Volume-10 Issue 08, August -2026
ISSN: 2456-9348 (Online)
SJIF Impact Factor: 8.232

iJETRM
INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

DEEP LEARNING BASED CIVIL STRUCTURE CRACK DETECTION AND STRUCTURAL SEVERITY ASSESSMENT SYSTEM

MRS. K.S.S SOUJANYA KUMARI
Assistant Professor, Department of Computer Science and Systems Engineering Applications, Andhra University, Visakhapatnam, Andhra Pradesh, India

UGRANGI ROHITH
Student, Master of Computer Applications - Department of Information Technology and Computers Applications,
Andhra University, Visakhapatnam, Andhra Pradesh, India,
Corresponding Author: Ugrangi Rohith
Email: ugrangirohith566@gmail.com

ABSTRACT
Civil structures like buildings, bridges, roads, pavements, tunnels and masonry buildings need frequent monitoring to ensure structural safety and serviceability. The traditional inspection methods are mainly based on visual inspections by a human; which are generally time-consuming, subjective and challenging on large-scale infrastructure. While efforts over the past few years using deep learning have substantially enhanced automated crack detection, there is currently limited support for engineering assessment and maintenance planning for cracks detected on the surface, which are present in many existing crack detection systems. This paper introduces the Autonomous Structural Health Monitor (ASHM), an intelligent multi-modal software technology platform that assists structural engineers to monitor infrastructure through deep learning and computer vision. It supports three operations: Batch Image Inspection, Static Camera Inspection and Live Infrastructure Inspection, which allows an inspection in various practical scenarios. The AI engine combines Deep ResNet50 (Crack classification) and U-Net (Pixel-level crack segmentation). The segmented regions of the crack are further processed using OpenCV contours, pixel count and skeletonization to try and estimate area of crack, length of crack and maximum width of crack. The information from the measurements is taken into account by a rule-based module to assess and classify the damage and its grade, and to provide maintenance recommendations. Lastly, ASHM generates a professional PDF inspection report automatically with the identified properties of the cracks, structural assessment and recommended measures for maintenance works. A set of images of concrete cracks (Concrete Crack Images, CFD) and an in-house image database were selected for experimental evaluation combined with SDNET2018. The results achieved prove the reliability of the proposed platform that combines practical inspection workflows in a single software solution, while detecting cracks. ASHM's modular structure also opens the door to possibility of future integration with a variety of other IoT devices, as well as drones and physical, non-destructive testing methods for advanced, structural health monitoring. This work employs a Deep Learning network (ResNet50), a super pixel segmentation algorithm known as U-Net, Computer Vision techniques for crack detection and OpenCV software for further report generation to carry out Structural Health Monitoring of civil structures.

Keywords:
Structural Health Monitoring, Deep Learning, ResNet50, U-Net, Crack Detection, Computer Vision, Civil Infrastructure Inspection, OpenCV, Report Generation.

INTRODUCTION
Economy and safety are dependent on civil infrastructure. Bridges, roads, schools, tunnels, retaining walls, roads and buildings are constantly under the influence of the environment, traffic stresses, ageing, wetness, temperature changes and natural disasters. Such factors tend to cause the formation of surface cracks that are one of the earliest visible damages of the structure. Undetected defects may gradually accumulate to decrease the performance and longevity of the structure. Hence, the periodical inspection is an integral part of a maintenance program for infrastructure and asset management.

iJETRM
INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

Conventional infrastructure assessment primarily relies on qualified inspectors performing on-site visual examinations using standard inspection equipment. Although widely adopted in practice, this approach depends heavily on human expertise and often requires considerable time and manual effort, particularly for large or inaccessible structures. Though this is the most common practice, there are a few drawbacks. The inspection process is time-consuming, subjective, relies heavily on the experience of the inspector and is labour intensive. Limited access, safety issues and the volume of visual information to be analysed make it even more complicated to carry out the inspection when large infrastructure projects are added to the mix. Writing the inspection reports manually is also time consuming and can lead to differences in reporting between inspectors. With the latest developments of Artificial Intelligence (AI) and Computer Vision and Deep Learning, automation of structural inspections has also become a possibility. The ability of Convolutional Neural Networks (CNNs) for crack detection from digital images has proven to be excellent and the utility of semantic segmentation networks such as U-Net for the pixel-by-pixel localisation of crack regions can be seen as very advantageous. The procedures not only facilitate an examination speedup but also enhance the detection of cracks uniformity in comparison to the classic image processing methods.

