4.2.1 Data Acquisition Devices

There are a wide variety of devices and sensors that can be attached to UAVs to give an extra dimension to the data being collected during the SHM process. Some of the important ones are listed below.

##### 3.4.2.1.1 RGB Image Capturing Devices

Undoubtedly one of the most important data collection devices used with UAVs, Image capturing devices are used to obtain digital images using vision sensors. Also called RGB cameras, they are often observed to be lightweight and can easily be attached due to their compactness. Inspections such as edge detections require high-definition cameras, which can capture even minor details in high frames per second. Cracks in the concrete walls and metals are difficult to detect, and this difficulty could explain why practitioners prefer cameras with high-resolution capabilities (such as 1080p or even 4K resolution) with high FPS (frames per second) for inspection [12]. For example, Yoon et al. [33] have explained how they achieved superior image quality for health inspection of bridges by using a high FPS 4K camera mounted on the Phantom 3 professional UAV. Yoon et al. [33] mentioned in their research project that they were able to collect 6000 images of 4K resolution with a 24 FPS speed of capturing (frames Per Second) .Combining multiple cameras is one of the techniques used to achieve more depth in the images. Having an additional camera creates a stereo vision, similar to the combined effect of human vision, and this feature helps to reconstruct 3D models of the infrastructure. For example, Reagan et al. [25] have implemented 2 digital cameras and performed health inspections using 3D-DIC (Digital Image Correlation) techniques. In particular, Time of Flight (ToF) cameras can help measure the distance between the object and the camera. This feature can benefit both image-capturing and navigation systems.

#### 3.4.2.1.2 GPR (Ground-Penetrating Radar)

The GPR data collection device consists of a sensor that uses radar pulses to capture even the subsurface of civil structures. Using GPR in the UAVs would help us identify below the surface damages in the concrete, which are not visible to the naked eye or even to traditional cameras but are important to find. GPR's EM (electromagnetic) waves achieve this goal perfectly.

#### 3.4.2.1.3 LiDAR (Light Detection and Ranging)

LiDAR sensors use laser pulses in quick intervals to calculate the distance between the sensor and objects and map them into a 2D/3D image. LiDAR sensors particularly useful in low light conditions, and where high accuracy 2D/3D models are required. For example, A. Khaloo et al. [50] have shown how well LiDAR can be used with point-cloud techniques to extract features from infrastructure surfaces. LiDAR sensors are being adopted for UASHM more commonly, and it is expected that research projects combining LiDAR technology with UASHM would be on the rise as the LiDAR sensors get cheaper and compact.

#### 3.4.2.1.4 RGB-D Sensors

These devices create RGB (Red Green Blue) images of the infrastructure with color-codes on the basis of per-pixel depth. In SHM inspection, RGB-D images are used to identify the depth of the cracks and the condition of the infrastructure surface. They are useful in distinguishing the distance between objects as well.

#### 3.4.2.1.5 NIR Sensor (Near Infrared)

NIR sensors are rarely used on account of being expensive. They combine RGB images with infrared and can be used to differentiate between the various types of infrastructure surfaces.

#### 3.4.2.1.6 Thermal Sensor

Thermal sensors gauge temperature and map them as images. A range of colors is used to assess temperature variation. UAVs mounted with thermal sensors are found to be useful especially in factory infrastructure, where they can detect gas leaks and cracks more efficiently.

#### 3.4.2.1.7 Chemical Sensor

In addition to detecting defects in the infrastructure, UAVs equipped with chemical sensors can identify gas leakage and are thus also convenient where inspections are carried out in factory environments.

### 3.4.2.2 Navigation and Control Devices

UAVs are steadily becoming more capable and easier to fly, in view of the advancement being made in navigation assistance sensors. These sensor devices provide much more control and stability over the flight and enable autonomous capabilities. Some important navigation systems that are used in UAVs are listed below:

#### 3.4.2.2.1 GPS (Global Positioning System)

GPS devices calculate their geographical position using their radio receiver to detect signals from satellites orbiting around the world. Combined with other sensors, GPS enables UAVs to detect their position accurately and even use geo-tagging to tag the objects and locations when called upon. They have consequently become an indispensable part of UAVs.

#### 3.4.2.2.2 INS (Inertial Navigation System)

INS use a wide array of sensors like motion sensors and rotation sensors for dead reckoning the position, velocity, and orientation of the UAVs on a continuous basis [36]. The ability to correlate sensor readings is the main contributor to their success. Accelerometer and gyroscopes are preferred as motion and rotation sensors, respectively, due to their low cost and compactness. Combined with GPS data, INS can be used to track UAV motion so that autonomous flight between geographical checkpoints is made possible during SHM.

#### 3.4.2.2.3 Obstacle Avoidance Systems

Obstacle avoidance systems are used to detect obstacles in the way of flight so that they can avoid collision between other objects while monitoring a civil structure. Examples of these systems are ultrasonic sensors and light-pulse distance sensors where the former uses sound waves and the latter uses lasers to measure distance. The data obtained from these sensors can be analyzed using techniques like SLAM (Simultaneous Localization and Mapping) algorithms to intelligently steer the UAVs away from obstacles.

#### 3.4.2.2.4 Geomagnetic Sensors

Geomagnetic sensors are used to calculate the reference and heading of the UAVs compared to the earth. It is made possible by reading the earth's magnetic field lines and comparing its intensity against the standard measurements.

### 3.4.2.3 Communication Devices

These devices are used to communicate and transfer data between the UAV and its control/data receiving device. UAVs commonly use radio waves as a medium of communication. A specific radio frequency bandwidth is set as default between the UAV and the controller in order to enable communication between them. As a safety measure, RFIDs (Radio Frequency

Identification) are provided to all devices, and the RFIDs between the UAVs and controllers must match for communication to be established. Most of the recent products have set the frequency at 900 megahertz. Lower frequency signals have a higher range and they can pass through obstructions better than higher frequency signals. Some of the recent iterations of UAVs are Wi-Fi enabled so that they can perform a live transfer of high-definition images and other data to the controller. Wi-Fi works on two frequency bandwidths, 2.4 GHz and 5GHz.The former is preferred at the moment for its long-range.

#### 3.4.2.4 Custom Payloads for Specific Use Cases

These are devices or materials that are mounted on the UAVs for specific reasons according to the users. For example, Myeong et al. [21] have demonstrated the use of wall climbing UAVs that can fly and stick on walls to perform inspections. Here, the wall-sticking equipment can be considered as a special payload that is mounted for this user-specific case [21]. Similarly, various types of payloads have been observed that are significant for that specific user.

As is clear, payload capacity is unmistakably one of the major deciding factors in terms of how well you can employ UAVs in health inspection of infrastructure. The development of lightweight sensors and devices will enable UAVs to carry more devices and provide longer flight time.

### 3.5 Applications and Techniques in UASHM

***RQ. 5 What are the different techniques and applications of UAVs to support civil structures which have been exploited by researchers in the last decade?***

With the recent advancement in the area of UAVs and the associated sensor devices, their applications in the field of structural health monitoring are limitless. With their greater freedom of movement, UAVs can get visuals of unattainable areas of civil structures that were previously considered near impossible through conventional methods. Their inspection methods are primarily visual, and they enlist the help of image capturing devices and sensors to detect damages and defects on infrastructure surfaces [27].

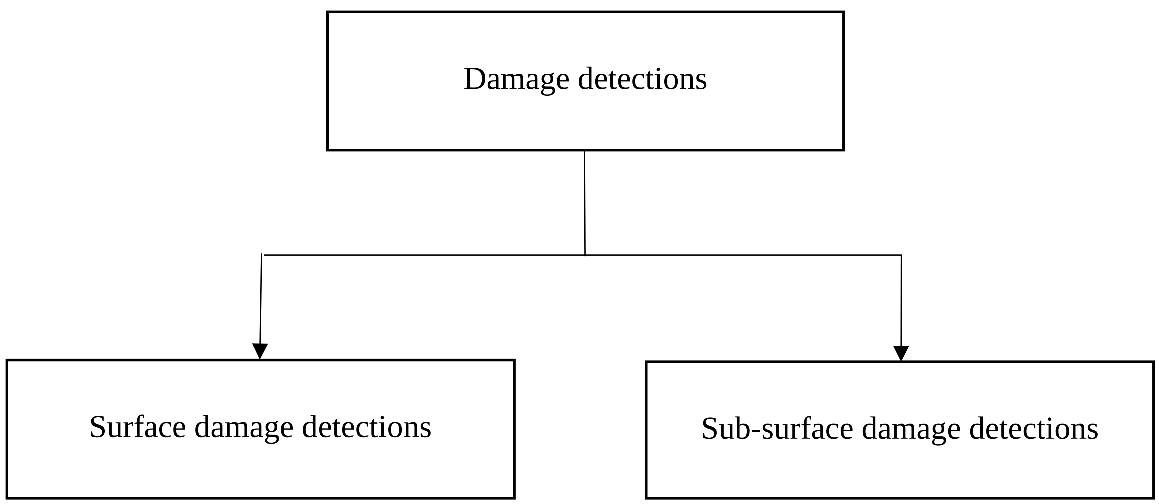



**Figure 12: Primary classification of damage detections in UASHM**

In the field of civil SHM, the damage detection techniques can be categorized into 2 types as shown in Figure 12, namely, surface damage detection and subsurface damage detection. As the name suggests, the former is visible on the surface of the civil infrastructure. They are relatively easier to inspect and identify with the help of conventional UAV data acquisition sensors like RGB cameras. The types of surface damage detection techniques that are discussed in UASHM are crack detection, corrosion detection, and displacement detection.

Sub-surface damages originate below the surface of the infrastructure and in most cases show no visual signs of developments at the surface. These are harder to detect with conventional visual data acquisition devices and as such, researchers generally use additional payloads such as Infrared sensors to detect them. The type of sub-surface damage detection this research study discusses is Delamination detection. To give an overview, Figure 13 shows that the majority (87%) of research studies concentrate on surface damage, and the remaining 13% focus on sub-surface detection.

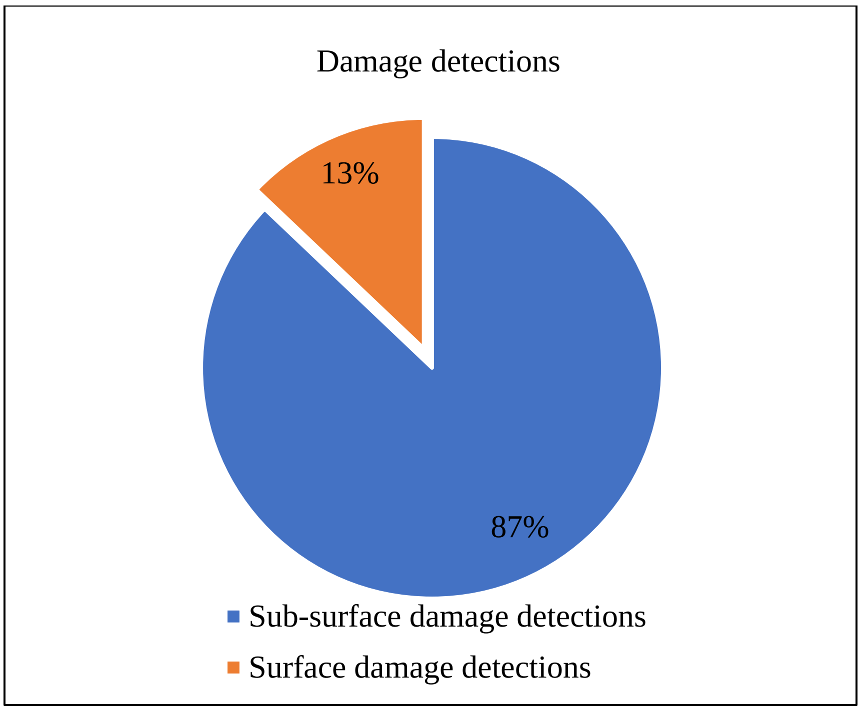



**Figure 13: Research grouped according to primary damage level detection.**

The studies are further classified into specific categories as represented in Figure 14 to understand the trends in UASHM research. These include crack detection, delamination detection, displacement detection, corrosion detection, and supporting work for the abovementioned techniques.

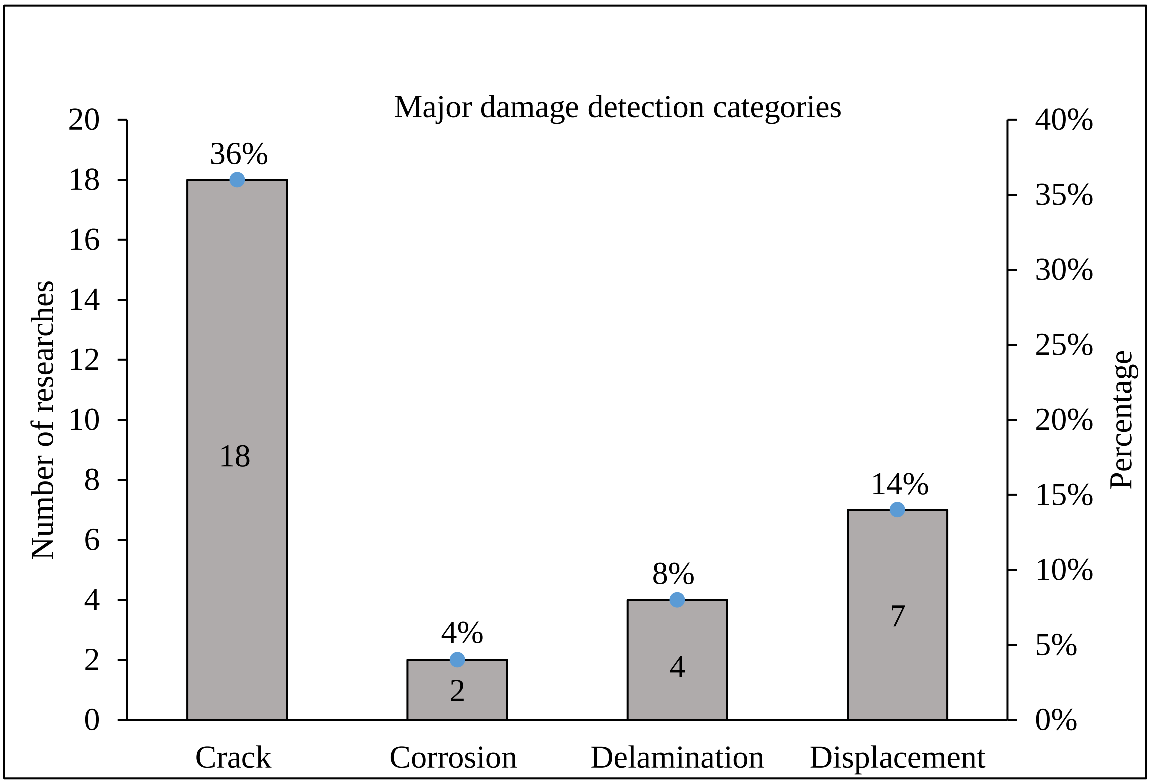


**Figure 14: Major damage detection categories**

*Crack detection* is the application of detecting cracks in infrastructure materials like concrete and metal. *Delamination detection* focuses on the formation of damaged layers on the surface.  *Displacement detection* deals with finding the displacement of objects which are part of the infrastructure to its reference position. *Corrosion detection* work is related to UASHM to identify the parts of the infrastructure that are corroded and tag them accordingly. Researches and techniques that are related to the application of UASHM are grouped as the final category, i.e., *Support work.*

### 3.5.1 Research Works Related to Crack Detection

A majority of the literature papers have addressed crack detection as the primary concern in infrastructure safety inspections, and rightfully so. They are the main cause of damage and fatalities in most cases [37].

Back in the year 2012, Eschmann et al. [10] investigated conventional means of inspecting large scale infrastructure and observed that the main goal was to analyze cracking conditions. Eschmann et al. [10] continued to point out the laborious nature of these procedures and underlined the importance of much-needed UAV assisted inspection methods. Although onfield experiments were promising, the struggles of mounting heavy payloads used for crack detection on UAVs were evident. Collected geo-referenced high-definition RGB images were stitched together to form a large 1.27 Gigapixel image, mostly done manually since it was too complex for the then-existing pattern recognition algorithms [10]. Detection of cracks was performed by applying Gaussian blur and greyscale intensity to the images and performing edge detection algorithms. The major drawback was that the method was successful only with white or grey walls [10].

Hallermann and Morgenthal [6], [15] observed the great effectiveness of computer vision algorithms for identifying cracks in the images by reconstructing them into 2D or 3D models. They also brought attention to the fact that there would be a lack of crack detection accuracy due to motion blur and identified the need for slow and steady motion in UAVs during data acquisition periods. This requirement signified a clear win for multi-rotor UAVs due to their hovering and VTOL capabilities [6], [15].

As mentioned previously, UAVs primarily depend on vision-based inspections and there remained a desperate need for filtering out the noises in the data for image-processing. Ellenberg et al. [3], [52] demonstrated how researchers improved crack detection by applying Prewitt edge detection algorithms and converting the images to binary. In this way, noises in the image data could be avoided and there would be better efficiency for crack detection [3], [52].

The areas that suffer fatigue from high pressure are more prone to cracking than normal. The type of cracks thus formed are called fatigue cracks. Yeum and Dyke [32] have performed crack detection in metal components of bridge infrastructure where they noted cracks close to the bolts in the metal frame due to fatigue. Yeum and Dyke [32] introduced pattern detection for identifying cracks and enhanced the accuracy of detection with the help of Frangi filter and canny edge detector. Frangi filter and canny edge detector are multi-stage pattern recognition algorithms that can accurately identify continuous edges [32]. Frangi filter is also capable of finding the intensity of the edges and can relate that to the whole image. By applying these extra steps to the proposed method, Yeum and Dyke [32] were able to reduce false-positive images in the experiment.

