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Detection of Corrosion and Crack in the Structure of a Bridge Using Computer Vision Techniques

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Abstract - Corrosion and cracks pose significant challenges to the structural integrity and safety of bridges. Early detection and monitoring of these defects are crucial to ensure timely maintenance and prevent catastrophic failures. In recent years, computer vision techniques have shown great promise in automating the inspection process. This paper proposes the utilization of two state-of-the-art object detection algorithms, YOLOv5 and Faster R-CNN, for corrosion and crack detection on bridges. A dataset comprising images specifically focused on cracks and corrosion is utilized, with bounding boxes meticulously annotating the regions of interest. Subsequently, the images in the dataset are employed to train both a Faster R- CNN model and a YOLOv5 model, enabling the detection of cracks and corrosion within the images. Comprehensive analysis is then conducted based on the outcomes of these detection models.
Index Terms—Corrosion, crack, faster-RCNN, Yolov5.

Introduction

Bridges assume a pivotal role in contemporary infrastructure, serving as vital conduits that facilitate transportation and expedite the movement of individuals and commodities. The preservation and soundness of bridges are of paramount significance to ensure the seamless operation of transportation networks and safeguard the well-being of those who rely upon them. However, as time elapses, bridges endure myriad environmental factors and operational strains that can result in damage and deterioration. Among the most substantial challenges confronted by bridge engineers and maintenance teams are the identification and surveillance of corrosion and fractures. Corrosion, brought about by exposure to the elements, and fractures, arising from diverse factors such as fatigue and stress, pose substantial threats to the structural stability and longevity of bridges. Timely detection of these imperfections is crucial for implementing appropriate maintenance and repair strategies, averting potential catastrophic failures, and prolonging the lifespan of bridge structures. Conventional inspection and monitoring methods frequently rely on manual inspections, which can be laborious, time consuming, and susceptible to human fallibility. As bridge networks expand and age, there arises an escalating demand for automated and efficient systems capable of accurately and swiftly detecting and assessing corrosion and fractures. In recent years, advancements in computer vision and machine learning have opened up new avenues for automating the process of bridge inspection and defect detection. This study explores the utilization of two cutting-edge object detection algorithms, namely YOLOv5 and Faster R-CNN, in the realm of corrosion and fracture detection on bridges. By harnessing the potential of these sophisticated algorithms, it becomes conceivable to analyze bridge images and identify regions of interest (ROIs) that exhibit indications of corrosion or harbor fractures.YOLOv5, an acronym denoting "You Only Look Once," has gained renown for its real-time object detection capabilities. With its exceptional swiftness and accuracy, YOLOv5 has proven to be highly effective in detecting objects in diverse domains. By training the model on an extensive dataset of bridge images, it can learn to discern specific patterns and features associated with corrosion and fractures. Conversely, Faster R-CNN excels in precisely localizing objects, rendering it suitable for detecting minute fractures and subtle corrosion patterns that may necessitate more meticulous analysis. To assess the proposed approach, a comprehensive dataset encompassing images of bridges exhibiting varying degrees of corrosion and fracture severity is compiled and annotated. This dataset serves as the cornerstone for training the YOLOv5 and Faster

R-CNN models employing transfer learning techniques, leveraging pre-trained weights from extensive image recognition datasets. Through a rigorous experimental setup, the performance of both algorithms is scrutinized in terms of accuracy, speed, and resilience. The outcomes of these experiments highlight the effectiveness of YOLOv5 and Faster R-CNN in the detection of corrosion and fractures on bridges. YOLOv5, with its real- time processing