Though these advances, there are many available AI-based crack detection algorithms that mainly generate the mask or detect cracks. In reality in engineering applications, however, engineers need more information, including crack sizes, severity levels, maintenance advice, etc. and a documented inspection report before deciding on maintenance. However, it remains a significant challenge between AI-based crack detection and engineering inspections processes in the field.

To remedy this, this paper presents the novel architecture of the Autonomous Structural Health Monitor (ASHM) - an intelligent software platform, which combines the power of deep learning with image processing and rule-based structural assessment in one inspection system. ASHM can be used as a standalone AI system, but is built as a unified inspection platform, allowing users to seamlessly integrate the tool into their workflow. To support different field conditions, the proposed platform provides three complementary inspection workflows: offline image analysis from stored datasets, direct acquisition through a connected camera, and continuous real-time inspection using a live video stream.

ASHM incorporates ResNet50 for the classification of the cracks and U-Net for semantic segmentation into the AI engine. The segmented crack regions are analyzed by using the algorithm of contour analysis, pixel counting and skeletonization with the OpenCV library, to estimate the area of the crack, crack length and maximum crack width, respectively. These measurements are then evaluated through a modular structural assessment module that identifies the level of damage, and gives appropriate maintenance suggestions. Last but not least, it also automatically produces an impressive PDF inspection report that covers all inspection findings which makes it appropriate for engineering documentation.

The proposed platform will fully integrate automated crack detection, quantitative crack analysis, engineering-based assessment and application report generation to solve the problems of the gap between deep learning models and actual tools for assessing cracks and the real condition of the bridge infrastructure.

Contributions of this work

Summaries of the major contribution of this research are presented as follows:

1) Developed the Autonomous Structural Health Monitor (ASHM) which is an Intelligent Software Platform to Automate Civil Infrastructure Health Assessment.
2) Design of the multi modal inspection framework for batch image analysis, static camera inspection, and live monitoring of the infrastructure.
3) The third is a combination of ResNet50 and U-NET, which automatically classifies the crack and segments it into each specific pixel.
4) Automated estimation of crack area, crack length and maximum width of the cracks using OpenCV accelerated contour analysis, pixel count and skeletonization methods.
5) The building of a rule-based structural assessment module to calculate development of severity class and maintenance recommendation.
6) Generating professional inspection Reports automatically in pdf format with ReportLab.

OBJECTIVES

Artificial Intelligence (AI), Computer Vision, and Deep Learning techniques have made remarkable progress in the last few years and this has led to tremendous progress in the field of Structural Health Monitoring (SHM). Many crack detection techniques using images have been proposed to enhance the speed, uniformity and

iJETRM
INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

reliability of infrastructure inspection. Traditional inspection methods were mainly based on manual visual inspection, which was time-consuming, subjective and challenging to be conducted for large-scale infrastructure assets. In recent decades, therefore, automatic crack detection and intelligent inspection systems [9, 10, 11, 13] have attracted more and more attention in research.

Traditional methods of crack detection largely used classical image processing algorithms like thresholding, edge detection, morphological techniques, and texture analysis. These techniques worked well under controlled lighting, surface, shadow, and background noise, but were very dependent on lighting, surface texture, shadows, and background noise. Consequently, they were unable to identify complex patterns of cracks, which were not common in real-world conditions pertaining to infrastructure [7], [10], [12].

With the advent of deep learning, convolutional neural networks (CNNs) have been used to learn discriminative image features automatically without manual feature engineering, and this has greatly enhanced the automated crack inspection technology. CNN architectures have been explored for the problem of crack classification, and one of the most widely used CNN architectures is the ResNet50 due to its residual learning structure, which allows it to be trained efficiently, avoiding the vanishing gradient problem that occurs with deeper architectures. Therefore ResNet50 has a high feature extraction and good classification performance in various crack data sets [1], [4], [9], [13].

Image classification can identify or not identify a crack, but does not give information on the geometry of the crack. This makes semantic segmentation techniques more and more significant for inspecting infrastructures. In particular, U-Net has shown promising results due to its encoder-decoder structure and skip connections, which help maintain the spatial information in the images during the reconstruction process. This allows for precise location of crack areas at the pixel level and thus allows the use of U-Net for crack dimension estimation and quantitative structural analysis, as in [2] [6].