As the field of UASHM has grown, the technology and techniques related to UAVs have grown with it. Researchers have started to focus more on image processing techniques since it was one of the areas that called for desperate innovation Sankarasrinivasan et al. [26] investigated the drawbacks of the Canny edge detection algorithms and other techniques like Bayesian classifiers and wavelet approach. The above-mentioned techniques rely on greyscale images, and they are prone to misidentify the corners and edges of walls as cracks while performing health inspection via UAVs [26].To overcome these shortcomings, Sankarasrinivasan et al. [26] introduced a new strategy that collaborated Hat transform and HSV threshold technique to successfully resolve excessive detection issues. Thresholding techniques normally work on differentiating data with respect to value (generally called threshold value) that has been set as the boundary between two sides of the spectrum. It is a widely used and simple technique when it is required to filter your data from anomalies and noises and even for classification. While the Hat transform technique is just like other techniques that use greyscale images, HSV thresholding introduces color-based filters that detect cracks by low saturation and threshold values [26]. Also, it is inferred that this technique could possibly resolve the shortcomings of the approach Eschmann et al. [10] used since they faced issues with the color of the infrastructure walls.

By the year 2016, the aggressive development of Vibration-based non-destructive testing sensors resulted in them being lighter, smaller, and cheaper. This movement in the industry implied that mounting a various array of sensors to the UAV was now less of a challenge than before. Vibration-based sensors work based on the physical properties of the materials such as stiffness, mass, and dissipation of energy through them [43]. Variation in any of the abovementioned properties can exhibit changes in frequencies, modal damping, and mode shapes, etc. To industrialize this concept in UASHM, Na and Baek [22] proposed the concept of integrating vibration-based NDT sensors to improve the data capturing capabilities of UAVs. They used piezoelectric (PZT) sensors to detect cracks at an early stage [22]. This technique is called EMI (Electromagnetic inference), introduced by Liang et al. [38]. Although it has been proved that even minute cracks and damages could be detected by mounting the PZT sensor in UAVs, Na and Baek [22] were unsuccessful in establishing an industry-standard model that could work wirelessly in UAVs.

Vibration-based detection methods did not see much practical success in 2016, and the industry focus switched back to computer vision algorithms employed in UASHM. In 2017, Dorafshan et al. [8] claimed that implementing real-time onboard crack detection systems in

UAVs could increase productivity. The recommended system could also reduce latency issues since results are generated in real-time without adding post-processing in the workflow. Dorafshan et al. [8] preferred Sobel filters to detect cracks as the authors claimed the system had the highest accuracy (true positive=96%), among other experimented filters like Roberts and Gaussian high pass.

Laser technology came into the picture when Phung and Hoang [24] demonstrated that laser sensors could automatically detect paths for UAVs and thus automatic crack detection could be implemented. The authors also utilized a histogram analysis to automatically stitch the images together [24]. For crack detection, Phung and Hoang [24] used the peak detection algorithm. Unlike the general threshold technique approaches, here threshold values are computed for each pixel in the image and are modified based on the neighbor's greyscale intensities [24]. By considering a dynamic range for global threshold value and the locally adaptive threshold value, the method put forward by Phung and Hoang [24] could resolve illumination and over-exposure issues in the image capturing process to some extent.

The emergence of convolutional neural networks has been the quantum leap in the innovation of Computer Vision, and their applications are endless. Identifying different types of cracks is too complex a task for conventional techniques. In course of tackling the issue of sub-par damage detection capabilities, increased adoption of Deep Learning techniques among researchers in the past few years have been observed. Yang et al. [31] demonstrated their Deep inspection system which uses convolutional neural networks to detect damages including concrete cracks. Since they mainly relied on the RGB camera, which was mounted as default, this technique did not require any extra payload on the UAVs. Yang et al. [31] built a large Concrete Spalling and Crack database (CSSC) from internet resources, which was claimed to be the first released database for Deep Learning inspection. The choice of CNN (convolutional neural network) type was a widely used VGG-16, developed by Simonyan and Zisserman [39] from The University of Oxford. The experiment took place in Manhattan, USA where the entire data collection was performed by UAV. The field tests were successful with over 70% accuracy [31]. The early struggles the authors had to go through involved building the CSSC database for training the machine learning model [31]. Adjusting and reshaping the images taken with UAVs for inspection was difficult as well since authors had to match the resolution and size of images to the standard recommended for the specified CNN model [31].

The overwhelming amount of research studies on Deep Learning based damage detection techniques became evident by the year 2018. Gopalakrishnan et al. [13] conducted a case study on UASHM focused on crack detection using pre-trained VGG-16 DCNN (Deep Convolutional Neural Network), a highly recommended model by researchers for transfer learning as it is trained on a large data set and the hyper-parameters are highly optimized. The authors compared the results with other techniques like SVM (Support Vector Machines), RF (Random Forest), and ERT (Extremely Randomized trees) with classical NN (Neural Networks) and LR (Logistic Regression) techniques which are trained on the pre-trained VGG-16 DCNN [13]. Performance results justified the claim that both NN (Neural Networks) and LR (Logistic Regression) achieved 89% accuracy in testing [13]. The authors also pointed out the opportunities that exist for building the DL (Deep Learning) model capable of identifying multiple types of defects and the need to integrate UAV based SHM to big data systems such as MapReduce and Hadoop to manage complex computing requirements of crack detection algorithms [13].

Kang and Cha [19] also opted for a similar approach to use DCNN (Deep Convolutional Neural Network) for UAV based crack detection. Unlike Gopalakrishnan et al. [13], Kang and

Cha [19] used the classical CNN model instead of the transfer learning approach, developed in Mat Lab, with which the authors claimed to achieve 97.6% accuracy in testing even though the proper validation methods and the test environment were beyond an extent unclear. The authors also introduced the Ultrasonic Beacon system (a new technique introduced by the authors as an alternative for GPS) with geotagging for navigation, which could be successfully utilized in GPS denied areas such as beneath bridges and in indoor inspections of buildings [19].

One of the challenges of implementing DL based crack detection techniques in UAVs is their latency caused by the complexity in calculations and the need for brute force computational needs. To address this issue, Cha et al. [5] introduced a time-efficient method to identify Multiple-damage types with Deep Learning algorithms. As opposed to the conventional approaches, authors used a region-based model, called Faster R-CNN (a type of Convolution Neural Network with ‘R’ stands for Region) to identify multiple damage types. Faster R-CNN is a region-based technique where a convolutional feature map is generated by passing images through CNN, following which region proposals are performed by a separate region proposal network and then RoI (Region of Interest) pooling fixes them into standard sizes [41]. Softmax methods are used to classify the output in the convolutional neural network [41]. Faster R-CNN is quicker because it prevents featureless regions from passing through the entirety of the timeconsuming analysis process and uses a quicker region proposal network instead of slow special region proposal methods. Having such low latency algorithms are promising since it can be implemented in a UAVs’ onboard computer so that it could unveil real-time detection methods [5].

To further establish the recent success of UAV assisted crack detection methods, Dorafshan and Maguire [7] investigated the financial aspect of crack and damage detection.

According to the authors, UASHM methods used for crack and damage detection are 37% faster and 66% cheaper than conventional methods [7], [40]. In 2019, Shakhatreh et al. [28] and Agnisarman et al. [1] conducted surveys on research papers that study the potential of UASHM methods. Agnisarman et al. [1] pointed out that Artificial Neural Networks are widely used for defect detection along with other machine learning models for specific use cases. One of the mentioned examples is Hilditch's algorithm for asphalt crack detection with pixellevel classification F measure for finding accuracy [1], [42]. Shakhatreh et al. [28] reiterated the crack detection model proposed by Sankarasrinivasan et al. [26] which was one of the most robust approaches executed on UAVs at the time.

### 3.5.2 Research Works Related to Delamination Detection

Delamination is a type of failure that happens to the surface of a structure when the material loses its coating adhesion, resulting in the formation of layers. It is commonly seen on concrete surfaces. Although there had been multiple attempts to do so, identifying delamination defects had proven to be painstaking. According to our observation, the first literature out of the selected ones which address this issue came out in the year 2016. Ellenberg et al. [9] tried to tackle this issue by implementing IR (infrared) sensors in the UAVs. Figure 15 shows the postprocessing of the UAV images where authors stitched the images together to reconstruct the structure surface to ascertain the potential defects. FLIR a325sc delamination detection algorithm was used to identify surface delamination [9]. The experiment was successfully conducted on a bridge deck. Omar and Nehdi [23] adopted the same approach as Ellenberg et al [9]. The IRT (infrared thermography) technique for subsurface delamination works on a simple principle. When the surface is under sunlight, it absorbs radiation and heats up the areas where delamination has occurred. Those areas tend to have lesser heat transfer due to their detachment from the main structure, resulting in increased temperatures relative to the surrounding surface. These areas of higher temperature can be spotted as “hot spots” by IRT sensors mounted on the UAVs during inspection [23].

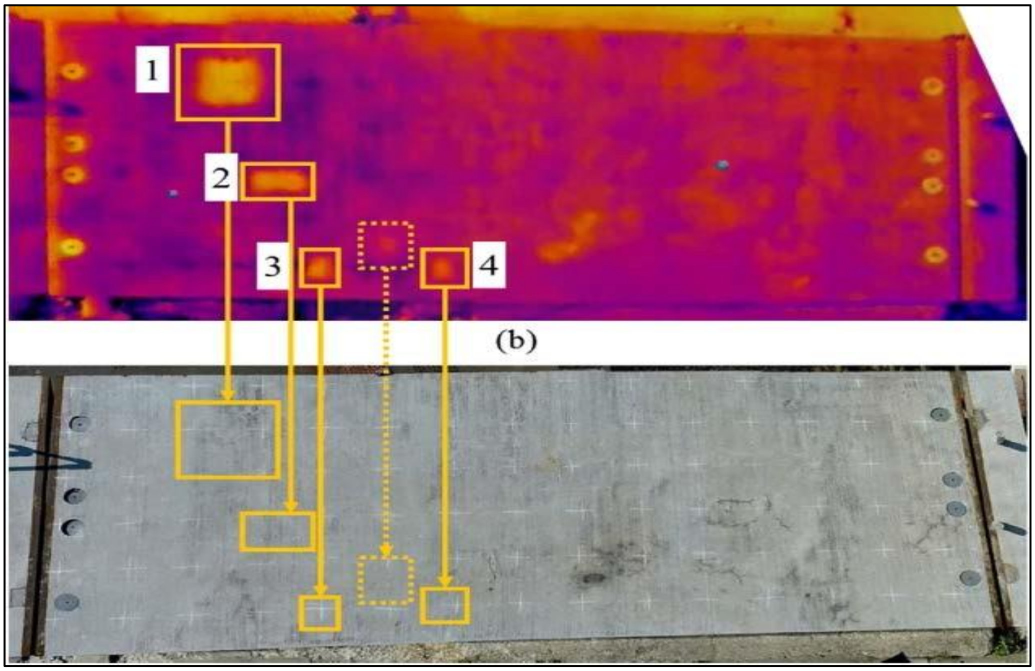



**Figure 15: UAV infrared images (a) used for delamination detection and UAV color images (b) stitched together.**
The figure is referenced from Ellenberg et al. [9].

In addition, when the entire surface cools down, delaminated areas lose heat quicker, and IRT sensors in the UAVs can spot them as “cool spots” [23]. Based on this technique, Omar and Nehdi [23] experimented on a bridge deck and IRT images were created to identify the delaminated subsurface. The experiment results were validated by conducting Hammer sounding test and Halfcell potential tests, which yielded similar results.

Yang et al. [31] took a different approach for identifying subsurface delamination, where authors relied mainly on the RGB camera instead of adding IRT sensors to the UAV. Yang et al. [31] preferred DCNN (Deep Convolutional Neural Network) to identify delamination defects from the attached RGB camera images. The above-introduced method was tested on a bridge situated in Manhattan, USA. The preferred pre-trained model was VGG-16 and performed well with over 70% accuracy in real-world testing [31]. Also, Dorafshan et al. [8] conducted a study on identifying subsurface delamination. The testing environment was created to resemble a bridge deck consisting of concrete and steel. Even though the authors claimed that multiple damage types were identified, the detection techniques were focused on identifying cracks, and negligible details about delamination identification techniques were documented [8].

Cha et al. [5] focused on delamination defects that appear in steel. Steel is one of the integral materials used in a majority of civil infrastructure, and any such critical defects/damages must be identified and evaluated since they could potentially lead to dangerous consequences. Cha et al. [5] used the combination of RPN (Region Proposal Network) and Faster R-CNN to successfully identify steel delamination in infrastructure. The experiment was conducted on a building complex and two bridges where the accuracy of the detection system was 83.1% overall for steel delamination [5].

Dorafshan and Maguire [7] discovered that the delamination detection method efficiency might vary according to data collection methods. The authors suggested that standard procedures such as ASTM D4788-03, an IRT (infrared thermography) based standard test, could address this concern. As sensors are becoming lightweight and compact, future development of higher resolution IRT sensors with better sensitivity could result in improved UAV assisted delamination detection.

### 3.5.3 Research Works Related to Displacement Detection

Displacement defects are formed when a portion of the entire structure or the structure as a whole is moved away in relation to its original position of reference. These misplacements could compromise the structural integrity of the structure so much so that the need for identifying these defects is one of the major priorities in health inspection.

One straight forward example of a displacement defect would be the retaining walls that can be seen beside roads. The first detailed study on displacement detection among the selected research papers took place in the year 2014 where Hallermann and Morgenthal [6] examined a large retaining wall for potential displacement defects. These walls retained landmass, which was elevated with respect to the road and prevented landslides by providing extra support. Eventually, due to the extreme amount of pressure caused by the landmass, they would develop a tendency to push away along the direction of pressure. These kinds of displacements could be visually identified easily from a distance for us to relate the positional displacement of the structure to its referential surroundings. Hallermann and Morgenthal [6] tested the potential of UAVs for displacement detection using photogrammetric methods and computer vision algorithms. Figure 16 shows the test case, a 700m long retaining wall with a height of 20m and inclination of 70 degrees which was examined using UAVs and generated airborne images for analysis. They validated the accuracy of the method by removing some of the bricks intentionally and replacing a few with thinner plates to simulate the movement of the portions [6]. The images were collected from the same pre-planned flight path of UAV and both cases were compared for detecting displacement [6].

**Figure 16: Retaining wall taken as a case study.**
The figure is referenced from Hallermann and Morgenthal [6]

Hallermann and Morgenthal [16] continued the same research on the retaining wall shown in Figure 16 in their next literature and displacements based on 3 dimensions were documented. They used a patch-based Multi-View Stereo algorithm which ran on PMVS2 software and a customized version of CMP-MVS (Furukawa and Ponce [44]; Jancosek and Pajdla [45]). PMVS2 is a software used to reconstruct 3D structures by inputting several raw images and camera parameters. The experiment was thus carried out and the results validated. Hallermann and Morgenthal [17] continued their research in the year 2015, where they examined their previous test case (retaining wall shown in Figure 16). This time, the authors used Orthophoto mosaics and 3D point clouds for displacement detection on aerial images collected from High-end UAV Hallermann and Morgenthal [17]. The post-processed images were color-coded according to displacement intensity [17].

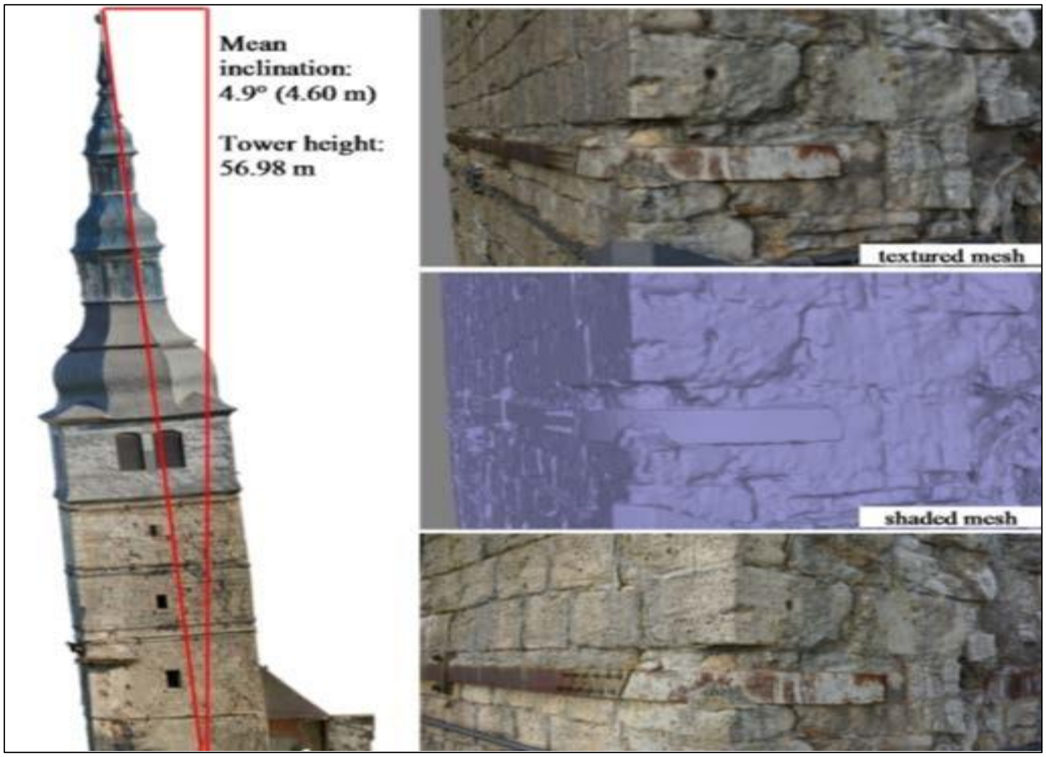



**Figure 17: Angular displacement detection in tall structure, right: 3D construction model using dense point clod method.**
The figure is referenced from Hallermann et al. [14].

In another research study, Hallermann et al. [14] performed an aerial image-based survey using UAV on heritage monuments to inspect the structural health. The authors used the dense point cloud approach to identify displacements in the structure [14]. “Point cloud” is a type of computer vision method used to produce significant data points in space to replicate or represent the 3D shape of any test object. Here, the authors used dense point clouds, which is a more concentrated version containing an increased number of data points in unit space [14]. With this improved technique, which was collaborated with UAV based aerial images, Hallermann et al. [14] identified displacements of tiles on the roof of the monument structure. They also performed angular displacement detection in tall structures as shown in Figure 17. Angular displacement is the change in the vertical angle in which a structure is built with respect to the ground. In 2016, Gillins et al. [12] proposed a cost-effective Bridge safety inspection using UAVs. Even though it was stated that displacement detection methods were applied, there was little to no detail about the techniques used in the study.