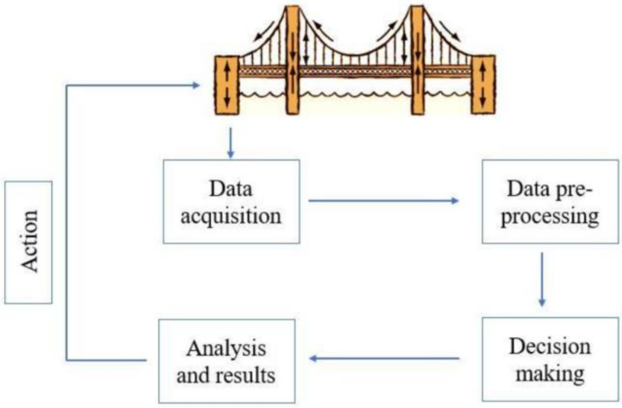

Fig 1: Flow for health monitoring

capabilities, showcases remarkable accuracy while maintaining high-speed performance. This renders it suitable for real-time monitoring applications where timely intervention is of critical importance. Conversely, Faster R-CNN demonstrates superior performance in localizing minute fractures and subtle corrosion patterns, enabling meticulous analysis and precise identification of affected areas. By integrating these sophisticated object detection algorithms into the domain of bridge inspection and maintenance, it becomes feasible to enhance the accuracy, efficiency, and automation of corrosion and fracture detection processes. This holds significant implications for the safety, maintenance, and longevity of bridge infrastructure, as timely defect detection facilitates proactive maintenance interventions and forestalls potential disasters.

A. Motivation

Structural Health Monitoring systems analyze and monitor the structures such as bridges, and buildings, for safe, reliable transportation and living. Here, we have considered the Bridge health monitoring system as this will provide information necessary for a safe transportation system. Based on visually recognized defects, human and automotive moments on the bridge and vibrations resulting from environmental and other effects which holistically contribute towards the health of the bridge can be continuously monitored. Depending on the region where the bridge is constructed and the environmental and traffic conditions there, the condition of the bridge can be analyzed. With the aging of the infrastructure, the maintenance frequency increases which results in economical investments as well as keeping human life at stake. If the bridge health is monitored then it will result in economic benefits by decreasing the operations costs by optimizing the maintenance frequencies. Traditionally used methods for bridge health monitoring uses structured deformation and the necessary tools such as strain gauge, sensors like accelerometer, etc. Through the analysis, it has been observed that these traditional methods are restricted to certain regions and may vary from bridge to bridge. The main objective of this paper is to build a bridge health monitoring system that is scalable and suitable for different regions and bridges constructed there. This gives a generalized solution to infrastructure health monitoring. Such systems can be developed through approaches to machine learning and computer vision techniques. The vision-based health monitoring can be characterized into two groups such as motion based and appearance based methods. Based on various computer vision and machine learning algorithms initially, motion based methods seem to be appealing but furthermore, the limitations of this are encountered in previous research. Thus, considering the vision-based approach due to the fast evolution of high level imaging features, symmetry, etc proves to be beneficial. Corrosion and cracks are the prime factors that contribute to structure deformation along with a few others. Corrosion occurs due to various factors such as environmental conditions and strain. Corrosion damages the strength of the bridge and further leads to cracks. Cracks can occur as a result of strain, load, and vibration along with corrosion being one such reason behind it. The detection of the extent of corrosion and crack can be the main objective in determining the health of the bridge. For which collection of a dataset that includes a wide range of images of corrosion and crack followed by the selection and implementation of efficient and suitable computer vision algorithms serves the research aim. Future specifying the objectives and carrying out training and testing of algorithms is done subsequently.

B. Objectives

Objectives provide different tasks and features of our project and they are completed accordingly.

- Pre-processing dataset for crack and corrosion detection using computer vision techniques.
- Develop machine learning(ML) models that are used to be trained with the preprocessed dataset.
- Test model performance using a separate dataset and.