Deep learning algorithms have been paired with image processing algorithms using the OpenCV library to detect geometric features of cracks including crack area, crack length, and crack width by several researchers. The measurements give useful engineering data other than just crack classification and can aid in wise maintenance judgments. However, many of the previous studies end with feature extraction and do not provide automated interpretation and maintenance advice or uniform inspection report [5], [7], [10], [12].

Structural Health Monitoring systems have been developing increasingly from being standalone Artificial Intelligence models to intelligent platforms combining Artificial Intelligence and software-based decision support. Even with all these advancements, present system only focuses on the precision of the model and not on the entire engineering inspection process. The multi-modal image acquisition, the automatic crack quantification, the maintenance recommendation and generation of the inspection report are not usually combined into a single software platform [5, 11].

To overcome these challenges, the proposed Autonomous Structural Health Monitor (ASHM) integrates multiple inspection modes, deep learning-based crack analysis, geometric crack measurement, rule-based structural assessment and the generation of the report in a single software platform. ASHM, unlike traditional crack detection models, is conceived as a total engineering inspection system, to help engineers during the complete infrastructure inspection process.

Table 1. Comparison of Existing Studies and Proposed ASHM Platform

Study/Approach	Crack Detection	Crack Segmentation	Crack Measurement	Maintenance recommendation	Report Generation
Traditional Image Processing	YES	NO	LIMITED	NO	NO
CNN-Based Classification	YES	NO	NO	NO	NO
ResNet50-Basede Models	YES	NO	NO	NO	NO
U-Net Segmentation Models	YES	YES	PARTIAL	NO	NO
Hybrid AI Models	YES	YES	YES	LIMITED	NO
Proposed ASHM	YES	YES	YES	YES	YES

iJETRM
INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

Platform					

Research Gap

From the reviewed literature, one can see that there has been a lot of progress already in automated crack detection and segmentation using deep learning techniques. Most of the current studies, however, focus on promoting classification accuracy, decomposition performance and do not adequately support practical engineering inspection workflows. Engineers must still hand-crank calculate measurements of the cracks, prioritize maintenance activities and create inspection reports.

This is where the proposed Autonomous Structural Health Monitor (ASHM) comes in, which combines together crack discovery based on Artificial Intelligence (AI) technology, geometric measurement of the crack size and location, rule-based structural evaluation, and automatic reporting in a single software package. This embedded process helps engineers overcome basic crack detection, and deliver useful structural inspection data with a single application.

METHODOLOGY

A. System Overview

The proposed "Autonomous Structural Health Monitor (ASHM)" is an intelligent software providing for automatic inspection of civil infrastructure using Artificial Intelligence and Computer Vision techniques. In contrast to most previous crack detection systems, which are limited to detecting cracks, ASHM offers the entire inspection process - and not just detection - through a single application which includes crack measurement, structural assessment, maintenance recommendation and the automatic production of the inspection report.

The platform can be used as a platform to support various inspection scenarios a field engineer might face during inspections. Depending on the requirement of the inspection, the user is able to analyse the images taken some time ago, inspect buildings with an attached camera or connect to an existing live camera feed for continuous monitoring. This multi-modal design enhances the flexibility of the proposed system and allows it to be applied to various forms of civil infrastructure such as buildings, roads, pavements, bridges, tunnels, retaining walls and masonry structures.

ASHM can be divided into 5 main processing stages. First images of the infrastructure are obtained by one of the inspection modes available. Preprocessed images acquired are then sent to the AI Analysis Engine, where the preprocessed image is analyzed using ResNet50 to classify the cracks, and using a semantic segmentation technique called U-Net to identify crack regions. The segmented images of the cracks then analyzed by image processing techniques based on OpenCV to calculate the crack area, crack length and maximum crack width. These measurements are fed into a Rule Based Structural Assessment Module, that Analyses the damage level and advises on maintenance activities. In the end, a professional PDF report of all inspections is made for documentation and future reference.