Moving on to the year 2017, Reagan et al. [25] demonstrated a new method to identify displacements in infrastructure using a 3D-DIC (Digital Image Correlation) sensor mounted to the UAV as an additional payload [25]. The experiment was carried out on a concrete bridge. As shown in Figure 18, the expansion joints in the bridges were closely examined, and displacements were identified using the 3D-DIC sensor [25].

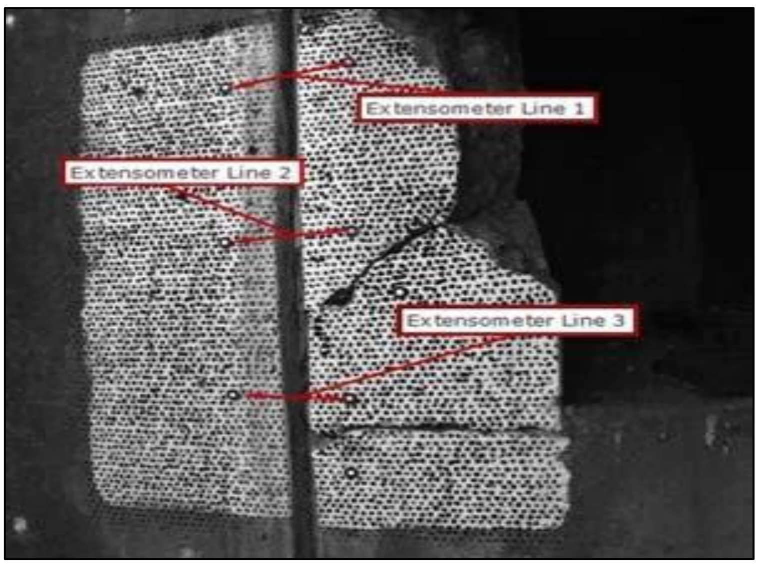



**Figure 18: Displacement detection in the expansion joint.**
The figure is referenced from Reagan et al. [25]

3D-DIC sensors are non-contact optical sensors used to find the deformation and strain in materials and to determine their shape [53][46]. Reagan et al. [63] followed up their researches on UASHM using DIC sensors and how to automate the process. The authors used extensometers (instruments used to find deformation of materials subjected to stress) mounted on the UAV to calculate axial displacements of X, Y, and Z axes and averaged each of them by repeating the procedures to get optimal results [25][63]. The experiment was conducted on a timely basis, and displacement values were graphed with respect to the date of the experiment [25][63]. The results are validated accurately by dial caliper measurements which the Reagan et al. [25][63] took side by side.

In the following year, Yoon et al. [33] kept their main focus on displacement detection by UAVs equipped with professional video cameras. As the authors demonstrated, they followed 3 steps. The first step was to measure the target-free displacement followed by the next step of estimating the 6 Degree of Freedom (DoF) motion [33]. The third and last step was the measurement of displacement. Yoon et al. [33] used the Kanade-Lucas-Tomasi (KLT), a feature tracker. KLT tracker is a type of feature extraction technique which is relatively faster than conventional approaches. This approach used spatial intensity information to improve the direction of the search and to identify features. A railroad bridge was chosen to validate their claim and documented reasonably accurate results [33].

Spencer et al. [29] re-emphasized the convenience of choosing video cameras in UASHM for displacement detection. The authors demonstrated their opinion by developing a computer-vision based displacement detection system that worked with UAVs. Very similar to what Yoon et al. [33] emulated in their work, Spencer et al. [29] also tested their model on a railroad bridge, and stress-induced displacements were recorded with Finite-Element (FE) simulation.

### 4.5.4 Research Works Related to Corrosion Detection

Since metals are widely used as parts of building infrastructure, the possibility of corrosion is omnipresent. Corrosion is a natural phenomenon commonly occurring in metals where it undergoes an electrochemical process to liberate positive charge to become a stable compound. When these corroded components begin to degrade, they become a weak link for the entire structure. Yeum and Dyke [32] brought up the need for corrosion detection in UASHM in the year 2015. Even then, authors could not introduce any detection technique that solely focused on corrosion detection rather than depending on traditional vision-based inspection methods [32]. Following the same path, Henrickson et al. [18] considered corrosion detection for their UAV based infrastructure assessment methods. However, the authors were unsuccessful in developing any such detection method.

The first real corrosion detection method in UAV was introduced by Ellenberg et al. [47]. The experiment was conducted in two ways. The first one was performed manually with the help of MatLab. The second approach was to apply K-means algorithms to determine the size of the corroded areas. The experiment was performed with minimal errors where the manual method (10% error) achieved a slight edge over the K-means algorithms method (15% error) [47]. Unfortunately, no method had been found in the article which could detect corroded areas in the first place.

Even though Omar and Nehdi [23] conducted UASHM in their research, they used Half-cell potential tests for detecting corrosion, which is not a UAV based detection method. Na and Baek [22] took a different approach from traditional methods. The authors noted that corrosion reduced the thickness of the material and the reduction of thickness could be identified by UAV based inspections. Na and Baek [22] used piezoelectric (PZT) sensors to perform the experiment.

However, they were unsuccessful in developing a wireless platform to handle the increased data transfer and could manage only wired UAV inspection.

A robust model was ultimately proposed by Cha et al. [5] in the year 2018, which had the capability of detecting two types of corrosion: steel corrosion, and bolt corrosion. The corrosion in steel occurs when iron in the compound starts to oxidize and produce rust. As a consequence, the steel becomes weak. In the case of a bolt, localized corrosion happens between two joints of the metal surface, and it is usually more aggressive. Cha et al. [5] used the Faster R-CNN model to detect multiple damage types. Since it was a region-based model, this technique best-suited corrosion detection [5]. The many-steps process ended with the Softmax method for the final classification. In addition, Cha et al. [5] categorized steel corrosion into two: medium steel corrosion and high steel corrosion. This move was intended to improve the accuracy of the model and it worked out to be an excellent one for a high-speed algorithm like Faster R-CNN. The average precision of the models was documented to be around 82% for High steel corrosion and 84% for Medium steel corrosion [5]. Bolt corrosion precision was recorded to be around 90% which was really promising considering the 38 test cases that the authors tried on [5].

Moving on to Spencer et al. [29] where the authors conducted a literature review on damage detection in general including corrosion detection. As the authors observed, researchers have been using physical properties such as texture, spectral, and color information to classify corroded areas [29].

To conclude, in spite of the introduction of some new efficient techniques, such as Faster R-CNN to identify multiple types of corrosions by Cha et al. [5], the research studies are insufficient, and the development is in a relatively premature stage. In effect, the first meaningful research study came in as late as in the year 2015 when Yeum and Dyke [32] addressed the need for UAV assisted SHM for corrosion detection but were unsuccessful in realizing it at the same time. If one model has to be picked out of the entirety of the research studies on corrosion detection, it would be the Faster R-CNN model developed by Cha et al. [5], primarily owing to the sound technique used and its successful validation. Although it's difficult to attribute it to any single cause, what is evident is that shortcomings in computer vision techniques and detection algorithms have been contributors to the bottleneck in the effective growth of UAV assisted corrosion detection methods.

### 3.5.5 Supporting Research Works

Apart from directly studying or introducing new UASHM damage detection techniques, there have been a few types of research studies that have been developed and examined to support the UAV assisted SHM. These have a wide variety of applications, such as in navigation, computer vision, communication, and in the development of various kinds of lightweight sensors.

One of the supporting techniques which have been extensively studied is image stitching and 3D reconstruction [64]. In the last decade, many researchers have extensively worked on creating 3D models of civil structures to assist UASHM.

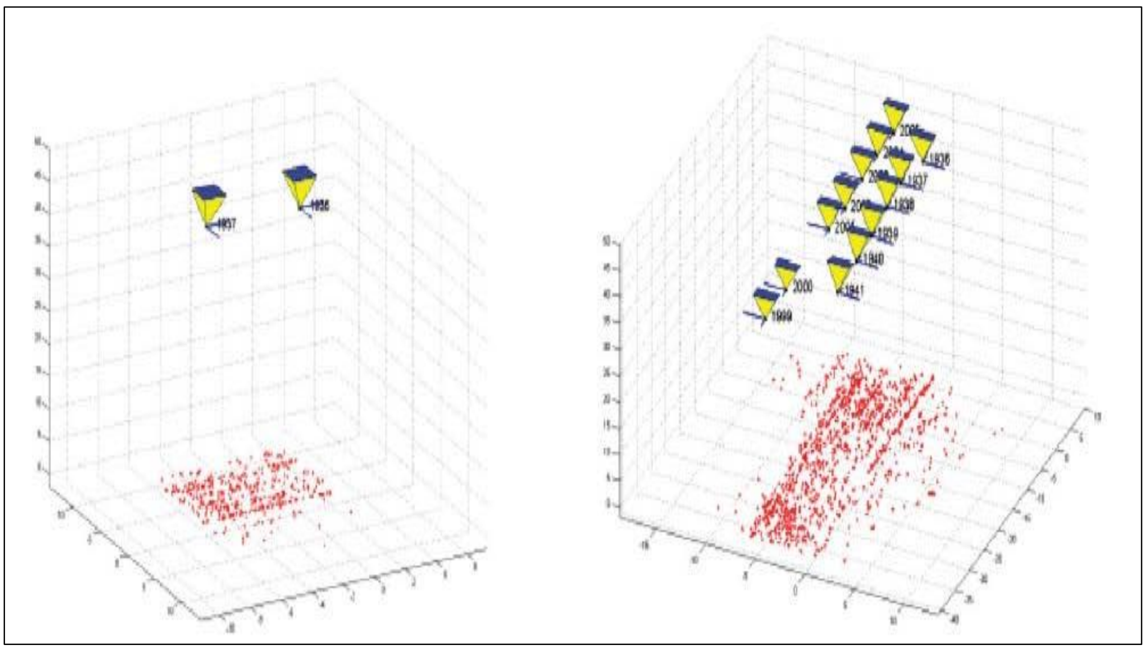


**Figure 19: 3D block formation and point generation. Inverted pyramids represent the camera position and the red points represent the spatial position of the object under analysis.**
The figure is referenced by Zhang and Elaksher [34].

As early as 2012, Zhang and Elaksher [34] introduced 3D feature extraction and measurement algorithms in their research study and successfully calculated surface distress on the unpaved road. The entire framework consists of image orientation algorithms, automated 3D model extraction, and 3D feature extraction algorithms [34].

In the image orientation process, the UAV-acquired images go through relative image orientation pair by pair, and 3D point coordinates are generated [34]. Next, neighboring images are added, and space resection is performed. Once this process is finished, the process moves on to automated 3D model extraction [34]. Zhang and Elaksher [34] developed computer vision algorithms that can reverse the imaging process by identifying spatial coordinates of the position where images are taken, and object space points are generated as shown in Figure 19.

Once the Object spatial points are generated, with the help of computer vision algorithms, Zhang and Elaksher [34] created a 3D surface of the unpaved road. The surface distresses were identified, and the study was validated by manually placing cones on the surface of the road and identifying them in the 3D model that was created.

One of the challenges in UASHM is that since the images are taken during the flight, there is a factor of noise in the data because of a lack of stability. Kuo et al. [20] put forward a vector thrust propulsion for multi-copter aerial vehicles to address this issue.

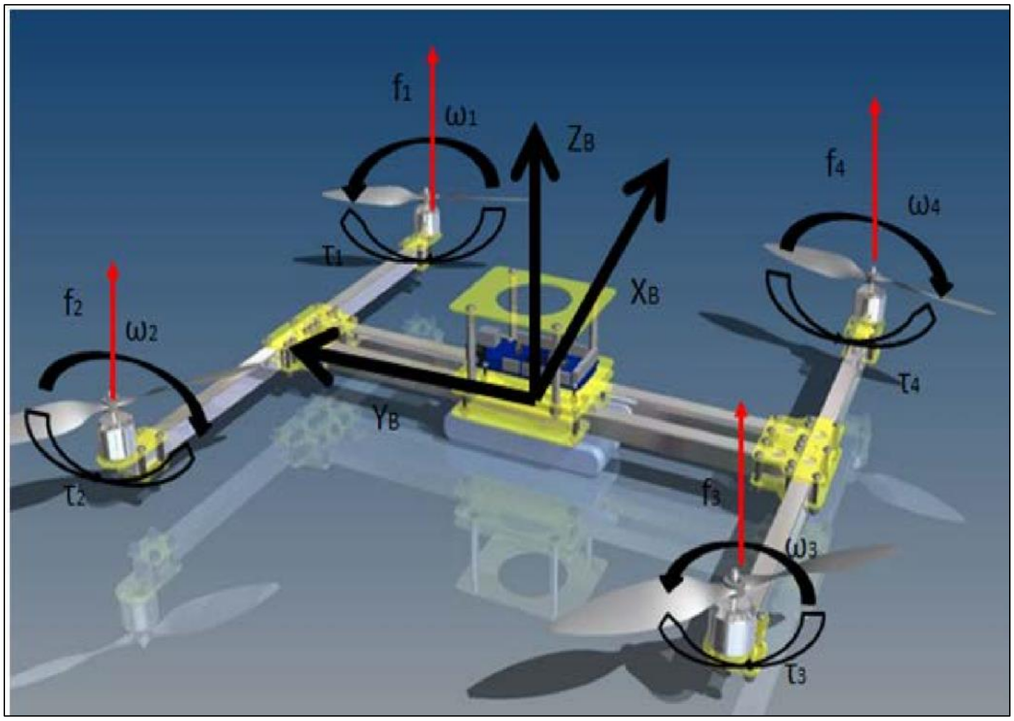



**Figure 20: Proposed prototype design for the application of vector thrust mechanism.** The figure is referenced from Kuo et al. [20].

The authors stated that vector thrust could be realized in UAVs by twisting the rod along which the rotor is attached [20]. The proposed technique was tested with the prototype model as shown in Figure 20. With this technique, added stability and hence less noisy image acquisition was achieved [20].

It is common to use additional RGB sensors such as DSLR cameras or GoPro cameras in UASHM. The purpose of this practice is to enhance image quality. Lens distortion correction and Image flattening were the two main problems that researchers had to deal with on such occasions where additional cameras were used for data acquisition. Ellenberg et al. [3] integrated readily available algorithms in MatLab to their UASHM framework to address these two concerns. The experiment results are shown in Figure 21and Figure 22 given below.

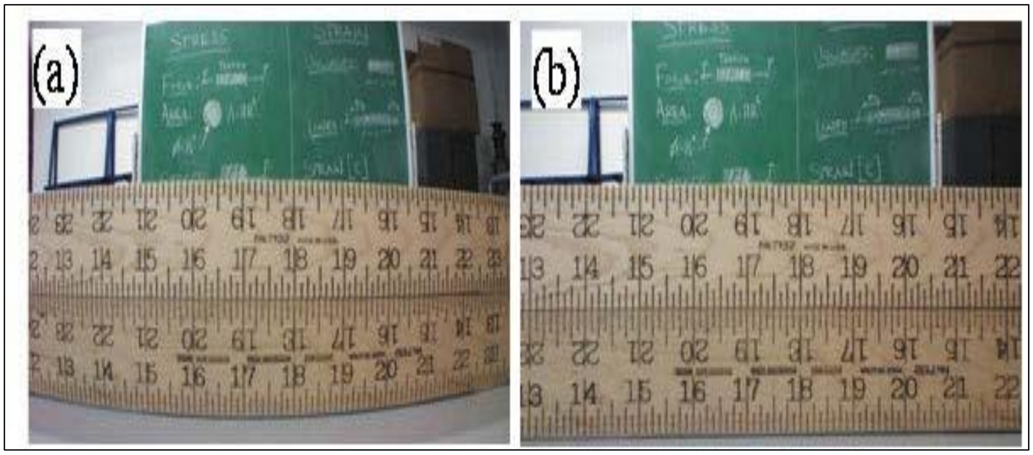



**Figure 21: Lens distortion correction (a) image with distortion (b) corrected image with MatLab algorithms**

The figure is referenced from Ellenberg et al. [3]

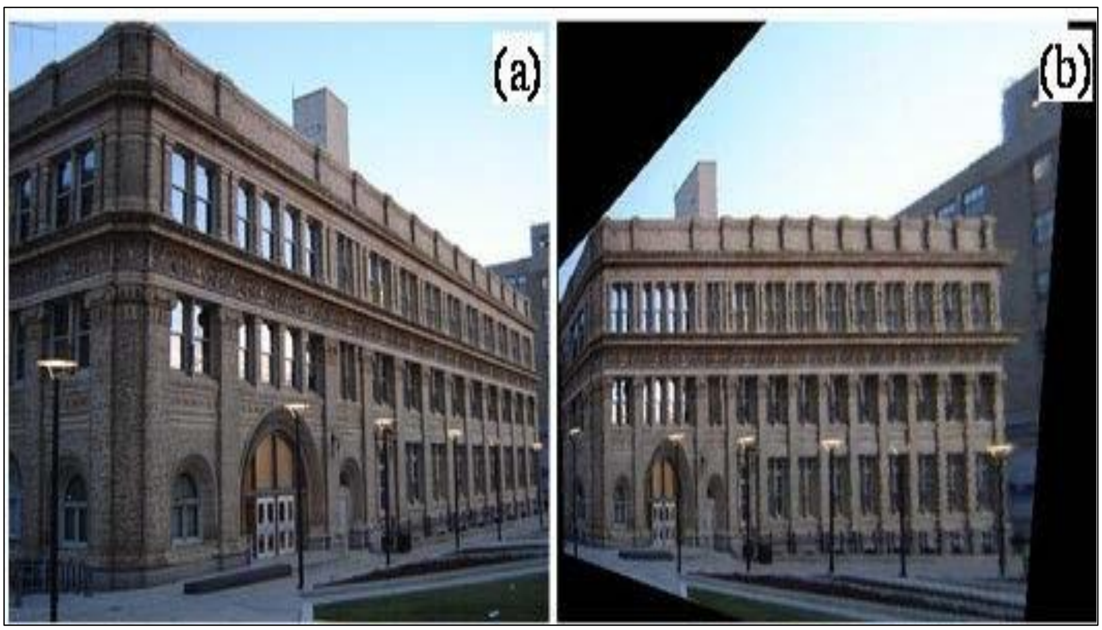



**Figure 22: Image flattening technique (a) original image (b) flattened image with MatLab algorithms.**

The figure is referenced from Ellenberg et al. [3].