Literature Survey

A. Data-Driven Structural Health Monitoring and Damage Detection through Deep Learning: State-of-the-Art Review [1]

This paper provides an overview of the current state-of- the-art research in the field of data-driven structural health monitoring and damage detection using deep learning techniques. The paper starts by discussing the importance of structural health monitoring and how traditional methods have limitations in terms of accuracy, speed, and cost. It then explores the potential of deep learning techniques to overcome these limitations and improve the accuracy and efficiency of structural health monitoring. The paper provides a comprehensive review of various deep learning models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), auto encoders, and generative adversarial networks (GANs), that have been applied for damage detection in various structures such as bridges, buildings, and wind turbines. The authors also discuss various data sources, including sensors, images, and videos, that have been used for damage detection through deep learning. The paper also highlights the challenges associated with deep learning based structural health monitoring, such as the need for large amounts of training data, the potential for overfitting, and the need for the interpretability of results. The authors discuss various techniques and approaches to overcome these challenges, including transfer learning, data augmentation, and explainable AI. In conclusion, the paper presents a comprehensive overview of the current state-of-the-art in data driven structural health monitoring and damage detection through deep learning. The paper is a valuable resource for researchers and practitioners interested in the application of deep learning techniques for structural health monitoring and damage detection.

B. Data-Driven Structural Health Monitoring and Damage Detection through Deep Learning: State-of-the-Art Review [2]

This paper provides an overview of the current state-of- the-art research in the field of data driven structural health monitoring and damage detection using deep learning techniques. The paper starts by discussing the importance of structural health monitoring and how traditional methods have limitations in terms of accuracy, speed, and cost. It then explores the potential of deep learning techniques to overcome these limitations and improve the accuracy and efficiency of structural health monitoring. The paper provides a comprehensive review of various deep learning models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), autoencoders, and generative adversarial networks (GANs), that have been applied for damage detection in various structures such as bridges, buildings, and wind turbines. The authors also discuss various data sources, including sensors, images, and videos, that have been used for damage detection through deep learning. The paper also highlights the challenges associated with deep learning based structural health monitoring, such as the need for large amounts of training data, the potential for overfitting, and the need for interpretability of results. The authors discuss various techniques and approaches to overcome these challenges, including transfer learning, data augmentation, and explainable AI. In conclusion, the paper presents a comprehensive overview of the current state-of-the-art in data driven structural health monitoring and damage detection through deep learning. The paper is a valuable resource for researchers and practitioners interested in the application of deep learning techniques for structural health monitoring and damage detection.

C. Automatic damage detection using anchor-free method and unmanned surface vessel [3]
Damage detection is a critical stage in assessing the security posture of infrastructure. Yet, some essential components are so difficult to obtain using both people and equipment that they significantly impair detection (e.g. the bottoms of small and medium bridges, urban underground culverts, etc.). This research proposes a systematic approach based on a deep learning algorithm and an autonomous surface vessel to efficiently detect damage (USV). The proposed detection technique is a revolutionary anchor-free net- work called CenWholeNet that stresses center points and holistic information. As a novel approach to including the attention mechanism in the model, the parallel attention module (PAM) was suggested. Ablation experiments have provided enough data to validate PAM's claim that it can enhance model representation with a negligibly increased computational load. It is advised to adopt a USV system for mobile devices that supports real-time lidar and video data transmission but excludes GPS navigation. When the suggested method was applied to evaluate a bridge group, its efficacy and adaptability for usage on challenging projects were validated. Furthermore, the results demonstrate that CenWholeNet outperforms well-known objective detection methods like Faster R-CNN and YOLOv5 in detecting a wide range of diseases with variable slenderness ratios and complex morphologies. We therefore expect CenWholeNet to establish a new benchmark for intelligent infrastructure damage detection.

D. Structural Health Monitoring of Bridges: Data-based damage detection method using Machine Learning[4]
This paper presents a data-based damage detection method for Structural Health Monitoring (SHM) of bridges using machine learning. The proposed method uses sensor data to analyze the health of the bridge and detect any damages present, such as cracks or corrosion. However, due to limitations in collecting the required sensor data, the authors proposed a computer vision-based approach instead. The vision based models were trained using a dataset of annotated images of cracks and corrosion, using Faster-RCNN and Yolov5 models to detect damage in an image. The severity of the damage was determined by the size and location of the bounding box around the affected area. The proposed method allows for early detection of damages, enabling timely maintenance and reducing the cost of the physical removal of old bridges. The use of machine learning for SHM also provides a more efficient and accurate approach compared to traditional methods. Overall, this paper presents a promising approach to SHM of bridges using machine learning, demonstrating the potential for improved bridge maintenance and safety.