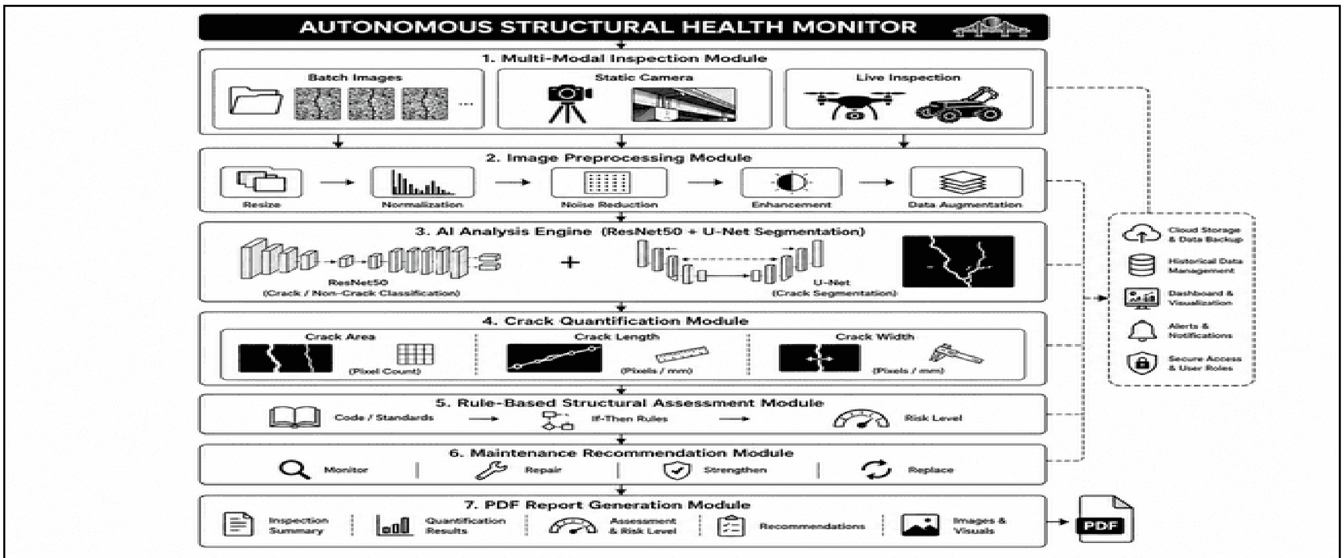


Figure 1. Overall Architecture of the Proposed ASHM Platform

iJETRM
INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

The modular design used in ASHM allows the independent development, as well as the subsequent enhancement of each processing stage. Other AI models, sensors or inspection technologies can be added on the platform without impacting the environments of the other software.

B. Multi-Modal Inspection Module

A key feature of ASHM is its ability to use three modes of operation to inspect infrastructure. The infrastructure will run multiple inspection policies, and the core AI processing pipeline will not need to be modified.

1) Batch Image Inspection

In this mode, users can upload an Infrastructure image file saved on their local computer(s) to be used in an offline analysis. It is specifically helpful for performing image analysis from drone surveys, scheduled inspections, or old infrastructure assessments. Individual images are uploaded and the inspection results are automatically created.

2) Static Camera Inspection

The static camera mode allows engineers to grab the picture from the connected camera. Through an image capture, it will be instantly moved into the AI processing pipeline for crack detection and the assessment of the structure. This mode will work for walls, bridge components, pavements, etc., in a stationary condition during pre-project site visits.

3) Live Infrastructure Inspection

In the live inspection mode, live video frames streaming from a live camera feed are processed. The frames are analysed in real-time, enabling inspectors to check the results of crack detection as they tour the building. This mode can be applied to future applications such as drone-based inspection, mobile inspection vehicles, or continuous monitoring applications.

Table 2. Operational Modes of ASHM

Inspection Mode	Input Source	Typical Application
Batch Image Inspection	Stored Images	Drone surveys, historical inspection records
Static Camera Inspection	Connected Camera	Buildings, bridges, pavements, walls
Live Infrastructure Inspection	Live Video Stream	Field inspection, mobile inspection, future drone applications

C. AI Analysis Engine

At the very heart of the proffered ASHM platform will be the AI Analysis Engine. It integrates image classification and semantic segmentation based on infrastructure images to accurately identify surface defects from infrastructure images. The system being proposed uses deep learning models that are able to automatically learn complex crack patterns from the training data, rather than relying on handcrafted image features.

All input images are preprocessed for the input of a deep learning model, which takes place for image resizing, normalizing and converting to tensors. For the processed image, a pretrained network (ResNet50) decides whether or not the image contains a crack. The chosen ResNet50 model was selected due to its residual learning architecture that allows efficient training of deep neural network that but still provides high classification accuracy.