Myeong et al. [21] introduced the wall-sticking and climbing robot UAV prototype as shown in Figure 23. The proposed model could potentially reduce noise in the image due to its stability during data acquisition. The research showed promise in selected areas. Unfortunately, the prototype is not yet a proven product and the new technique currently remains to be in its beta phase.

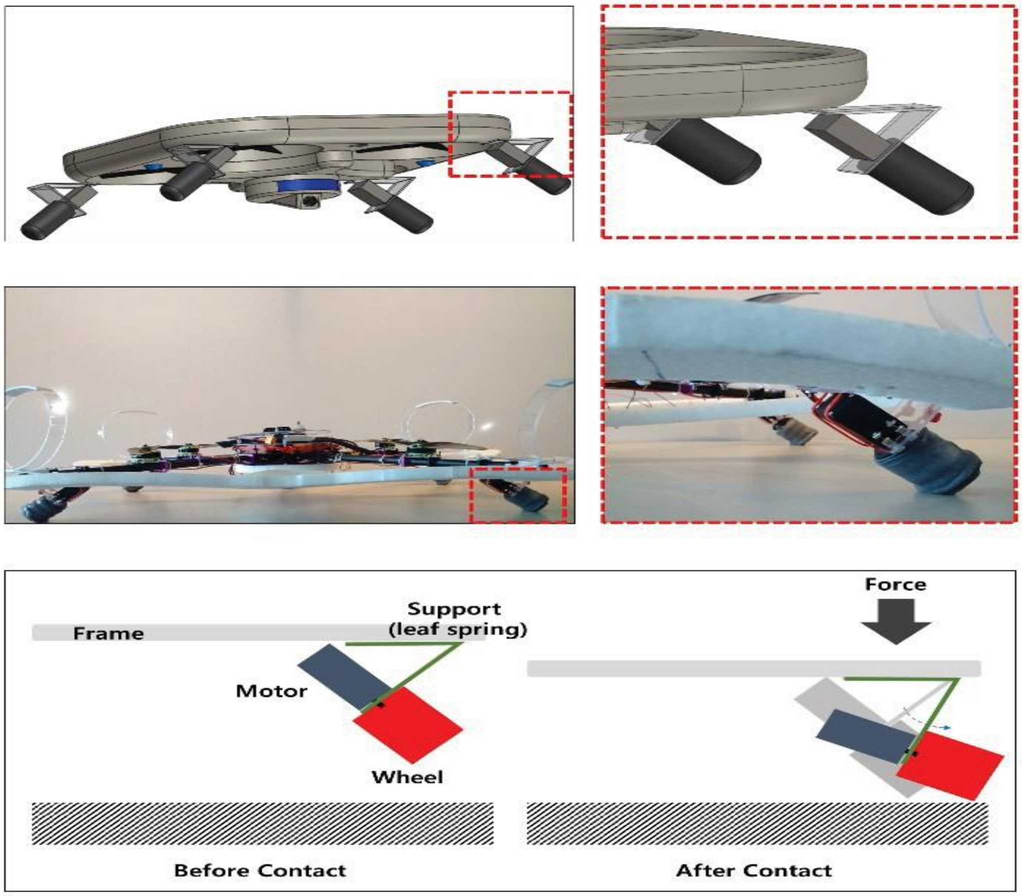



**Figure 23: Wall-sticking and climbing robot UAV prototype.**
The figure is referenced from Myeong et al. [21]

### 3.6 UASHM Workflow

***RQ. 6 What is the distribution of research studies utilizing UAVs for SHM process?***

UASHM, in general, goes through four major steps: Data acquisition, Data modeling, Data analysis, and Condition-assessment. The figure shown below represents the UASHM process cycle.

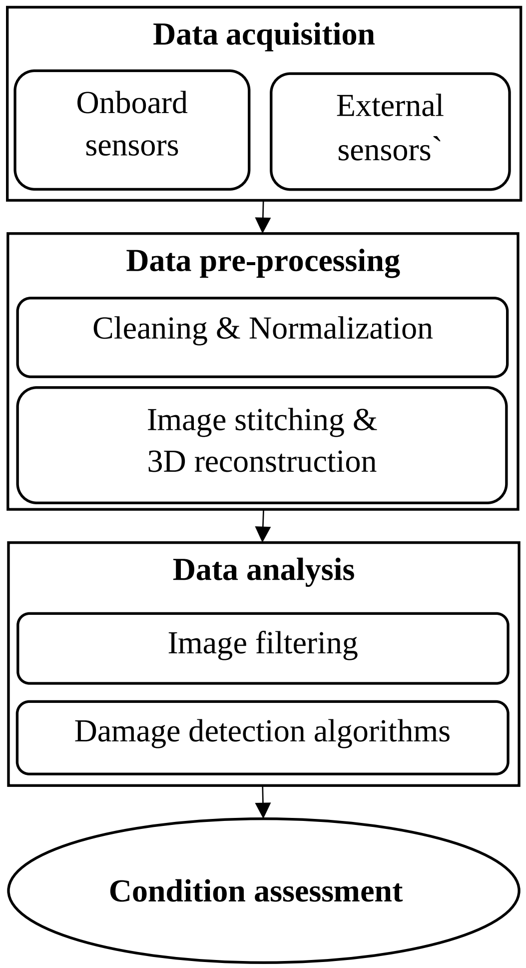



**Figure 24: UAV assisted SHM workflow**

After thoroughly analyzing the seminal research studies in the field of UASHM, it has been observed that the focus of the studies varied according to the SHM steps. Figure 25 illustrates the numerical representation of the available literature grouped with respect to the SHM process they have focused on. It is important to note that a study could have more than one topic of focus which would effectively put them under multiple categories.

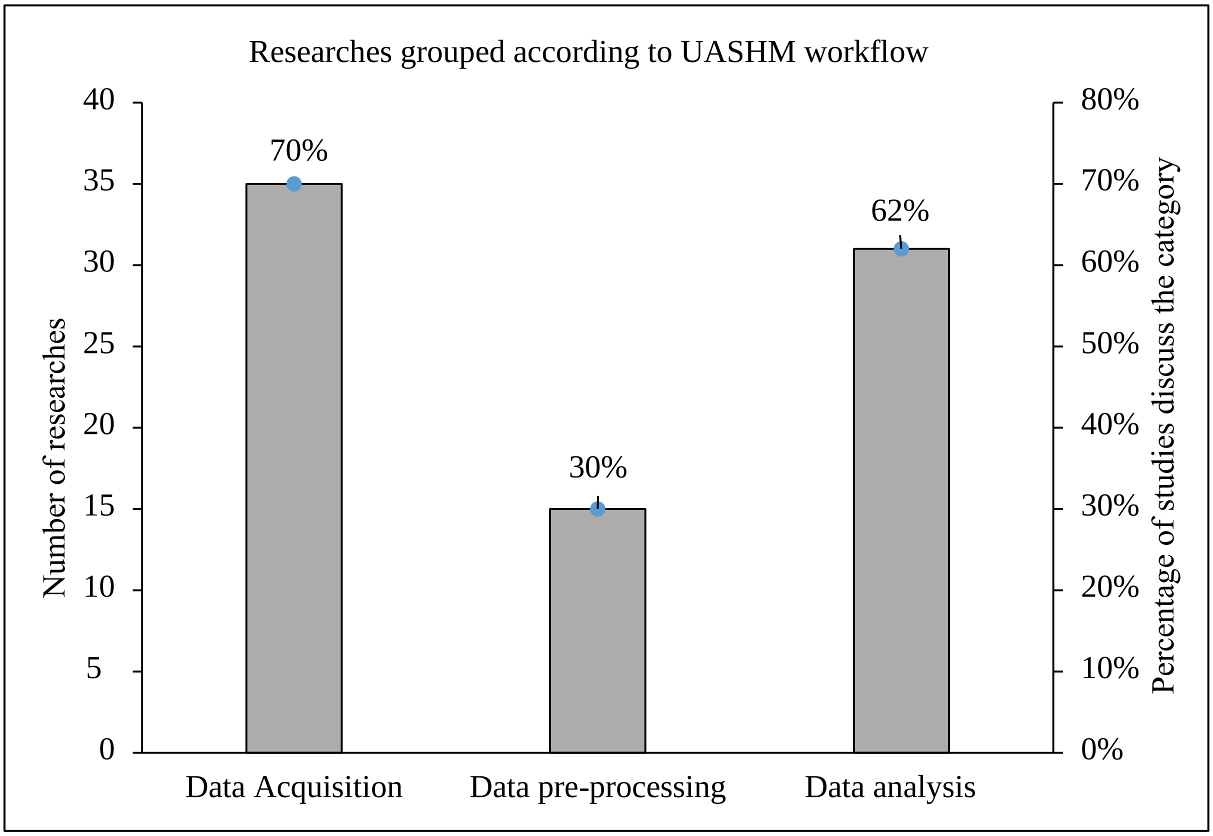



**Figure 25: Researches grouped according to UASHM workflow**

As Figure25 denotes, Data acquisition, closely followed by Data analysis, has been hugely favored by researchers in the last decade. To rephrase in a percentage format, it is observed that 70% of existing research studies have their focus on Data acquisition (out of 50 selected research articles), 62% on Data analysis, and 30% on Data preprocessing. To get a deeper understanding of how this trend has evolved over the years, Fig has been plotted as a number of articles against time.

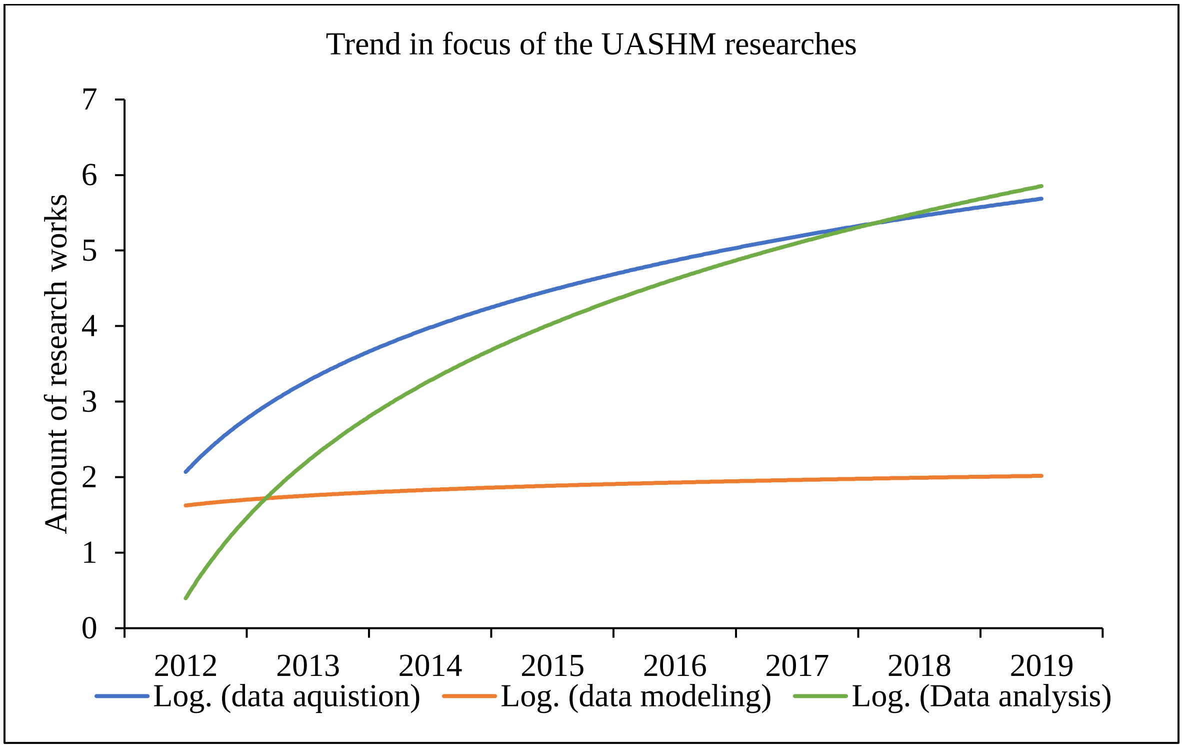



**Figure 26: Trend in research focus according to SHM steps**

Figure 26 provides insights on how the trends in UASHM varies over time. which has,, in turn, paved the way towards the addition of newer and more efficient techniques throughout the UASHM process. It is observed that the number of studies focused on Data pre-processing has not experienced a rising trend over time as the other SHM fields have. The following content focuses on further breaking down the SHM steps and exploring the research studies and new techniques related to it.

### 3.6.1 Data Acquisition

**S**ince the time that UASHM was in its early stages, a large number of studies have identified Data acquisition as the primary research focus. Data acquisition deals with the gathering of sufficient data that can be used to analyze infrastructure health. In the UASHM environment, data can be images, videos, or any other kind generated by associated sensors.

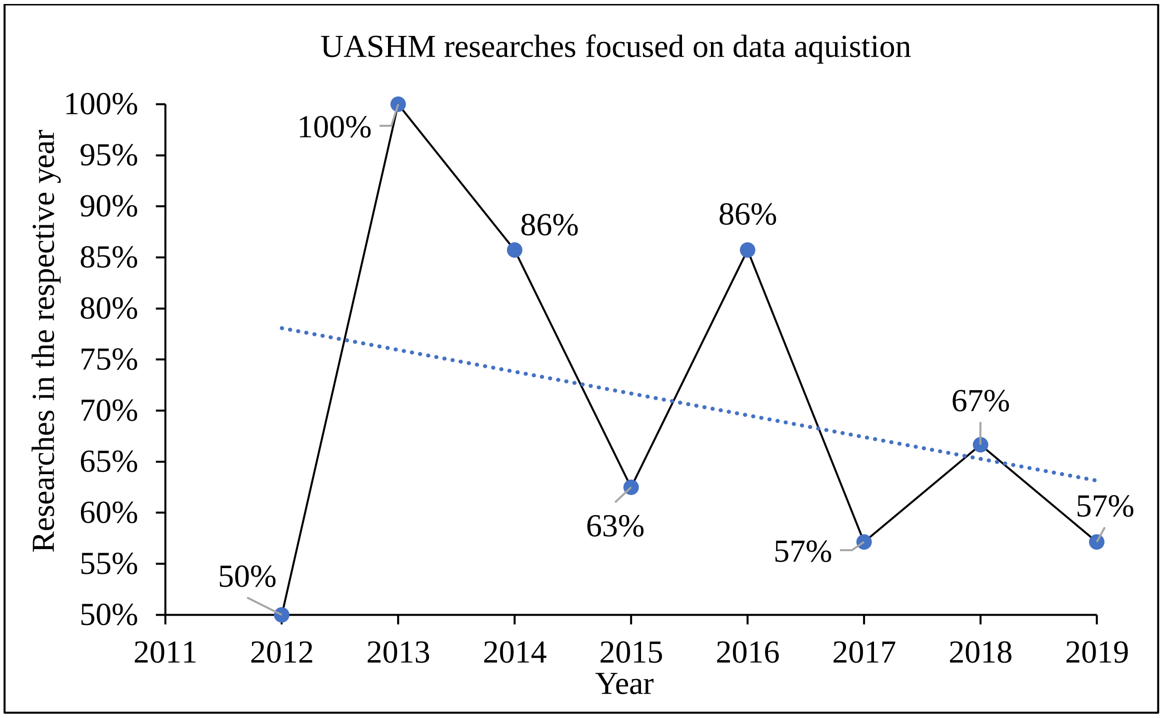



**Figure 27: Data acquisition focused literature studies over the years.**

The values in Fig refer to the percentage of research studies per year that extensively focus on Data acquisition methods in UASHM. As ascertained earlier, Data acquisition stands out as the most researched step in the SHM process. However, data does suggest a depreciating trend in its importance among researchers over time. The reasoning could be that UASHM based data acquisition has become really advanced and reliable enough in recent years that there is no need in giving extra focus on improving data acquisition methods.

The majority of prior research studies have opted for high-resolution RGB sensors as their principal data acquisition devices. Considering again, the visual nature of UAV assisted inspection, this observation comes as no surprise. The most notable mentions and contributions in the field of Data acquisition have been discussed extensively below.

To start with, Zhang and Elaksher [34] in 2012 explored the opportunity of UAV based data acquisition. The purpose of the study was to illustrate how UAV can be efficiently used to acquire data.

Ellenberg et al. [3] introduced IR (Infra-Red) based data acquisition in addition to RGB images. The study illustrated how IR imagery contributes to detecting damages in bridges. In another research study that focused on IR-based data acquisition, Ellenberg et al. [9] identified the requirement of an IR camera along with RGB sensors to design a delamination detection system in UASHM. The study integrated IR imagery with RGB images to add different dimensions to the data.

In another study, Teixeira et al. [30] integrated UASHM with Google glass. The proposed benefits of the study were to produce natural visuals of the infrastructure and assist domain specialists to obtain a closer look at existing damages.

Myeong et al. [21] proposed a wall-climbing UAV robot-based data acquisition method. Apart from being the only RGB sensor-based method, it was also able to collect steadier images with comparatively less noise when the UAV was stuck to the wall [21].

Reagan et al. [62] in 2016 studied displacement defects in bridges and used 3D-DIC (3Dimensional Digital Image Correlation) to measure the displacements. The study proposed a stereovision payload-based data acquisition method. Stereovision, as the name suggests, consists of two parallel vision sensors that capture images which can then be compared to each other to calculate the displacements at given points.

Integrating UAV based data acquisition to the existing IoT (Internet of Things) sensor network in the infrastructure can augment the information gained. Flammini et al. [11] studied railway infrastructure and identified an immense potential in including UASHM into the legacy framework that would result in enhanced data acquisition and thus improved SHM.