E. Development of a wireless sensor network system for suspension bridge health monitoring [5]
The paper titled "Development of a wireless sensor network system for suspension bridge health monitoring" discusses the development of a wireless sensor network (WSN) system that can be used to monitor the health of suspension bridges. The authors recognize that suspension bridges are critical infrastructure assets that require continuous monitoring to ensure their safety and reliability. To address this need, they propose a WSN system that is capable of monitoring the behavior of suspension bridges in real time. The WSN system comprises various sensors that are installed at different locations on the bridge, including strain sensors, temperature sensors, and accelerometers. The data collected by these sensors is wirelessly transmitted to a central data acquisition system that processes the data and sends it to a remote server for analysis. To validate the proposed WSN system, the authors conducted experiments on a real suspension bridge. The experimental results demonstrate the effectiveness of the WSN system in detecting changes in the structural behavior of

the bridge. Overall, the paper presents an innovative approach to bridge health monitoring that can help identify potential issues before they become critical. The proposed WSN system has the potential to enhance the safety and reliability of suspension bridges, making them more resilient to natural disasters and other external factors.

Application In Societal Context

Bridges play a very important role in societal context since it connects people and communities and facilitates the movement of goods, people, and services from one place to another. Thus, any irregularity or damage that happens to the bridge, affects the transportation by causing disruptions and hence leading to the potential risk of injuries and accidents. For the longevity of these structures, it is necessary that damage detection is done. The structural health monitoring of these structures plays a very important role in determining the present conditions of the bridge structure. This plays a very important role to pave a significant impact on the society by improving the structures safety and increasing the reliability of these structures. The use of computer vision technology for damage detection on bridges has been an added advantage in the analysis of bridge health. By accurately detecting the cracks formed on the structure and identifying the corroded areas on the structure as soon as possible, computer vision helps to facilitate the repair, maintenance of the bridges in a timely manner and thereby reducing the risk of accidents, injuries, and thus shrinking the disruption of transportation that happens due to closure of the bridges. Over and above that, the use of computer vision, artificial intelligence, and machine learning can also have economic benefits to society. The above mentioned methods help to decrease the time and cost associated with traditional inspection methods. Computer vision can provide valuable information for maintenance and repair planning which helps to improve the performance and longevity of the bridges. These methods also help to reduce the time associated with traditional inspection methods which can help to save money on maintenance and repair. In addition, computer vision technology helps to detect damage earlier and helps to know the minute details which can get missed at the time of human inspection. It can also help reduce the environmental impact by reducing the need for major repairs and replacements which indirectly saves a lot of resources. The damages such as cracks and corrosion can be detected very soon with the help of computer vision methods. Moreover, the use of sensor technologies and drones for data acquisition and analysis can reduce the need for human inspection and thereby reduce the risks that might occur at the time of human inspection.

System Design

In this chapter, the various approaches have been discussed depending on the given problem statement.

A. Reason to select computer vision based approach for structural bridge health monitoring:

The adoption of computer vision-based approaches in structural bridge health monitoring offers numerous advantages over traditional sensor based methods. This selection presents a compelling solution for several reasons:

- Computer vision based approaches eliminate the need for expensive and time consuming sensor installation and maintenance. By leveraging existing cameras and employing sophisticated computer vision algorithms, these approaches become more cost effective and easier to implement.
- Computer vision based approaches possess the capability to detect and monitor a wide array of structural issues, such as cracks, deformations, corrosion, and other visual anomalies. In contrast, sensor based methods are limited to measuring specific physical parameters and may fail to identify certain types of damage.
- Computer vision based approaches provide real-time monitoring of structural health, enabling prompt identification of potential issues. By promptly alerting maintenance personnel, preventative measures can be taken to mitigate risks and prevent further damage. In comparison, sensor based methods may only detect issues after significant damage has already occurred.