The post-processing is done using a U-Net segmentation model and the images where segmentation is detected are taken care of. U-net is a pixel level segmentation model which can identify the boundaries of the crack area accurately at the pixel level instead of the image level in the classification network. This binary segmentation mask is used as the basis for measuring the cracks and performing structural assessments in subsequent steps.

iJETRM
INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

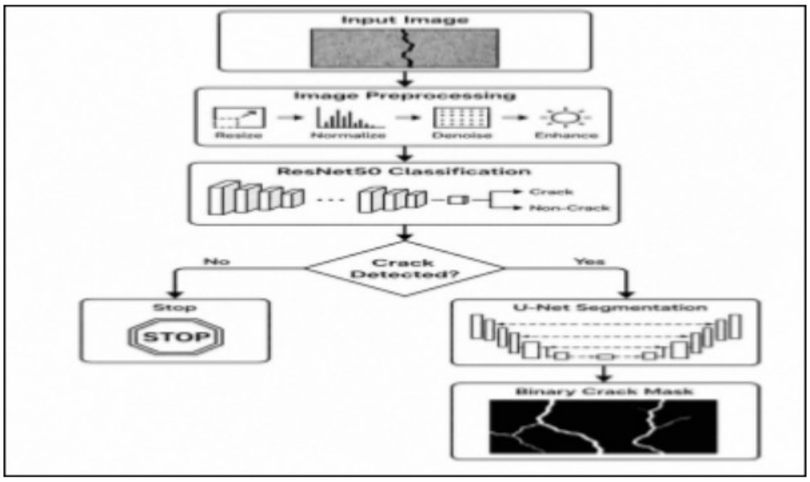


Figure 2. AI Processing Pipeline

D. Crack Quantification Module

Simply the presence of a crack is often not enough to conduct a practical inspection of infrastructure. Engineers need quantitative knowledge of gap size and shape before determining if the crack needs to be repaired or deepened. To this end, the proposed ASHM platform includes a unique Crack Quantification Module which automatically determines the properties of the identified crack in the segmented output.

The Crack Quantification Module takes the input of a binary crack mask produced by the U-Net segmentation model, and works on it using OpenCV image processing tools. First the contour detection is applied for the purpose of determining the external boundaries of each crack region. The detected contours are then analysed for estimating the crack area from the total number of pixels detected as cracks in the segmentation mask.

The region of the crack is segmented and skeletonized to obtain the lengths of cracks. Skeletonization renders the crack region with the original topology but with the centreline being a single pixel long. The number of pixels along the skeleton is then summed up and a length of the crack is estimated based on the pixel-to-distance conversion factor predefine.

The maximum crack width is estimated on the basis of analysing the perpendicular distance between crack boundaries at various locations of the skeleton profile. The greatest distance measured is taken as the "representative crack width" for the surface under examination.

Extracted measurements are saved and sent to the Rule-Based Structural Assessment Module where they are classified as to seriousness and recommended for maintenance.