Henrickson et al. [18] researched data acquisition methods using various UAVs for infrastructure assessment. The authors stated that fixed-wing UAV based data acquisition is more desirable for covering large areas while multirotor UAVs are better suited for close-range inspection and have improved quality during data acquisition [18].

One way of upgrading the data acquisition quality is by adding more sensors in the UASHM framework. Sensors can be mounted on the UAV as an additional payload. Na and Baek [22] explored the PZT (Piezoelectric) sensor-based data collection method. Using PZT, it was possible to perform vibration-based NDE (Non-destructive evaluation) methods to measure displacement and thickness reduction [22].

Delamination defects are generally difficult to ascertain because they are not clear on visual surface inspection. To tackle the difficulty of detection, Reagan et al. [25] used IR(InfraRed) sensor-based data acquisition methods to identify delamination in bridge decks. IR images provided temperature variation data of the bridge surface, and image segmentation algorithms were applied to the images to localize the defects [25].

Reagan et al. continued their focus on developing a 3D-DIC method-based data acquisition. The authors claimed that stereovision-based displacement and crack detection had a significant advantage over conventional RGB sensor-based detection systems.

LIDAR (Light Detection and Ranging) sensors can generate precise 3D models of objects. Practitioners have been using LIDAR for decades in the aviation industry to measure the distance between the sensor and the obstruction in front of it. Khaloo et al. [50] integrated the LIDAR sensor to their UASHM by mounting the LIDAR sensor to the UAV as an additional payload. The purpose was to generate a 3D point cloud of the infrastructure from the acquired data.

Na and Baek [22] demonstrated how PZT (Piezoelectric Electromechanical Impedance) transducers could add a new dimension to the conventional data acquisition methods. PZT transducers are used to measure the change in pressure, strain, temperature, or force. The measured values are then converted into an electric charge which can be considered as an equivalent of the physical property that requires to be measured. The advantage of mounting the PZT transducer in a UAV is that it can detect the internal damages in the infrastructure. Nevertheless, due to its complexity and additional payload requirements, very few papers have opted to use this technique.

Kang and Cha [19] introduced UBS (Ultrasonic Beacon System) navigation facilities in UASHM for GPS-denied environments. The vast majority of UAV based data acquisition utilizes GPS based location and control systems. GPS comes as a default feature in most UAVs and it is, more often than not, highly effective. Unfortunately, for SHM, GPS(Global Positioning System) denied areas such as those beneath bridges, tunnels, and the inside of buildings have to be considered as well. In such environments, a UBS (Ultrasonic Beacon System) can be useful to perform the inspection [19]. The technique works by placing multiple mobile beacons in the GPS-denied areas and one on the UAV and the navigation is made possible by effective communication between the beacon networks. The image data obtained can be geotagged after the processing and condition assessment steps are completed.

### 3.6.2 Data Pre-processing

Data pre-processing involves practices such as 3D model extraction, Image stitching, lens distortion correction, etc. This step tallies the tools and techniques which researchers use to better represent the data graphically so that domain specialists can get an overall view.

The activities are grouped into two in this step. The first one is cleaning and normalization of images. Images collected from the UAVs are sometimes noisy, so the immediate step after data acquisition would be to clean the data and normalize the dimensions and lens distortions. Later the image can be stitched together to form a panoramic view of the entire infrastructure.

One representative example of normalization is when Ellenberg et al. [47] used these techniques to rectify lens distortions. The researchers used the GoPro camera and the apparent distortion in the images was fixed before analyzing them to detect damages [47].

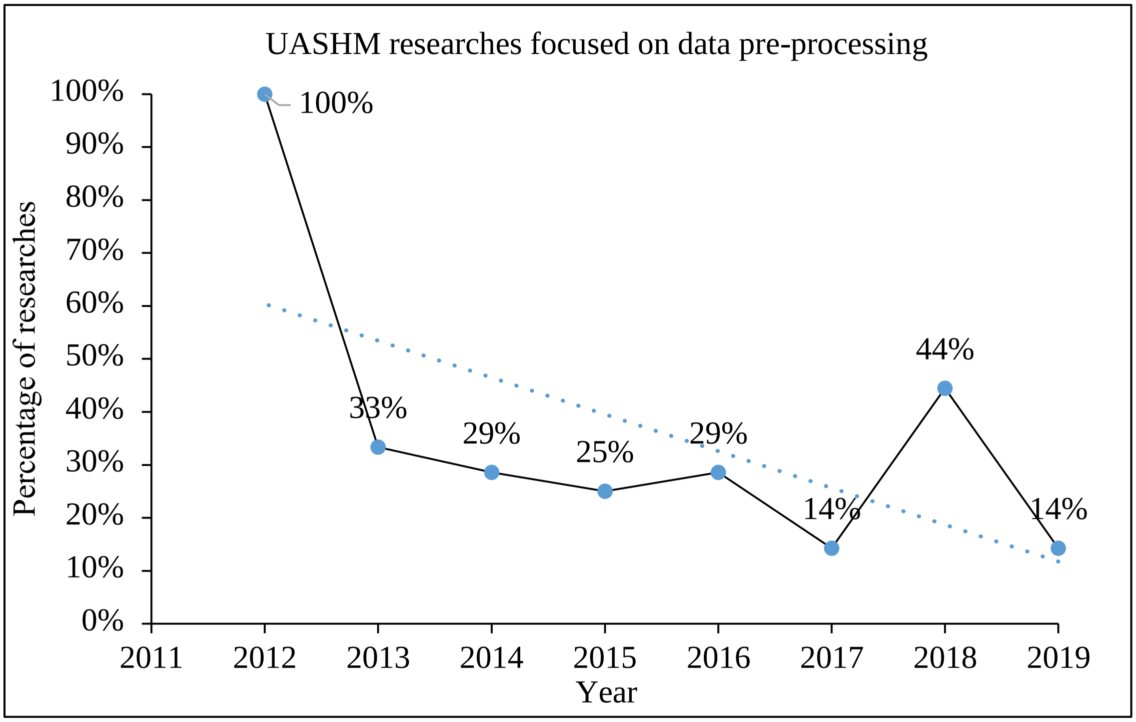



**Figure 28: Data pre-processing focused UASHM researches over the years**

Zhang and Elaksher [34] in the year 2012, performed 3D reconstruction using UAV images to determine surface distress in unpaved roads. The process included combining images from various angles to accurately calculate the distress on the surface [34]. Puppala et al. [65] followed a similar research study geared towards helping domain specialists by producing a 3D model of the infrastructure and integrating damage detection techniques into it. The study identified dams as the representative model and experiments on 3D reconstruction and modeling were performed on it [65].

Hallerman and Morgenthal [16] also used a dense 3D reconstruction to identify structural displacement in infrastructure. Hallerman and Morgenthal [17] continued their research on how 3D reconstruction and stitching could be of assistance in UAV assisted SHM. Dam infrastructure was chosen for its size and design [17]. Hallerman and Morgenthal [16] were successful in conceiving a 3D model replica of the infrastructure and suggested that this technique was easier for condition assessment specialists to inspect it.

Khaloo et al. [50] developed a technique to build a 3D point cloud with the help of LIDAR sensor-based data acquisition. The real-life experiment was conducted on bridge infrastructure [50]. The author used the Hierarchical Point Cloud Generation (HPCG) process for successfully generating the point cloud-based 3D model.

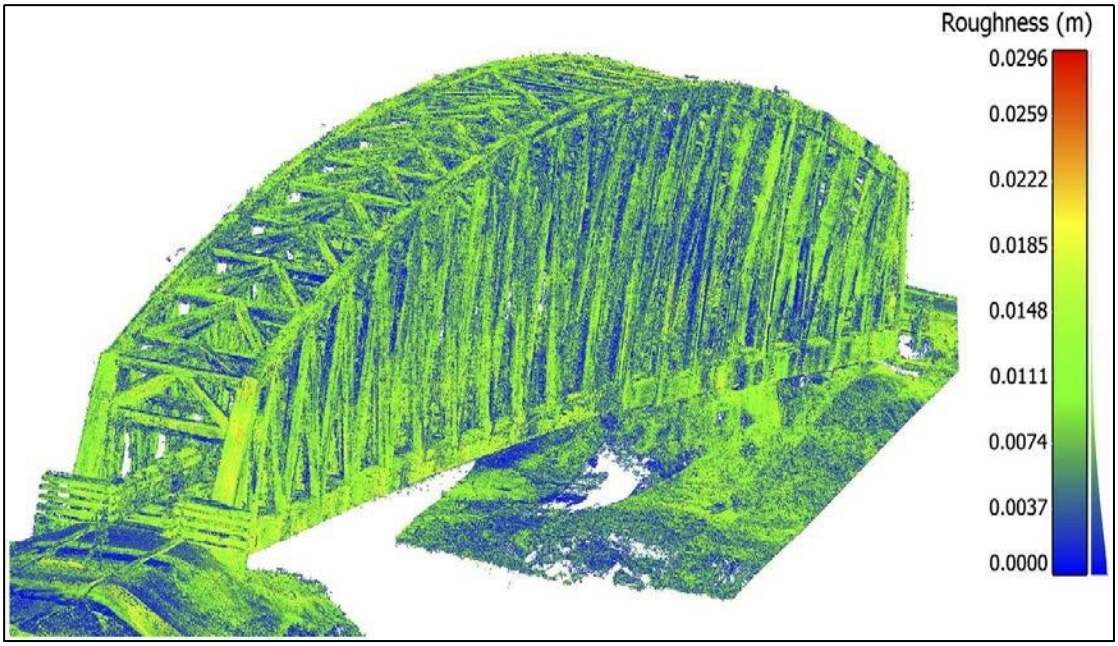



**Figure 29: Example of Hierarchical Point Cloud Generation (HPCG) based 3D point cloud generation.**
The figure is referenced from Khaloo et al. [50]).

LIDAR sensor-based 3D point cloud technique proposed by Khaloo et al. [50] had the advantage of generating a precise measurement of the distance between objects. Hierarchical Point Cloud Generation (HPCG) method used these measurements to generate point clouds that could be integrated into the infrastructure model as shown in Figure 29. Khaloo et al. [50] continued their research in 2019 and refined their model reconstruction techniques. The authors successfully integrated their 3D model to the damage detection data in the form of another dimension, resulting in a 4D point cloud [50].

### 4.6.3 Data Analysis

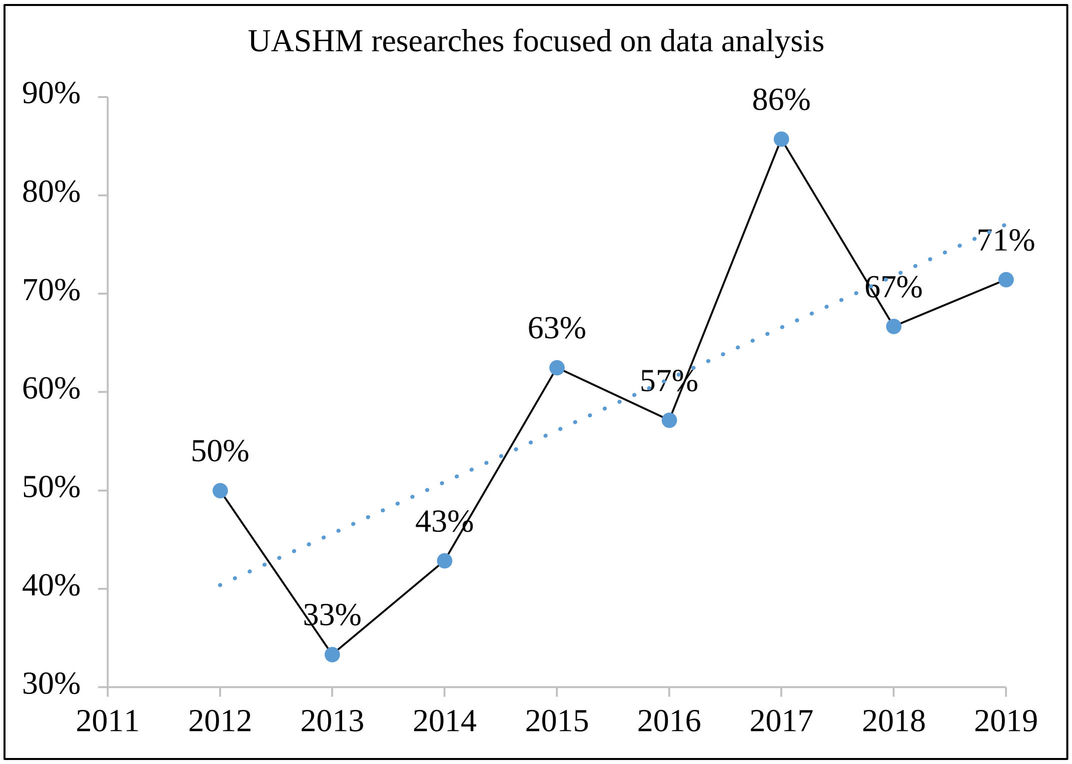



**Figure 30: Data analysis focused on literature studies over the years.**

Data analysis is a vital part of UASHM where computer vision and other techniques are used to extract information. It has been noted that practitioners in the past have used various algorithms and approaches to achieve the goal of detecting defects this way.

The most widely used technique to extract information from images easily is the application of filters on images. Widely referred to as Image filtering, it is the process of enhancing specific characteristics of the image in question by passing it through specified value kernels. Researchers have extensively worked on image processing to produce methods such as Edge detection to assist the specialist in easily observing damages.

Earlier in the last decade, most condition assessments were performed manually by field specialists. Later, however, the evolution of computer vision algorithms that could analyze and extract information made its way into the industry. The growth in the number of articles dealing with computer vision-based detection techniques justifies the above statement.

Eschmann et al. [10] notably studied edge detection algorithms and implemented them in their SHM process to highlight cracks, and Hallerman and Morgenthal [16], [17] conducted multiple studies on change detection assessment techniques to determine displacement in infrastructure. The studies incorporated a dense 3D cloud-based monitoring method to assess the depth and distress in infrastructure [16], [17].

Ellenberg et al. [47] added their contribution by introducing multiple damage detection methods in their study. The proposed techniques included bearing deformation, steel grid deflection, corrosion, and crack detection which were successfully integrated into the system [47].

The research conducted by Reagan et al. [62] had two areas of focus; namely, introducing the stereovision based data acquisition, and the 3D-DIC (3 Dimensional Digital Image Correlation) used to analyze images to extract information. With this approach, Reagan et al. [62] developed a condition assessment algorithm that successfully analyzed displacement defects.

Reagan et al. [25] proposed a delamination detection technique to assess the condition of a bridge deck. K-means clustering was taken as the choice of algorithm to distinguish between the defective and unaffected areas. The condition assessment technique worked on the principle that the delaminated surface would emit heat on a different scale compared to the normal surface [25].

In the data analysis model proposed by Dorafshan et al [8], the authors used the Sobel filter as the method to highlight cracks. The model worked as an assistive assessment tool for domain experts to identify cracks from the processed images [8].

Yang et al. [31] developed a convolutional neural network-based crack detection algorithm to identify and then classify the visuals containing infrastructural damages. The choice of the neural network was VGG-16, a widely used pre-trained deep CNN model. The field tests were performed, and 71.19% overall accuracy was achieved.

Cha et al. [5] identified the need for time-efficient damage detection algorithms that could effectively reduce the time taken for analysis whilst ensuring high accuracy. This idea drove the authors to develop a Faster R-CNN based damage detection model that performed with reduced latency in prediction while possessing multi-class damage identification ability.

### 4.6.4 Condition Assessment

It is the process of classifying visuals depending on the presence or absence of structural damage. Based on research, decision-making has been classified into three types; Manual classification, Computer vision assisted classification, and Computer vision-based automatic classification. This classification process can be done automatically or by a domain specialist. Earlier, decision making was reserved only for domain experts. Later in the last decade, development in computer vision lead to the evolution of efficient machine learning algorithms that could potentially highlight the defect or even classify damages in visuals. This trend is evident through the years from 2012 to 2019 with an increasing number of research papers mentioning the computer vision techniques in their decision-making phase.

In 2012, both Zhang and Elaksher [34] and Eschmann et al. [10] opted for manual classification-based decision-making methods. As it is observed from these research studies, computer-vision based decision making was still in its amateur stage and automatic decision making was not a viable choice during that time.

Reagan et al. [25] used a Computer vision-assisted classification method to filter visuals containing infrastructural damage. Multiple types of defect detection tests were conducted to cross-validate their proposed system. The UASHM based delamination detection results were compared to ones from the hammer sounding tests which boast a well-reputed and tested technique.

Phung et al. [24] developed a computer vision-based automatic classification method for identifying cracks in the infrastructure visuals. UAVs have been used primarily as a data acquisition device. Phung et al. [24] state that the performance of the computer-vision model for damage detection had been validated with several experiments and the condition assessment was done in real-time.

# CHAPTER 4

# LIMITATIONS AND CHALLENGES

The future for UASHM is promising. Nevertheless, the area has yet to mature. There is lots of room for improvement. The number of research literature surveyed over the decade had a monotonic increase, and the growth trend continues.  This chapter of the thesis identifies the current challenges and limitations of UAV assisted SHM along five dimensions. These dimensions include *Environmental challenges, Hardware limitations, Communication challenges, Software limitations, and safety factors.*

## 4.1 Environmental Challenges

Data collection is one of the most important steps in UASHM. Hence, ensuring high-quality data collection and reducing noise in the data are taken seriously by the researchers. Environmental conditions play a very important role in the data acquisition phase. The most notable environmental challenges faced by UASHM are listed below.

### 4.1.1 Lighting Condition

UASHM heavily dependent on vision-based detection methods to identify any structural issues, such as cracks, displacement, and corrosion. Most of the computer vision algorithms readily available in the market for UASHM have been trained on image datasets containing images captured under ideal conditions. Unfavorable lighting condition is a possible situation that can happen during data acquisition. The current computer vision algorithms face the challenge of keeping up with their damage detection accuracies under unfavorable lighting conditions.

Shakhatreh et.al [28] noted that the lack of lighting and exposure could severely affect damage detection accuracy. In contrast, overexposure to sunlight could leave image hotspots in the photo, and these hotspots lead to lower image quality in certain parts of the image [28].