In summary, the integration of computer vision based approaches in structural bridge health monitoring offers a cost effective, reliable, and efficient solution for the detection and continuous monitoring of structural issues. This research paper highlights the benefits of employing computer vision technology in this domain, emphasizing its potential to revolutionize the field of structural bridge health monitoring.

B. Computer vision in structural bridge health monitoring:

In the field of structural bridge health monitoring, computer vision plays a significant role in visually analyzing and assessing the structural integrity of bridges. This approach focuses on two crucial parameters that can impact the bridge's stability:

- Corrosion: Corrosion in bridges occurs when the metal components of the structure react with environmental elements, leading to the gradual deterioration and loss of material integrity.
- Crack: Cracks can occur due to various factors such as overloading, natural disasters, and structural fatigue. Identifying cracks at an early stage is crucial as they have the potential to lead to catastrophic failure if left unaddressed.

The following steps outline the operation of a computer vision based method for structural bridge health monitoring:

- Data Acquisition: Data related to corrosion and cracks are collected from different angles and distances of the structural bridge.
- Image Annotations: The collected dataset of corrosion and crack are annotated and the affected region in each image is visually inspected and a bounding box is drawn manually.
- Image Pre-Processing: The dataset is divided into training, testing, and validation sets. Pre-processing techniques are applied to extract relevant features, remove noise, enhance contrast, and resize images.
- Object Detection: Object detection algorithms such as Faster R-CNN and YOLOv5 are employed to identify specific features of interest in the images, such as cracks and corrosion.
- Feature Extraction: Once the objects of interest are identified, features are extracted from the images to capture important characteristics.
- Machine Learning/Deep Learning: The extracted features are utilized to train machine learning or deep learning algorithms, enabling the detection and classification of corrosion or cracks in the bridge structure.
- Analysis and Reporting: Finally, the analysis results are reported to the stakeholders responsible for maintaining the structural bridge. These reports provide essential information about the location, severity, and potential causes of defects, facilitating appropriate repair or maintenance actions. By employing computer vision techniques in structural bridge health monitoring, this research paper showcases an effective methodology for detecting and assessing corrosion and cracks. The proposed approach offers valuable insights into the condition of bridges, aiding in proactive maintenance and ensuring the longevity and safety of these vital infrastructure assets.

C. Functional block diagram

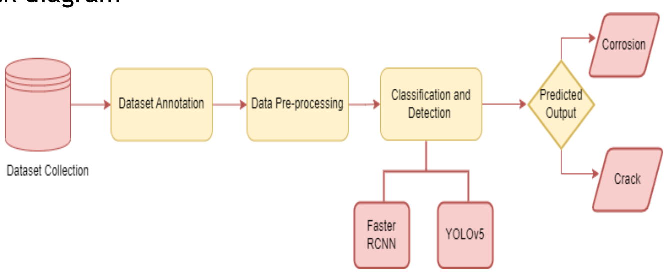

Fig 2: Block diagram

D. Object Detection Algorithms:

Here the two algorithms onsidered:

- Faster R-CNN
- YOLO v5.

Two prominent algorithms considered for our project are Faster R-CNN and YOLOv5. These algorithms offer significant advantages, including high accuracy and precision in object detection tasks. Their low rates of false positives and false negatives make them particularly well suited for our project, where precise detection of cracks and corrosion is crucial. Real-time performance is another key advantage of Faster R-CNN and YOLOv5. Given the need to monitor and detect cracks and corrosion in structures in real-time, these algorithms enable us to promptly identify and address any potential issues. Moreover, Faster R-CNN and YOLOv5 exhibit a high degree of customization, allowing easy fine-tuning for specific classification tasks. By training these models on our dataset of cracks and corrosion images, we can optimize their performance to meet our specific requirements. Additionally, the availability of pre-trained models serves as a valuable starting point, significantly reducing the training time and effort involved. In summary, the selection of Faster R-CNN and YOLOv5 as our object detection algorithms offers the advantages of accuracy, real-time performance, customizability, and the availability of pre-trained models. These algorithms form the foundation of our research, ensuring reliable and efficient detection and classification of cracks and corrosion in structural monitoring applications.