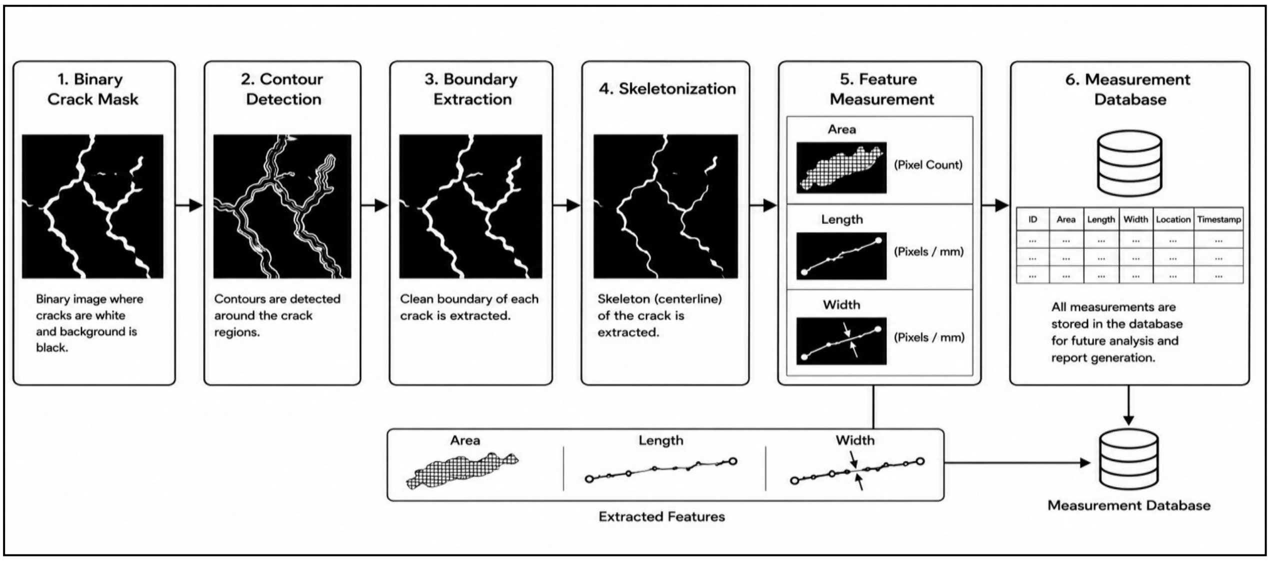


Figure 3. Workflow of the proposed Crack Quantification Module

iJETRM
INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

Crack Area Estimation

Crack area is the total surface area that is cracked. Once segmented, each crack pixel is recognized with the help of a binary mask. To get the total crack area the foreground pixels corresponding to the area of the crack is counted.

The crack area percentage is calculated as:

$$\text{Crack Area (\%)} = \frac{\text{Number of Crack Pixels}}{\text{Total Image Pixels}} \times 100$$

This normalized value enables the software to compare the severity of the crack in images of different resolutions.

Crack Length Estimation

The length of the crack gives clues about the length of the crack propagation on the surface being tested. Skeletonization is done to keep only the centreline of the crack and to delete unnecessary boundary pixels.

Once skeletonized, the length of the crack is found by adding up all of the skeleton pixel segments.

The crack length is computed as:

$$L = N_s \times S$$

Where:

The number of pixels that are not filled in the number of "skeleton" pixels.

S = Pixel-to-distance scale factor

Computationally efficient method to approximate the length of a crack for automated inspection.

Maximum Crack Width Estimation

Crack width is one of the most significant markers of degradation of structures. The proposed system is based on calculating the distance between the opposite side of crack boundaries at various cross-sections of the segmented crack for estimating the crack width.

The representative crack width is the maximum distance measured.

$$W = \max(d_i)$$

Where:

d_i is the distance from the crack at various positions along the crack.

Table 3. Crack Features Generated by ASHM

Feature	Extraction Method	Engineering Significance
Crack Area	Pixel Counting	Surface Damage Estimation
Crack Length	Skeletonization	Crack Propagation Analysis
Maximum width	Boundary Distance Measurement	Structural Severity Assessment

E. Rule-Based Structural Assessment and Maintenance Recommendation

Once the geometric characteristics of the crack are extracted, the proposed Autonomous Structural Health Monitor (ASHM) gives structure interpretation by employing a dedicated Rule Based Structural Assessment Module. This module is not only based on AI predictions, but also uses pre-defined engineering rules to transform crack measurements into meaningful structural information. This allows the software to provide engineers with a consistent guidance when making inspection decisions, but not the engineering judgement.

Two main parameters from the Crack Quantification Module are used in the assessment process: normalized crack area (%), and estimated maximum crack width. These parameters are compared with threshold parameters that are defined in the software. However, the threshold values are not set statically in the application, as different infrastructure projects can have different inspection criteria.

The system categorizes the detected crack based on the evaluated measurements as one of three severity levels: Minor, Moderate, or Severe. The inspection results are interpreted in a practical engineering context with the appropriate maintenance recommendation for each severity level.

ASHM greatly enhances the inspection workflow beyond simple image classification or segmentation by automatically converting image-derived measurements into actionable maintenance recommendations. This feature provides greater ability to be used for infrastructure inspection, condition assessment, and maintenance documentation.

Severity Classification Logic

The extracted measurements of the cracks are then compared against a set of inspection criteria in the Rule Based Structural Assessment Module. The decision process can be described as shown below:

Minor

iJETRM
INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

If both Normalized crack area and Estimated max crack width are less than the configured threshold values, then the crack is considered as Minor. These faults are usually a sign of early deterioration and only need to be monitored in future inspections.

Moderate

If the crack area is greater than the lower inspection limit, but less than or equal to the upper inspection limit, or if the estimated crack width exceeds the lower inspection limit, but is within the acceptable maintenance range, the crack is classified as Moderate. In this case, the software recommends scheduled maintenance or a detailed engineering inspection to prevent further deterioration.