### 4.1.2 Uneven Illumination in the Images

SHM community and researchers struggle when faced with the challenge of dealing with the variation of illumination, in different parts of the image frame. The movement of clouds on a sunny day can create glare and bright sunlight marks/shadows on the images captured. The marks on the images create an uneven illumination which affects the performance of the image processing techniques to recognize the structural damages [28]. This uneven illumination in the images is one of the major struggles for techniques such as aerial triangulation and digital elevation (a technique where UAVs take images of the land during flight and later stitch all the images together to make geographical maps) [28]. The triangular elevation is the technique where UAVs take images of the land during flight and later stitch all the images together to make geographical maps. Digital elevation is the technique used in the 3D representation of terrain surfaces in maps. Here, variance in illumination found in images may lead to miscalculation of the depth and height information of terrains.

### 4.1.3 Extreme Weather

Extreme weathers raise difficult challenges in UASHM. Weather conditions associate with heavy wind, rain, and snow are undesired conditions for UAV assisted data acquisition. The undesired weather conditions would lead to difficult handling and lapse instability of UAVs during flight. Considering all unfavorable conditions are frequent in normal scenes, the time window where the UASHM process can be carried out becomes limited.

## 4.2 Hardware Limitations

The UAV manufacturing industry has come a long way in terms of hardware improvements. The competition between global UAV manufacturing companies such as DJI and

Parrot has brought down the cost of UAVs in the consumer market. Despite the advancement, there yet exists a few hardware limitations that adversely impact the performance of UASHM. The most notable hardware limitations are listed below.

### 4.2.1 Energy Limitations

UAVs are typically equipped with limited electronic power supplies- in other words, batteries. These batteries power all the components such as electric motors, navigation, and control systems, etc. Due to the extreme power consumption, UAVs drain batteries quickly. Thereby reducing the flight duration. Shakhatreh et.al [28], identified that power limitation is one of the significant challenges faced by the UASHM in specific and the UAV industry in general.

The maximum flight time of UAVs is a crucial factor in UASHM. Considering the sheer quantity of the infrastructure, extended flight time would result in prolonged structural monitoring in each session. Unfortunately, the developments in the energy cell industry are said to be lag almost 20 years behind compared to other domains. It is evident as the hardware part of energy cells stayed the same. The shift from Li-ion (Lithium-ion) batteries to Li-Po (Lithium Polymer) has helped to improve the "energy/weight ratio" of batteries to some extent.

Considering the power draw requirements of UAVs, the current situation is still far from ideal for UASHM.

### 4.2.2 Lack of On-board Processing Power

UAVs are mostly equipped with less powerful CPUs and GPUs to reduce battery consumption. The use of weak CPUs and GPUs impacts the UAV's ability to active damage detection in structures. Generally, damage detection techniques can be classified into two; passive damage detection and real-time damage detection (active damage detection). In Passive damage detection, data acquisition is performed using UAVs and once the data acquisition is completed, the data can be transferred to an external source for data analysis. Meanwhile, the active damage detection techniques identify the damage in real-time during the data acquisition phase with the help of onboard processing power or external computer using real-time data streaming. The active damage detection requires the significant processing power of the onboard CPU and GPU (if available) to perform the detection in real-time. This real-time process helps damages to be geo-tagged and eventually helps the industry to push towards autonomous UAV navigation and damage detection systems. Unfortunately, the processing power available in the UAVs are limited. The trend in the shortlisted UASHM research papers suggests that, due to the weaker CPU and GPU in UAVs, researchers chose passive damage detection methods. The challenge of a lack of processing power still exists such that the trend of passive damage detection techniques would continue.

### 4.2.3 Maximum Takeoff Weight

The maximum takeoff weight is the maximum weight the UAV can carry during flight. From the 50 literature papers included in our survey, the Maximum takeoff weight average is found out to be 3.17 Kg (7 lbs. approximately). Another consideration is that 80% of the researchers have used additional payloads to incorporate their proposed techniques to UASHM (Unmanned Aerial Vehicle Assisted Structural Health Monitoring).

Since UASHM associates with various sensors and navigational devices, the need for the increased Takeoff weight capacity is omnipresent. To back up the claim, it is observed that 80 % of the researchers have used additional payload in UAVs to incorporate their proposed techniques during UASHM inspection. Due to the energy limitations and hardware constraints, the maximum takeoff weight is still one of the major bottlenecks in UASHM.

## 4.3 Communication and Connectivity

Communication and connectivity between UAVs and the control device/ station are essential to the success of UASHM. There are several limitations that this thesis addresses in this domain and the most notable ones are mentioned below.

### 4.3.1 GPS Denied Environments

GPS (Global Position System) is the backbone of the UAV's navigation system. One of the challenges faced in UAVSHM is working in an environment where GPS does not work due to a lack of signal. A few of the examples of such locations are under the bridges and indoors in buildings. Due to the heavy infrastructure obstruction, such places are prone to limit GPS signals to pass through. Even though there have been some researches such as UBS (ultrasonic beacon system), proposed by Kang and Cha [19] for the GPS denied environment, they remain as conceptual models that have hardly materialized to action. Besides, alternative techniques such as UBS mentioned above require carrying an additional payload (i.e., ultrasonic sensor) which has higher power consumption in contrast to GPS. Therefore, UASHM in GPS denied environments continue as one of the major challenges.

### 4.3.2 Radio Signal Range

UAVs communicate with controller/ data receiver via radio waves. Radio signals are set on a specific bandwidth so that the communication can be established. For a longer range, the signal bandwidths are often kept as low as 900 MHz. On ideal condition, a typical good quality UAV such as DJI Phantom can fly over 4 miles (6.4 km), considering the weather is clear, and there are no obstructions between the UAV and controller/data receiver. Considering a typical health inspection environment that has high civil infrastructure density, the communication range can get a serious hit. These unfortunate situations may lead to losing signal and control over UAV and failure of data transfer.

### 4.3.3 Live Data Stream

Generally, consumer-grade UAVs use radio signals to transfer data such as images and videos in real-time to the data receiver in the ground. This streaming provides live FPV (First Person View) of the infrastructure under inspections. In regular use cases, UAVs prefer 2.4GHz radio bandwidth to transfer the data, just like smartphones and other IoT devices. The introduction of 5 GHz signal bands allowed smart devices to transfer data at a higher rate with the sacrifice of reduced range. Having said that, 5 GHz is not usually preferred in UAVs since the signal range has major priority over the data transfer rate.

Damage detection systems using UAVs produce better accuracy when provided with images and videos with higher resolution and higher definition. Unfortunately, transferring high-quality visuals would require an improved data streaming method than what is presently available. As the industry prefers high-quality real-time active damage detection systems, the low data transfer rate can become a bottleneck.

## 4.4 Software Limitations

Operating system and software controls are major functionalities in UAVs. From INS (Inertial Navigation System) to active damage detection techniques are built on thousands of lines of codes. The software is the most rapidly improving segment in UASHM where rapid improvements are made possible infrequent basis. Even then, there are some challenges and shortcoming which have to address as follows.

### 4.4.1 Lack of Consolidated Dataset

The majority of the UASHM frameworks prefer machine learning-based damage detection systems. Although these machine learning models can perform with high accuracy, they are heavily dependent upon the dataset that they are getting trained on. Computer vision algorithms typically require large datasets. Currently, there are not many publicly available images datasets that are exclusively made for UASHM, according to Gopalakrishnan et al. [13]. The author continued to point out that the widely used alternatives (ImageNet database, for example) are experiencing contextual irrelevance to the domain.

### 4.4.2 Lack of Higher Accuracy Damage Detection and Component Recognition

Even though a combination of UAVs with computer vision algorithms for defect detection has been proved promising, the collective output of the entire system still lacks perfection in identifying various types of damages and their respective risk factors to the structural health (Spencer et al. 2019). As has been mentioned in section 4.5, there are multiple types of damages, such as cracks, delamination, and corrosion, to name a few. There have been noticeable attempts from researchers to address the issue of subpar damage detection systems. Cha et al. [5] and Gopalakrishnan et al. [13] have proposed frameworks that can detect a few damage types. Unfortunately, a framework that can detect all major types of damages is yet to be materialized.

### 4.4.3 Safety Factors

The commercialization of the UAVs in the consumer space has been a huge success. The rate of escalation in the number of UAVs in public now has become an influential factor for the safety and privacy of people and organizations. The most notable takes on such risk factors are given below.

### 4.4.4 Cyber-attacks

UAVs are rapidly growing tools in cyberspace due to their inexpensive aerial surveillance and ease of deployment [66]. UAVs work remotely or autonomously in the majority of cases such as Highway bridge inspection and building infrastructure monitoring. Nevertheless, both of the methods are prone to cyber-attacks, according to Hartmann and Giles [66]. Electronic attacks on UAVs are not rare anymore. Popular incidents, including RQ-170 sentinel UAV, got hacked in Iran during 2011 [67]. It is believed that the UAV got hijacked during the flight.

Major security concerns spread to consumer-grade UAV industries as the sheer number of UAVs purchased by the general public has exploded. To put the increase in UAVs into a statistical perspective, The US Federal Aviation Administration (FAA) predicted that there would be around 15,000 UAVs operating in the United States by the year 2020 [68]. In reality, by the year 2015, the UAV sales exceeded 15,000 per month [68]. Small consumer-grade UAVs are prone to hacking since they are built inexpensive without any high safety measures. In 2013, Hak5 (https://hak5.org/) showed how small UAVs such as DJI Phantom 2 vision and Parrot AR UAVs could be utilized for hacking by manipulating the Wi-Fi radio signals [69][70].

Considering UAVs used for the SHM process are comparatively inexpensive ones, so they are prone to all safety concerns mentioned above. By hijacking the signals, hackers can access live video and photo feeds of restricted areas or even control the UAVs, which could lead to security risks. Anti-UAV countermeasures are still under development and stay pragmatic at best currently.

# CHAPTER 5

# COMPARISON STUDY OF COMPUTER VISION MODELS FOR DAMAGE DETECTION

The systematic survey of research papers introduced upcoming trends in the computer vision techniques/algorithms for structural health monitoring using UAVs. There has been a consistent evolution in computer vision algorithms that resulted in the constant improvement of damage detection techniques in UASHM through the years.

More evidently, the literature review showed a numerical increment in Convolutional Neural Network (CNN) based techniques which documented superior performances. CNN can be designed and developed in various ways and some publicly available pre-trained models are popular in research and industry for their high accuracies and consistencies while also being open-sourced.

Convolutional Neural Network (CNN) is a type of neural network algorithms that differentiate the images they receive according to their characteristics/ objects in the image by adjusting the weights and biases. The very first CNN was developed in 1988 by Yann LeCun et al. [71]. Even though developments have been continuous in the research community, it was in the last decade (from 2010) that CNN emerged as a mainstream Computer Vision (CV) technique for real-world use cases.

## 5.1 Shortlisted Damage Detection Techniques

From a thoughtful analysis of the techniques, two main approaches have been observed by which CNNs can be modeled and trained for damage detections in UASHM: (1) traditional machine learning approach and (2) transfer learning approach. The thesis picks one model from each category and compares the findings.

### 5.1.1 Traditional Machine Learning Approach using DCNN (Deep Convolutional Neural Network)

Source literature: "*Autonomous UAVs for Structural Health Monitoring Using Deep Learning and an Ultrasonic Beacon System with Geo-Tagging*" by Kang and Cha [19].

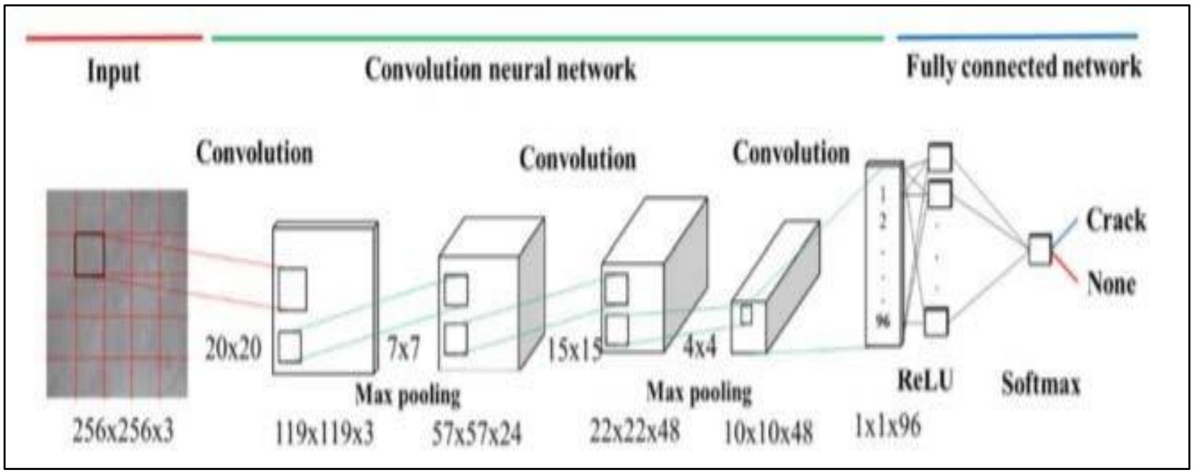



**Figure 31: DCNN architecture**
The figure is referenced from Kang and Cha [19]

The traditional machine learning approach consists of modeling the CNNs from scratch and training them with images that have been collected for identifying specific damage types such as cracks and corrosion. Here, the model that Kang and Cha [19] have proposed is based on Deep Convolutional Neural Networks (DCNN), which contain multiple hidden convolutional layers in their architecture. Kang and Cha [19] combined the sliding window technique in the DCNN to detect damages in the images. Their proposed model takes RGB (Red Green Blue) images with dimensions of 256*256. The images pass through the convolutional layers and get differentiated into two groups: (1) one group of images where damages have been detected in the visuals and (2) the other group with no presence of damages.

```
Model: "functional_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 227, 227, 3)]     0
_________________________________________________________________
conv2d (Conv2D)              (None, 227, 227, 3)       3603
_________________________________________________________________
batch_normalization (BatchNo (None, 227, 227, 3)       12
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 227, 227, 24)      3552
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 113, 113, 24)      0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 113, 113, 48)      259248
_________________________________________________________________
batch_normalization_1 (Batch (None, 113, 113, 48)      192
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 113, 113, 48)      36912
_________________________________________________________________
batch_normalization_2 (Batch (None, 113, 113, 48)      192
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 56, 56, 48)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 56, 56, 128)       55424
_________________________________________________________________
batch_normalization_3 (Batch (None, 56, 56, 128)       512
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 56, 56, 128)       147584
_________________________________________________________________
batch_normalization_4 (Batch (None, 56, 56, 128)       512
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 28, 28, 128)       0
_________________________________________________________________
flatten (Flatten)            (None, 100352)            0
_________________________________________________________________
dropout (Dropout)            (None, 100352)            0
_________________________________________________________________
dense (Dense)                (None, 96)                9633888
_________________________________________________________________
dropout_1 (Dropout)          (None, 96)                0
_________________________________________________________________
dense_1 (Dense)              (None, 2)                 194
=================================================================
Total params: 10,141,825
Trainable params: 10,141,115
Non-trainable params: 710
_________________________________________________________________
```

**Figure 32: Summary of recreated DCNN architecture in Python**

The entire model has been recreated by the thesis for analysis in a Python environment with TensorFlow 2 functional APIs. The final summary of the model is shown in Figure 32. Batch normalization and dropouts are used to get faster convergence of the model. There are more than 10 million trainable parameters that are optimal for the generalization of the images, but it increases the time complexity of the model.

### 5.1.2 Transfer Learning Approach Using VGG-16

Source literature*: "crack damage detection in unmanned aerial vehicle images of civil infrastructure using pre-trained deep learning model"* by Gopalakrishnan et al. [13], *"Autonomous Structural Visual Inspection Using Region-Based Deep Learning for Detecting Multiple Damage Types "* by Cha et al. [5], and *"Deep Concrete Inspection Using Unmanned Aerial Vehicle Towards CSSC Database''* by Yang et al. [31].

Humans often use the knowledge that is gained from performing one task to do similar tasks. This knowledge transfer technique has inspired the field of machine learning to train models in a better way. Transfer Learning (TL) is a domain in machine learning where a model that is built and trained for a use-case can be reused for a similar use-case. The Transfer Learning model tends to generalize better and perform better despite the lack of sufficient training data. It also trains faster and is less computationally intensive than the traditional machine learning model. Here in this thesis, VGG-16, a famous pre-trained convolutional neural network, has been chosen to showcase the Transfer Learning approach.