Implementation Details

A. Software specification

- Python programming language used to implement the model.
- Google colab is used for implementation of the codes.
- Specifications of the Google colab: RAM: 12 GB, GPU: Tesla K80.
- For the purpose of annotation a software named makesense.ai has been used.

B. Dataset description

The collection comprises 2000 photos showing corrosion and cracks in bridges that were gathered from a variety of sources, including Roboflow and Google. In order to anno- tate the photos for the YOLO v5 and Faster R-CNN models, the MakeSense.ai tool, a well-known online image annotation platform, was used. Annotations for each photograph include information on the location, size, and kind of corrosion or crack. The YOLO format has five values for each annotation: xmin, ymin, xmax, ymax, and class. The xmin and ymin values stand in for the coordinates of the top-left corner of the bounding box around the item, while the xmax and ymax values stand in for the coordinates of the bottom-right corner. The object type being identified, such as a crack or corrosion, is represented by the class value. In order to make the dataset larger and more diverse, it has been divided into two sets: a training set that makes up 70 percent of the dataset and a testing set that makes up 30 percent of the dataset. Optimizing model performance may involve normalizing pixel values and downsizing the photos to a uniform size. To comprehend the kind and degree of the corrosion and cracks, the dataset offers visualizations of the photos and comments. The YOLO format is unique to the YOLOv5 model and might not work with other machine learning models, it is crucial to mention. As a result, it is crucial to choose the right format for the planned model. For researchers and professionals interested in creating machine learning models for identifying and categorizing bridge deterioration, this dataset of bridge cracks and corrosion is a useful resource. A standardized and user-friendly method of annotating the photos is provided by the annotations created using the MakeSense.ai tool and the YOLO and CSV formats, making it simpler to train models and assess their effectiveness. The information may be used for different purposes, including monitoring the state of bridges and analyzing the need for maintenance or repair. The visualizations of the pictures and comments can be used to fully under- stand the types and severity of the fractures and corrosion, even though the annotations were produced manually and may have some errors or inconsistencies.

Labels	Number of raw images	Number of an-notated images
Corrosion	1000	1000
Crack	1000	1000

[1] Dataset description table


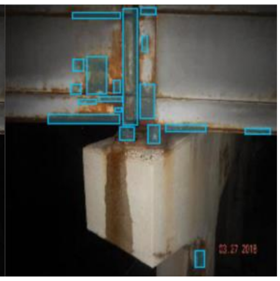

Fig 3: sample image of corrosion data

Fig 4: Annotated sample image of corrosion data


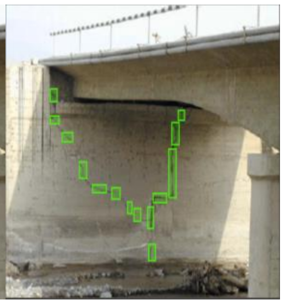

Fig 5: Sample image of crack data

Fig 6: Annotated sample image of crack data

Algorithm

In this project, deep learning algorithms have been em- ployed to address the task at hand, which involves solving a specific problem or accomplishing a particular task. To enhance the accuracy of the models, transfer learning techniques have been incorporated, enabling the utilization of pre-trained models as a starting point.