Severe

If the measured crack characteristics do not meet the inspection criteria, with the measured crack characteristic being greater than the range of the inspection criteria, the crack is classified as Severe. The report generated suggests immediate engineering inspection and structural evaluation before a component in service.

Table 4. Severity Levels and Recommended Actions

Severity Level	Assessment Criteria	Recommendation Action
Minor	Crack measurements remain within configured inspection thresholds	Continue routine monitoring during future inspections
Moderate	Crack measurements indicate moderate deterioration	Schedule maintenance and conduct detailed engineering inspection
Severe	Crack measurements exceed critical inspection thresholds	Immediate engineering inspection and structural evaluation recommended

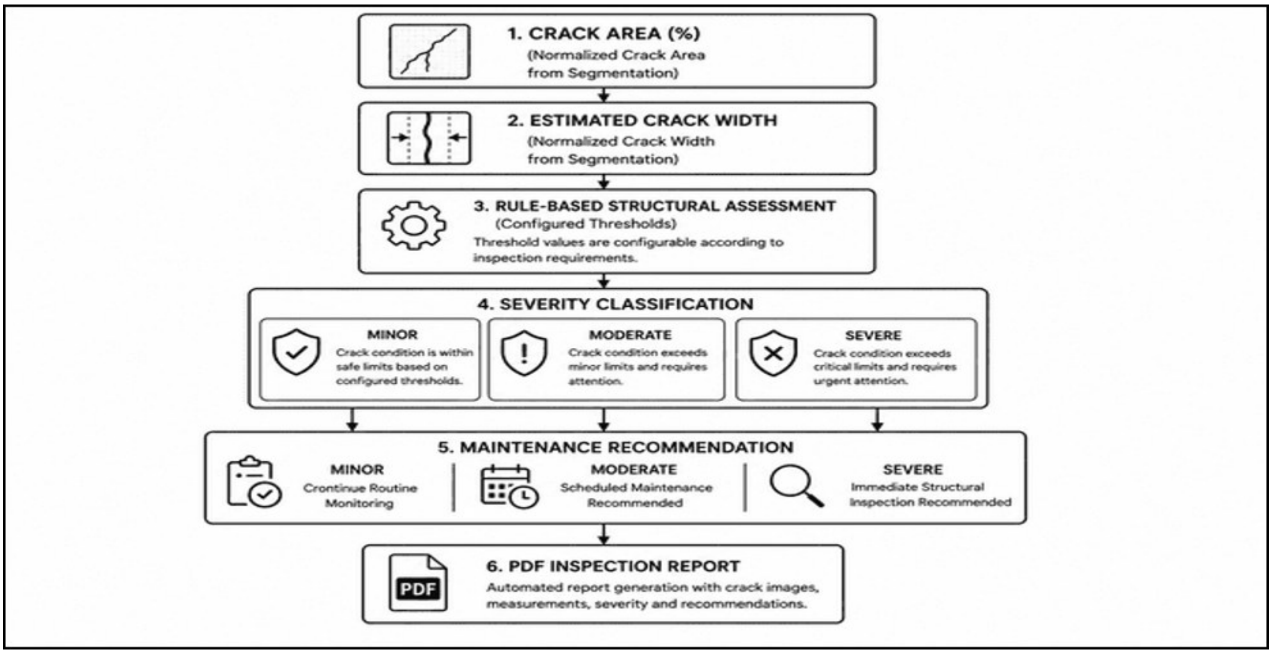


Figure 4. Rule-Based Structural Assessment and Maintenance

F. Automated Inspection Report Generation

The proposed ASHM platform generates a professional-based inspection report automatically upon completion of the structural assessment process to facilitate documentation and to decrease the manual effort for inspection reporting. The report uses the ReportLab Python report generating library and has a well-structured form in PDF with a complete summary of all the inspection's results.

The information gathered from all the previous processing steps, such as crack detection, segmentation, measurement, severity class and maintenance recommendation, is collected by the report generation module.

iJETRM
INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

The outputs are synthesized into a one report that can be stored electronically or turned over to engineers for further analysis.

The automatically generated report includes the following information:

- Inspection date and time
- Input image
- Segmented crack image
- Normalized crack area
- Estimated crack length
- Estimated maximum crack width
- Severity classification
- Maintenance recommendation

By automating report generation, ASHM minimizes manual documentation effort and ensures that inspection results are presented consistently across different inspection sessions.