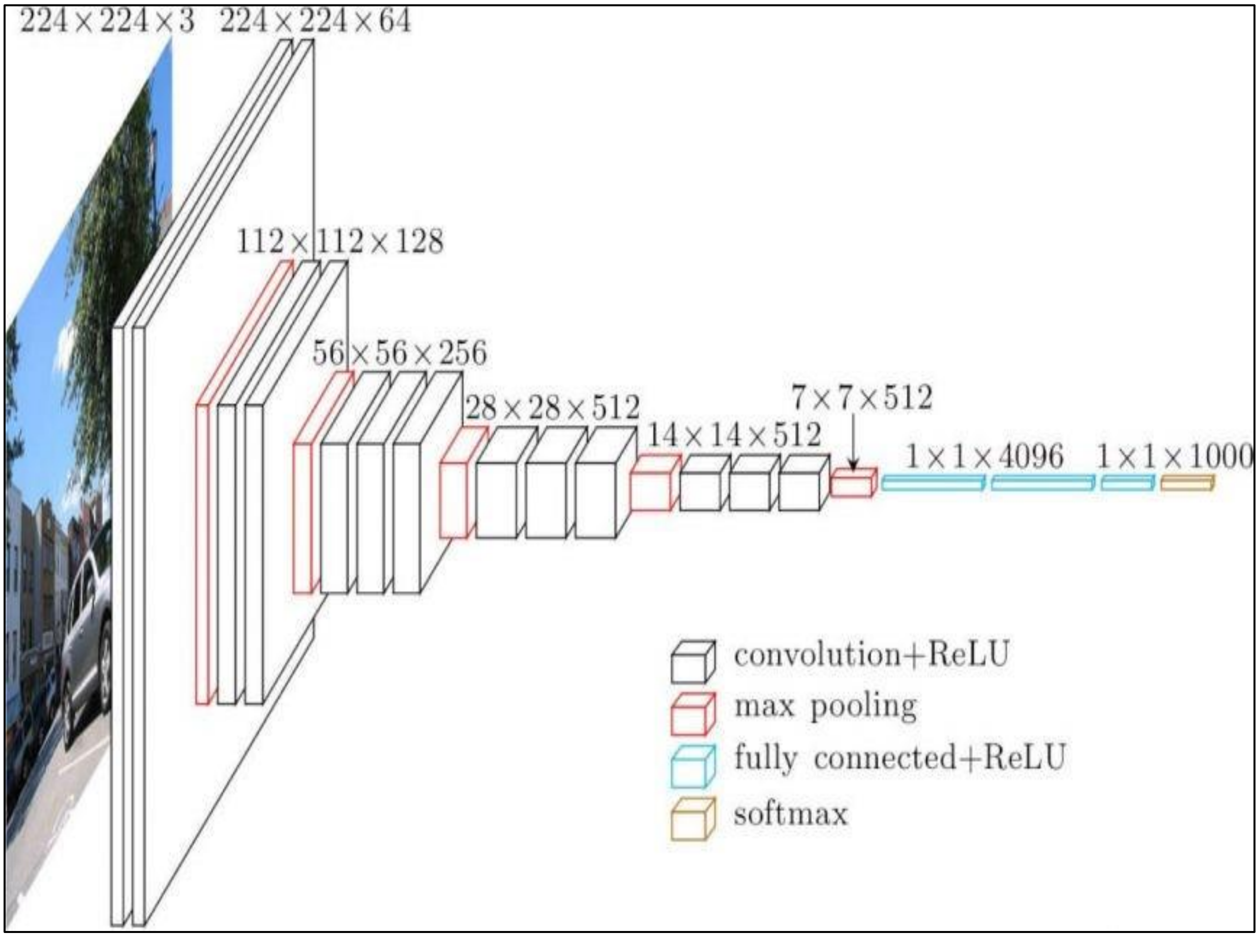



**Figure 33: VGG-16 architecture**

The figure is referenced from Hassan [74]