A. Faster RCNN:

The Faster R-CNN (Region-based Convolutional Neural Network) is a widely utilized object detection algorithm in computer vision applications. This section provides an in-depth explanation of the architectural design of the Faster R-CNN model employed in this paper as a training model. The Faster R-CNN model follows a two-stage architecture, incorporating a region proposal network (RPN) alongside a Fast R-CNN object detection network. The RPN generates region proposals by employing a small network to slide over the feature map, predicting objectness scores and bounding box regressions at each spatial location. These proposals are then fed into the Fast R-CNN network for subsequent object detection and classification. Typically, the backbone of the Faster R-CNN network consists of a deep convolutional neural network (CNN) such as ResNet or VGGNet. This backbone network extracts high-level features from the input image. These features are then passed on to the RPN, which generates a set of object proposals. The proposals undergo refinement and filtering based on their objectness scores and overlap with ground- truth objects. The final stage of the Faster R-CNN network involves the Fast R-CNN object detection network. This network takes the region proposals generated by the RPN as input and performs RoI (Region of Interest) pooling, extracting a fixed-length feature vector for each proposal. The feature vectors then pass through a fully connected layer that predicts class probabilities and bounding box offsets for each proposal. To train the Faster R-CNN model, a combined loss function is utilized, comprising the RPN loss and the Fast R-CNN loss. The RPN loss encompasses the objectness classification loss and the bounding box regression loss, while the Fast R-CNN loss encompasses the classification loss and the bounding box regression loss. Hence, the Faster R-CNN model is a robust object detection algorithm that integrates a region proposal network with a Fast R-CNN object detection network. The model utilizes a deep CNN backbone for feature extraction from the input image and is trained using a combination of the RPN and Fast R-CNN losses. This architecture proves effective in detecting and classifying objects accurately in various computer vision tasks.

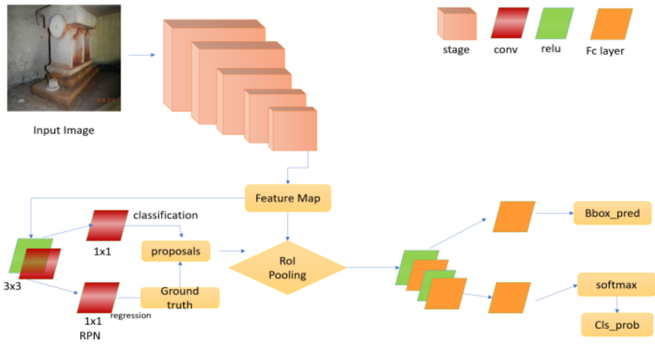

Fig 7: Overview of Faster RCNN

B. YOLOv5:

The YOLOv5 (You Only Look Once v5) is a state-of-the-art deep learning model that is used for object detection in computer vision applications. It is an extension of the previous versions of YOLO, which were able to achieve high accuracy in object detection while maintaining real-time performance. The architectural design of YOLOv5 is based on a convolutional neural network (CNN) architecture, which is composed of a backbone network and a detection head. The backbone network consists of a series of convolutional layers that extract features from the input image. The detection head is responsible for predicting the bounding boxes, class probabilities, and confidence scores for the objects in the input image. The backbone network in YOLOv5 is designed using the Efficient Net architecture, which is known for its efficiency and accuracy. It consists of a series of convolutional layers that down sample the feature maps while increasing the number of channels to capture more complex features. The Efficient Net architecture is designed to balance model size and accuracy, making it suitable for real-time applications. The detection head in YOLOv5 is composed of multiple convolutional layers that predict the bounding boxes, class probabilities, and confidence scores for the objects in the input image. It uses a feature pyramid network (FPN) to capture multi-scale features and improve the accuracy of object detection. The YOLOv5 model uses a single-stage detection approach, which means that it performs object detection and classification in a single pass over the input image. This approach is more efficient than the two-stage detection approach used in previous versions of YOLO, which required multiple passes over the input image. In summary, the YOLOv5 model is a state-of-the-art deep learning model for object detection in computer vision applications. Its architectural design is based on a convolutional neural network with an Efficient Net backbone network and a detection head composed of multiple convolutional layers. The model uses a single-stage detection approach to perform object detection and classification in a single pass over the input image.

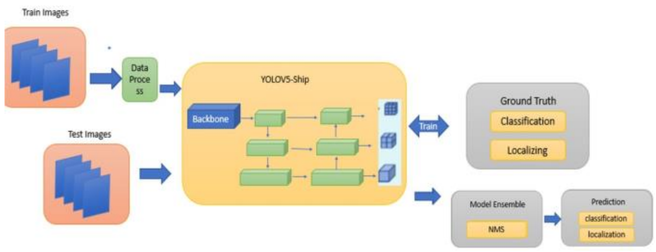

Fig 8:Overview of YOLOV5

Results And Discussions

This chapter focuses on the objective of proposing a data-based damage detection method for Structural Health Monitoring (SHM) of bridges using machine learning/deep learning. The approach incorporates two widely known object detection models, Faster R-CNN and YOLOv5, to identify cracks and corrosion in bridge structures. The Faster R-CNN model was initially trained for 184 epochs and successfully detected corrosion but failed to accurately identify cracks. To address this issue, a separate training was conducted using a single class for crack detection. However, even with this modification, the results remained unsatisfactory. Upon analysis, it was determined that the imbalance of labels within each image of the dataset contributed to the failure of the Faster R-CNN model. To overcome this challenge, the YOLOv5 model was employed. The dataset, as previously mentioned, consisted of 1000 annotated images for each class (crack and corrosion) in the bridge structure. The dataset was divided into training, validation, and testing subsets, with 80% used for training, 12% for validation, and 8% for testing. The YOLOv5 model underwent training for 200 epochs, with the model reaching saturation at 130 epochs and delivering exceptional results. The findings reveal that the proposed method using the YOLOv5 model achieved successful detection of both cracks and corrosion in the bridge structures. In comparison, the Faster R-CNN model demonstrated effectiveness in detecting corrosion but fell short in accurately identifying cracks. Therefore, the YOLOv5 model outperformed the Faster R-CNN model in terms of overall performance. Overall, the results highlight the significance of selecting an appropriate object detection model for specific tasks in bridge SHM. The successful implementation of the YOLOv5 model in this study underscores its superiority over the Faster R-CNN model in achieving comprehensive and reliable results.

A. Architectural design 1: Faster RCNN results


Fig 9: Input image of corrosion Fig 10: Predicted output of corrosion


Fig 9: Input image of **Fig 10: Predicted output of crack**

B. *Architectural design 2: YOLOv5 results*


Fig 11: Input image of corrosion **Fig 12: Predicted output of corrosion**


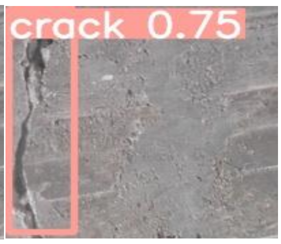

Fig 13: Input image of crack **Fig 14: Predicted output of crack**

Conclusion

Corrosion and cracks are crucial factors to contemplate when considering the Structural Health Monitoring (SHM) of bridges. Corrosion gradually enfeebles materials such as steel and concrete, while fracturing can arise from diverse influences such as temperature fluctuations, tension, and corrosion. Disregarding these concerns may culminate in structural deterioration and potential bridge collapse. By implementing SHM techniques, these predicaments can be discerned and monitored, furnishing valuable insights into
the overall well-being and remaining lifespan of the bridge.
Early detection facilitates prompt maintenance, guaranteeing the bridge's longevity and safety for its occupants. The objective was to adopt computer vision-based strategy, employing the Faster R-CNN and YOLO v5 models. The YOLO v5 model, specifically trained on annotated images concentrating on fissures and corrosion, attained a remark- able accuracy of 95.4% in identifying these issues, surpassing the performance of the Faster R-CNN model. This showcases the potential of machine learning in bridge SHM and underscores the significance of selecting the appropriate model for the task. The devised approach proffers a promising solution for precisely identifying and monitoring structural impairment in bridges, enabling prompt maintenance measures and diminishing the risk of failure.

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