VGG-16 is a very popular type of convolutional neural network named after Visual Geometry Group (VGG). Introduced by K. Finyoman and A Zisserman, the University of Oxford, VGG-16 attained 92.7% accuracy in the ImageNet competition [73]. VGG-16 has now become one of the best publicly available pre-trained computer vision models. In VGG-16, RGB images of 224*224 are passed through the first convolutional layer. In this case, the input layer has been modified to 227*227 RGB in lieu of it being the resolution of the dataset taken for the comparative analysis. The images are then passed through various Conv layers, with a 3x3 receptive field as a sliding window. The sliding mechanism is fixed 1 pixel at a time, and, combined with the effect of special padding, this ensures that the resolution of the image stays the same.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 227, 227, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 227, 227, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 227, 227, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 113, 113, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 113, 113, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 113, 113, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 2)                 50178
=================================================================
Total params: 14,764,866
Trainable params: 50,178
Non-trainable params: 14,714,688
```

**Figure 34: Summary of recreated VGG-16 architecture in Python**

In VGG-16, all hidden layers follow ReLU (Rectified Linear unit) activation function. In the next step, five max-pooling layers perform spatial pooling with a 2*2 sliding window, two strides at a time. The last section of the VGG-16 architecture consists of three fully connected layers linked to convolutional layers. Finally, the networks finish off with a soft-max activation function. Since the damage detection datasets have only two categories, the number of parameters on the output layers have been cut short to two.

As detailed above, VGG-16 is a very large CNN with a total of 14,764,866 parameters, as shown in Figure 34. The model is pre-trained with millions of images. The knowledge gained from such high scale training can be transferred to other use cases. More importantly, there is no need to train all the parameters in VGG-16 except the final dense layers of VGG-16 since convolutional layers are already pre-trained. In effect, the number of trainable parameters in VGG-16 is reduced to 50,178, which is relatively less computationally intensive, considering the sheer size of the VGG-16 architecture.

## 5.2 Methodology and Setup

The comparison was carried out under the specific conditions, with the help of resources as follows.

### 5.2.1 Environment

According to systematic literature reviews, Python is the programming language environment of choice for researchers to adopt and develop popular world-class machine learning algorithms. Within Python, the three most favored open-sourced libraries are detailed below.

#### 5.2.1.1 PyTorch

Developed by Facebook under the guidance of Soumith Chintala, one of the leading artificial intelligence researchers in the world, Pytorch is used primarily by researchers in computer vision, natural language processing, and machine learning in general [72]. The main attractions are its intuitive coding style and flexibility of inbuilt functions. There are plenty of prebuilt APIs (Application Programming Interface) and functions in PyTorch for the widely used Computer vision algorithms such as VGG-16 and RESNET.

#### 5.2.1.2 TensorFlow

Developed by the Google Brain team for Google LLC, TensorFlow is the most widely used open-sourced machine learning library in the industry. Its core has been built in Python and is available on multiple platforms, including Windows, macOS, Linux, Android, and JavaScript. The analysis was performed in the second (and as of 2020, the newest) iteration of TensorFlow.

#### 5.2.1.3 OpenCV

OpenCV is a computer vision focused open-sourced library originally developed by Intel Corporation. In addition to offering several functions for pre-processing of image data, applying filters, etc., the library supports functionalities for real-time processing of video footage, which is beneficial for real-time UASHM.

### 5.2.2 Hardware

As far as UASHM is concerned, there are three major hardware platforms on which computer vision algorithms can be run. Our study was conducted on a traditional computing unit, an edge node, and a cloud computing platform. The major hardware specifications are given below.

### 5.2.2.1 Traditional Computing platform

The machine learning model can be run on traditional computers like personal computers or laptops. Asus G703GM, the choice of traditional computing platform taken for this thesis study, is equipped with 6 core Intel 8750H processor (CPU) and a base minimum clock speed of 2.2GHz and 32GB of RAM (Random Access Memory). Besides, there is a dedicated GPU (Graphics Processing Unit) of Nvidia GTX 1060 with 6 GB of RAM.

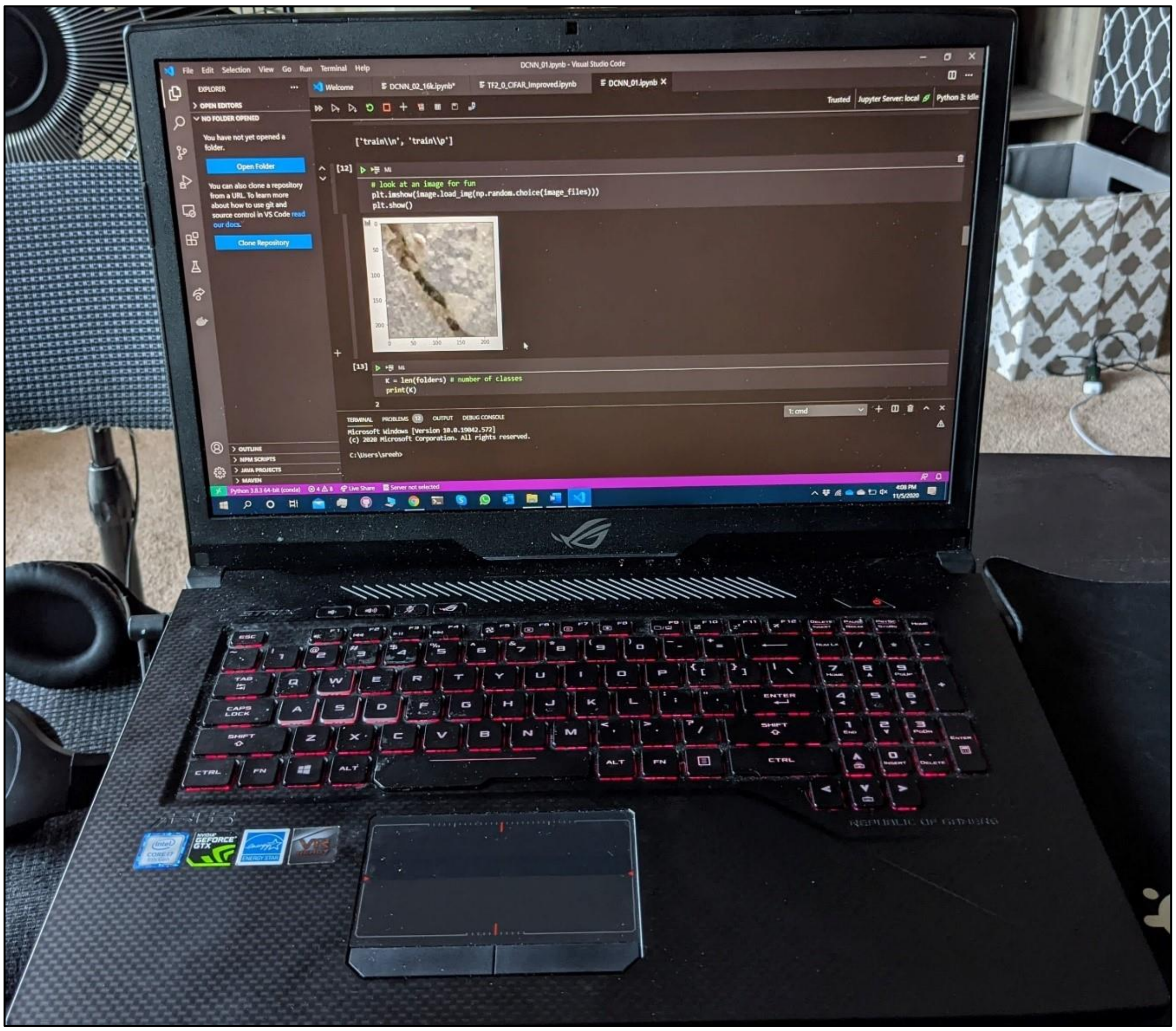


**Figure 35: The Windows laptop used as Traditional Computing Platform**

### 5.2.2.2 Cloud Computing Platform

Google Collaboratory is the cloud platform chosen for the analysis. Given that it is free of cost, Google Collaboratory is a great place for graduate students and academic researchers to take advantage of the free hardware resources. The information about the available hardware resources is limited. Collaboratory provides an Intel(R) Xeon(R) CPU at 2.20GHz with 25.51 GB DDR 4 RAM. The choice of GPU is Nvidia Tesla P100 with 16 GB of VRAM.

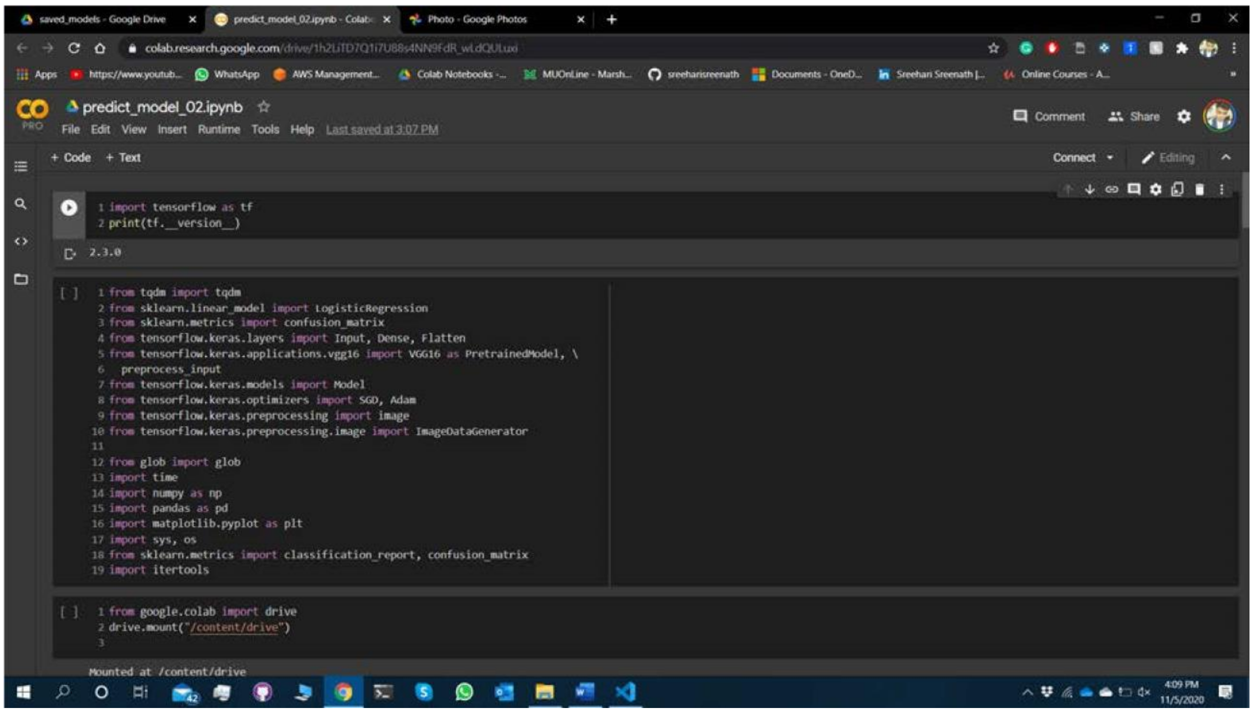


**Figure 36: Google Colaboratory as Cloud Computing Platform**

### 5.2.2.3 Edge Computing Platform

Edge computing is an approach by which computing is placed close to where the data is generated. By doing so, the data that is sent to the cloud server can be avoided- thus freeing up network bandwidth. In UASHM, real-time damage detection enables the damaged areas to be detected and tagged for immediate action rather than taking the long route of sending data to the cloud for analysis and waiting for results.

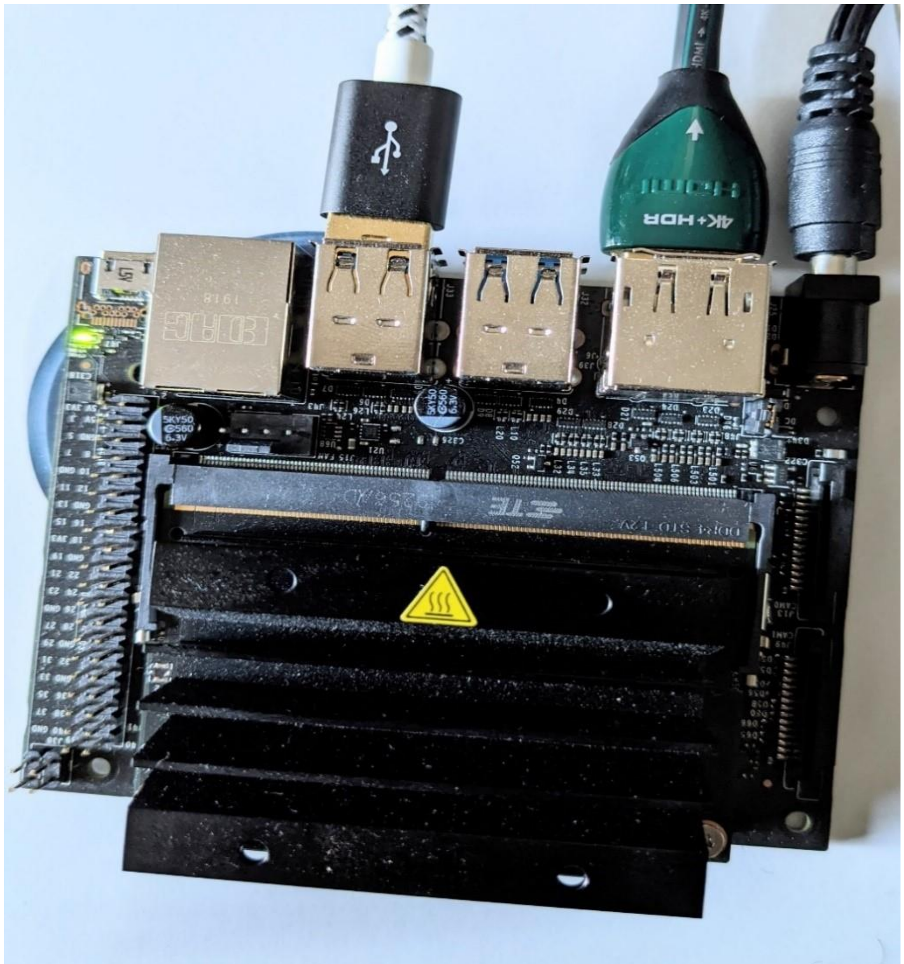


**Figure 37: Nvidia Jetson Nano as Edge Computing Platform**

The small computers that are placed close to the source (where data is generated) for edge computing are called edge nodes. They are designed to be smaller and more energy efficient. The edge node that is taken for the study here is Nvidia Jetson Nano. Unlike other small computers like Raspberry Pi, Jetson Nano boasts a powerful GPU that can run a deep learning model much faster than normal CPUs. The Jetson Nano packs a CPU- Quad-Core ARM@ A57 and RAM- 4GB LPDDR4. More importantly, Nano comes with the 128-core NVIDIA Maxwell GPU, which is essential for Deep Learning.

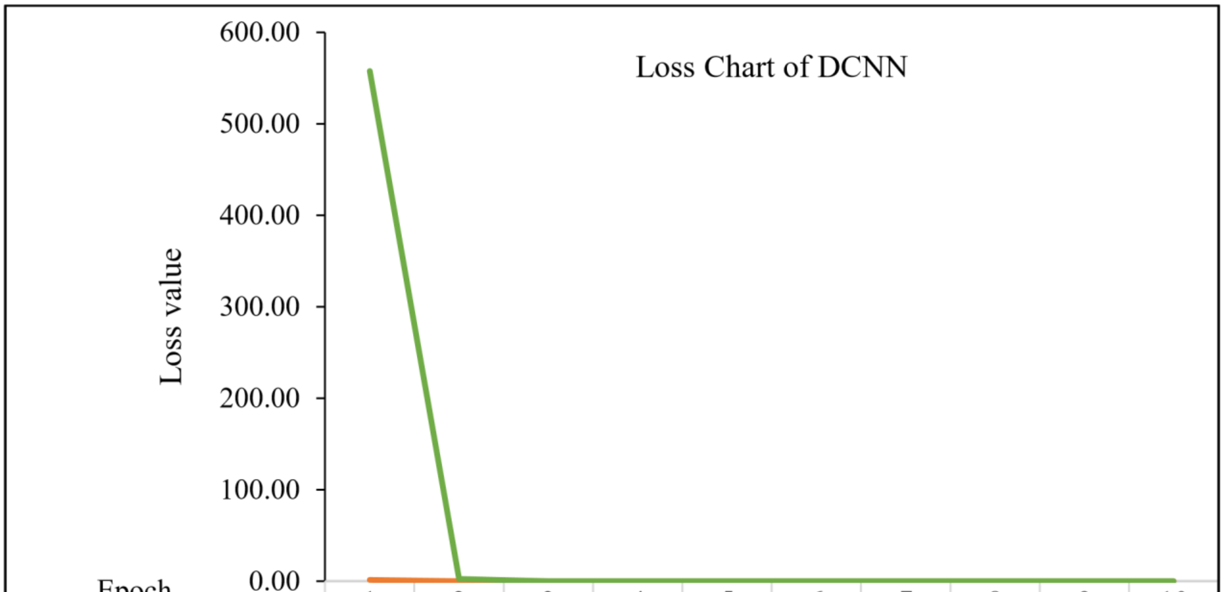
### 5.2.3 Dataset Selection

The thesis considered three datasets to analyze computer vision models [75][76][77]. All the data sets are open-sourced and publicly available. Concrete crack images have been used as the representative data for damage detection. There are 136,092 image samples with all 3 datasets that have been merged. All images have been standardized to 227*227 dimension to pass through the computer vision algorithms.

**Figure 38: Sample images from the datasets**
The figures are referenced from Pandian[75], Özgenel and Fırat[76], Maguire and Dorafshan[77]

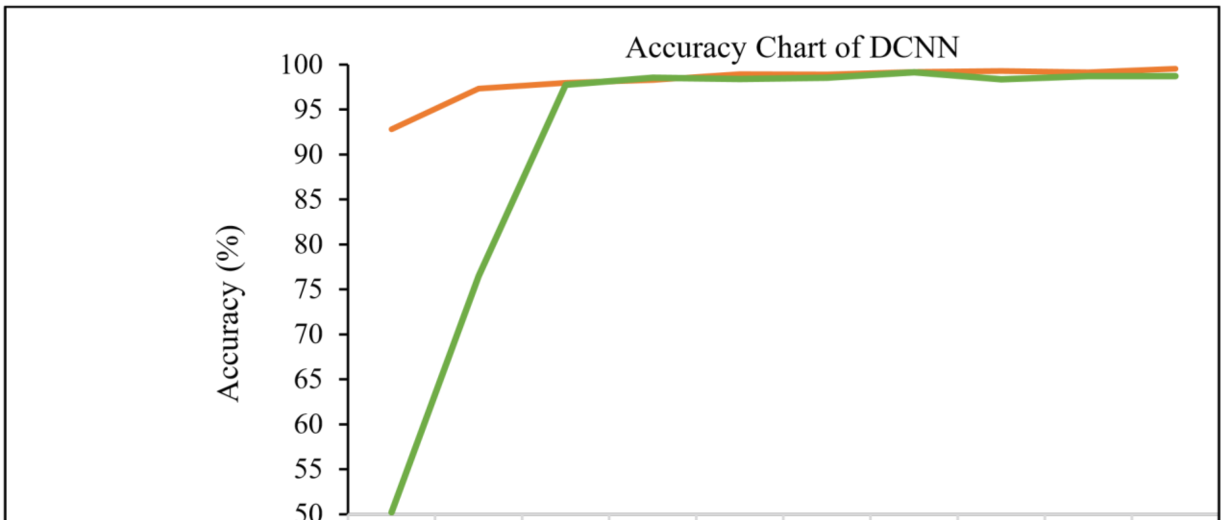
## 5.3 Model Training

For the model training for this thesis study, a dataset containing 10,000 images has prepared for the training and testing process with an 80:20 split (8,000 images for training and 2,000 images for testing). Dimensions of the images are standardized to 227*227 (height and width). Google Collaboratory was the choice of platform chosen for the process by this thesis. Both models used Adam optimizer for updating the weights and learning rate of the model and categorical cross-entropy as the loss function. The training has conducted for 10 epochs with a batch size of 128 images.




| Epoch | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Loss | 1.41 | 0.09 | 0.06 | 0.05 | 0.04 | 0.03 | 0.03 | 0.02 | 0.03 | 0.01 |
| Validation loss | 557.65 | 2.52 | 0.09 | 0.05 | 0.04 | 0.06 | 0.03 | 0.04 | 0.03 | 0.08 |

**Figure 39: Training Loss of DCNN model**




| Epoch | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Accuracy | 92.81 | 97.34 | 97.96 | 98.29 | 98.94 | 98.9 | 99.18 | 99.27 | 99.15 | 99.52 |
| Validation accuracy | 50.2 | 76.45 | 97.75 | 98.55 | 98.4 | 98.55 | 99.15 | 98.35 | 98.7 | 98.7 |

**Figure 40: Training accuracy of DCNN model**

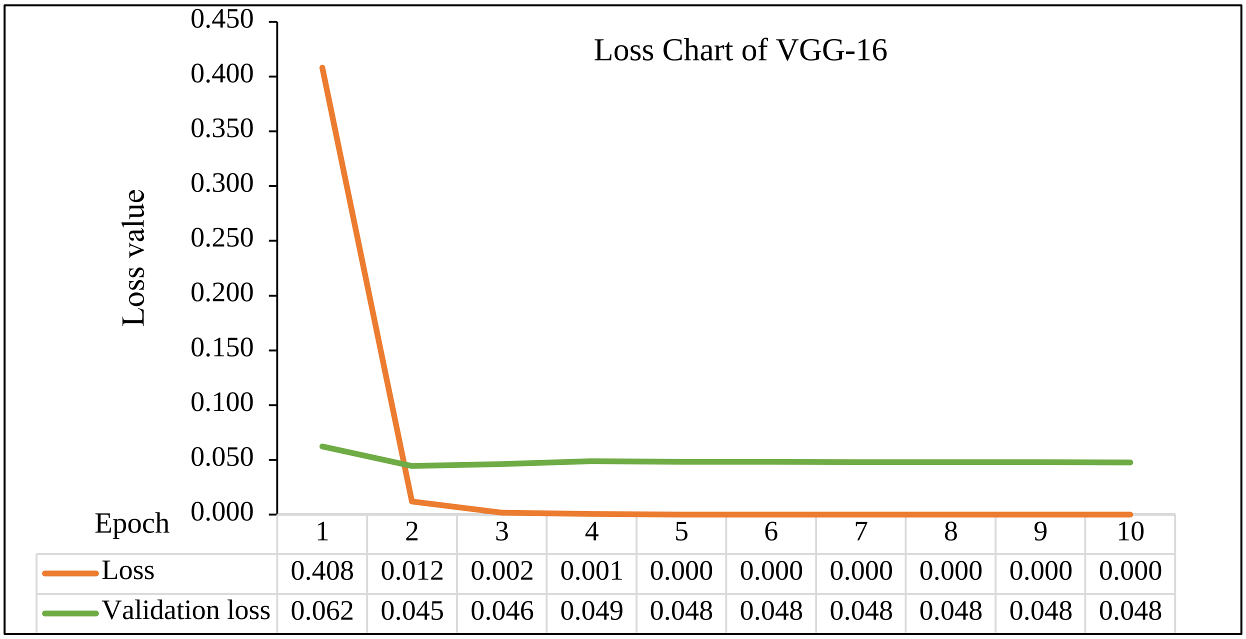



**Figure 41: Training loss of VGG-16**

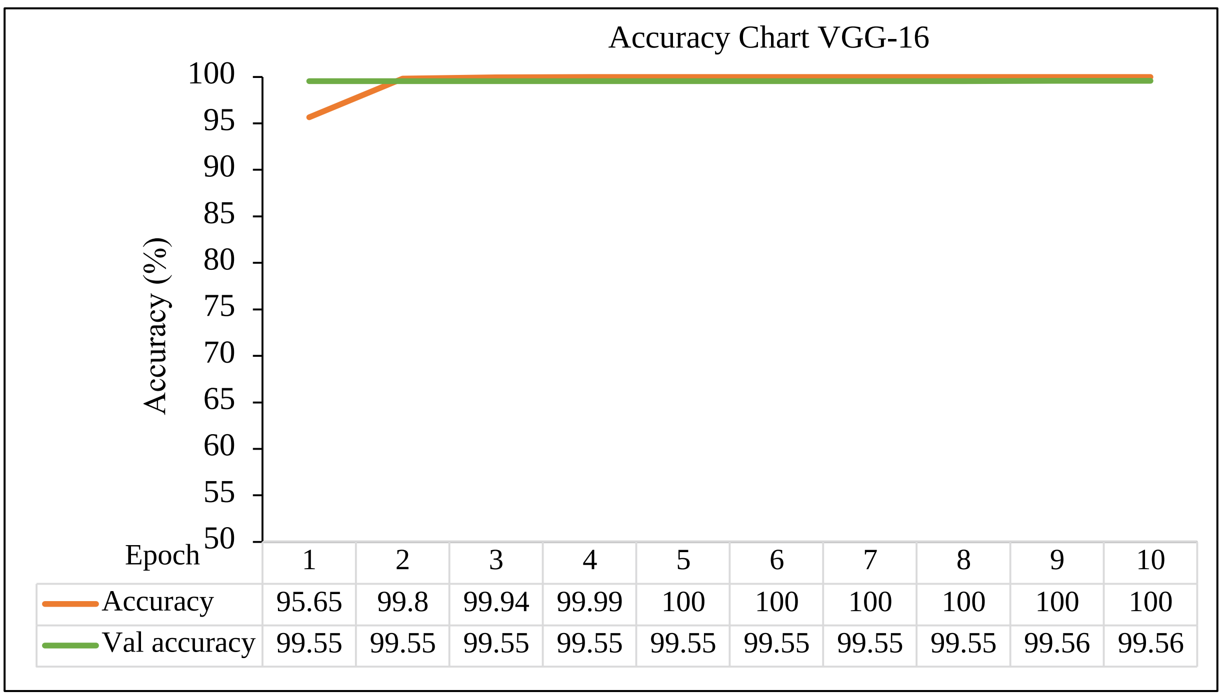



**Figure 42: Training accuracy of VGG-16**

Figure 40 and Figure 42 illustrates the accuracy curves of DCNN and VGG-16 models. Both models have performed well with a final epoch training accuracy of 99.52% and 100%, respectively. Also, the final validation loss of 0.08 for DCNN and 0.048 for VGG-16 (from Figure 39 and Figure 41) show that the models have good generalizing capabilities in terms of classifying images.

The training and validation loss curves of DCNN shows that the model had a high training loss (1.41) and validation loss (557.65) in the beginning stages of the training. It is normal for the traditional machine learning approach since the entire model is getting trained for the first time from scratch. In contrast, the VGG-16 model had a very low training loss (0.408) and validation loss (0.062). The VGG-16 underwent a transfer learning approach where the pre-trained VGG-16 model is used to train on the damage detection dataset.

The training and validation curves show that VGG-16 has a slight edge on the DCNN model. The difference is so minimal that it could be unnoticeable in real-world use cases. Despite this, the accuracy and loss curves show that the VGG-16 model converged faster. For evidence, the validation accuracy of VGG-16 of the first epoch is 99.55%, in comparison to 50.2% of DCNN. This fast convergence capability of the transfer learning models helps in situations where there is insufficient data available. In conclusion, both traditional machine learning and transfer learning approaches are completely advisable, even though the transfer learning approach could be better when there is not enough data.

### 5.4 Model Evaluation

After the training phase, DCNN and VGG-16 models are evaluated with a new, untested dataset of 400 images. The performance is documented with the help of various evaluation metrics such as confusion matrix, precision, accuracy, etc.

#### 5.4.1 Confusion Matrix

The confusion matrix is a table with informative numbers that describe how well the machine learning model has classified the data. The matrix contains 4 terms describing the model performance which are used for calculating other metrics like accuracy, precision, and recall.

- **True positives (TP)**: This represents the number of predicted positive images (images with damages present) that are actually positive images (according to the ground truth).
- **True Negative (TN)**: This represents the number of predicted negative images (images with damages present) that are actually negative images (according to the ground truth).
- **False positives (FP)**: This represents the number of predicted positive images (images with damages present) that are actually negative images (according to the ground truth).
- **False Negative (FN)**: This represents the number of predicted positive images (images with damages present) that are actually positive images (according to the ground truth).

**Table 2: Confusion matrix of DCNN model**

| | Predicted Negatives | Predicted Positives |
|---|---|---|
| Actual Negatives | **TN=177** | **FP=23** |
| Actual Positive | **FN=35** | **TP=165** |

**Table 3: Confusion matrix of VGG-16 model**

| | Predicted Negatives | Predicted Positives |
|---|---|---|
| Actual Negatives | **TN=186** | **FP=14** |
| Actual Positives | **FN=22** | **TP=178** |

Both DCNN and VGG-16 models have performed competitively as numbers from Table 2 and Table 3 suggest. VGG-16 documented more correct predictions with a total of 164 compared to 142 of DCNN. As far as UASHM is concerned, the False Negatives are the most important to consider since it denotes the number of false predictions on images where damages are present (according to ground truth). Once again, the VGG-16 model (FN=22) has outperformed the DCNN model (FN=35) with a fewer number of False Negatives.

### 5.4.2 Accuracy Metric

Accuracy is the most popular metric used to evaluate the machine learning model, especially in classification.

$$\text{Accuracy} = \frac{\text{Total number of correct predictions}}{\text{Total number of predictions}}$$

In terms of confusion matrix numbers, the accuracy can be represented as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

After calculation, DCNN documented 85.5% accuracy on the untested dataset, where VGG-16 recorded 91%. Both models showed a dip in the accuracy when introduced with a different dataset. Fortunately, the model accuracies can be increased with longer training sessions with larger datasets since both models are completely capable of complex multi-classification.

### 5.4.3 Precision and Recall

Precision can be defined as the number of true positives over the total number of positive predictions. Likewise, recall represents the number of positive predictions over the total number of true positive images (images where damages are present by ground truth). By equation, we can represent precision and recall as;

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

The DCNN was documented with 0.88 precision and 0.83 recall and VGG-16 received 0.93 precision and 0.89 recall. The trend continues as the VGG-16 produces better numbers in evaluation metrics. The field of UASHM suggests that wrongly detecting a positive image (image of structural damage) as negative (image of no structural damage) is more detrimental than vice versa. In that case, Recall is a more valid metric to consider than precision, as long as UASHM is concerned.

### 5.4.4 Time Complexity on various platforms

The analysis has taken place on three platforms: Traditional computing platform, Cloud computing platform, and Edge computing platforms. The time taken for classifying 1000 images by each model across all three platforms is noted down and compared to one another.

**Table 4: Time complexity on various platforms**

| | DCNN | VGG-16 |
|---|---|---|
| Traditional Computing | 13.3 seconds | 15.33 seconds |
| Cloud computing | 5.01 seconds | 5.12 seconds |
| edge computing | 28.02 seconds | 28.44 seconds |

It is observed that both machine learning models have completed their tasks the fastest in the cloud platform. Considering the raw processing power of cloud servers, this does not come as a surprise. In the traditional computing unit, the Windows laptop computer falls in the middle with 13.30 and 15.33 seconds taken for completing the task. At last place, the Jetson Nano (edge computing device) has managed to complete the task in 28.02 and 28.44 seconds despite being more power-efficient and compact.

The main takeaway here is that all three platforms are more than sufficient to perform damage detection in UASHM. Cloud computing and traditional computing techniques are preferred when there is a massive amount of data to be analyzed, and the need for real-time detection is not necessary. Edge computing devices are the preferred choice for real-time damage detection due to their power efficiency and compactness.

### 5.4.5 Time Complexity in various Processing Units

Machine Learning algorithms can run in various processing units such as CPUs (Central Processing Units), GPUs (Graphics Processing Units), and TPUs (Tensor Processing Units). The former two, being the most commonly used in UASHM damage detection, are chosen here to analyze 1000 images with dimensions of 227*227, and the time taken to complete the task is noted. The entire analysis is conducted on the Google Collaboratory environment (cloud computing platform).

**Table 5: Time complexity on various processing units**

| Models | Time complexity using CPU | Time complexity using GPU |
|---|---|---|
| DCNN | 68.88 sec | 5.00 sec |
| VGG-16 | 76.55 sec | 5.08 sec |

As is evident from the numbers documented, the GPU has a huge advantage, being at least 10 times faster at all times. This is a general trend as GPU is very powerful when it comes to parallel processing- a capability that researchers have been exploiting in the past decade. The difference in performance margin widens as the CNN models get deeper and have more parameters. The same is seen when the dimensions of the images (height, width, etc.) increase. Damage detection models in UASHM are complex and computationally intensive. Platforms with good GPU hardware help reduce the latency of the UASHM frameworks, especially when real-time detection is required.

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APPENDIX A: APPROVAL LETTER

MARSHALL UNIVERSITY.
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Office of Research Integrity

February 23, 2021

Sreehari Sreenath
523 Brandywine Dr., Apt 523
Bear, DE 19701

Dear Sreehari:

This letter is in response to the submitted thesis abstract entitled *"A Systematic Literature Survey of Unmanned Aerial Vehicle Based Structural Health Monitoring."* After assessing the abstract, it has been deemed not to be human subject research and therefore exempt from oversight of the Marshall University Institutional Review Board (IRB). The Code of Federal Regulations (45CFR46) has set forth the criteria utilized in making this determination. Since the information in this study does not involve human subjects as defined in the above referenced instruction, it is not considered human subject research. If there are any changes to the abstract you provided then you would need to resubmit that information to the Office of Research Integrity for review and a determination.

I appreciate your willingness to submit the abstract for determination. Please feel free to contact the Office of Research Integrity if you have any questions regarding future protocols that may require IRB review.

Sincerely,

Bruce F. Day

Bruce F. Day, ThD, CIP
Director

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