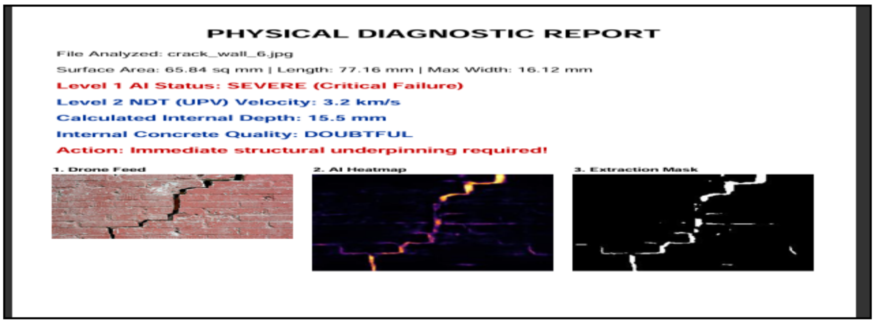


Figure 5. Automatically generated inspection report produced by ASHM after crack analysis and structural assessment

RESULTS AND DISCUSSION

B. Experimental setup

Proposed Autonomous Structural Health Monitor (ASHM) was designed and implemented in Python and is built as a software platform in interactive mode for inspection of civil infrastructure structures. TensorFlow and Keras were used to implement the deep learning models, and OpenCV was used to preprocess the images, calculate the length of the cracks, and visualize the results. The graphical user interface was created to accommodate various inspection methods: batch image inspection, static camera inspection and live inspection of the infrastructure.

To enhance the variety of crack patterns and surface textures, publicly available datasets were used along with infrastructure images collected in the experimental evaluation. The datasets include:

- Concrete crack images taken from bridge decks, pavements and walls from SDNET2018.
- Concrete Crack Images (CFD) – Surface crack images for crack classification and segmentation.
- Practical applicability of the proposed platform was evaluated through images collected from concrete, asphalt and masonry (brick) structures in the Custom Dataset.

Merging multiple datasets adds to the robustness of models that are trained by introducing a wider range of crack geometry, surface textures, lighting and infrastructure materials.

Table 5. Dataset Description

Dataset	Infrastructure Type	Purpose
SDNET2018	Bridge decks, pavements, walls	Model Training
CFD	Concrete surfaces	Validation
Custom Dataset	Concrete, asphalt, brick	Practical Evaluation

C. Model Training Configuration

iJETRM
INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

Transfer learning and semantic segmentation techniques were used to train the deep learning models. We used ResNet50 as the image classification network, and U-Net to produce pixel-level crack segmentation masks. All images were preprocessed to have the same input resolution to the neural networks and normalized prior to the pre-processing.

Table 6. Training Configuration

Parameter	Value
Classification Model	ResNet50
Segmentation Model	U-Net
Framework	TensorFlow / Keras
Image Processing	OpenCV
Programming Language	Python
Report Generation	ReportLab

D. Performance Evaluation

Performance of the proposed ASHM platform was assessed using the standard classification metrics, which are commonly used in deep learning research.

The following evaluation metrics were considered:

- Accuracy
- Precision
- Recall
- F1-Score

These metrics offer a holistic assessment of the crack detection ability, encompassing not only the overall accuracy of prediction but also the precision of detection, sensitivity to the presence of cracks and the balance between precision and recall.

Table 7. Performance Metrics.

Metric	Obtained Value
Accuracy	88.4%
Precision	85.1%
Recall	92.7%
F1-Score	88.7%

The experimental results show that the proposed AI engine can effectively detect crack patterns on various surfaces of infrastructure. The moderate value of recall shows that the system can identify the most important regions of cracks, which helps to decrease the chance of missing damaged regions during inspection. The F1-score has been obtained, which also verifies the balanced precision and recall performance of the model, and it is appropriate for cases in practical inspection.

E. Functional Evaluation of ASHM

In addition to model accuracy, the efficiency of ASHM was also assessed in terms of its functional capabilities, such as supporting a comprehensive inspection process.

The platform developed is successful in performing the following operations:

- Batch image inspection.
- Static camera inspection.
- Live infrastructure inspection.
- Crack classification.
- Pixel-level crack segmentation.
- Crack area estimation.
- Crack length estimation.
- Estimated maximum crack width calculation.
- Severity classification.
- Maintenance recommendation.
- Automatic PDF inspection report generation.

iJETRM
INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

ASHM also integrates all of the inspection stages into a single software package for engineering applications, unlike conventional crack detection models which end their run after making the prediction.

Table 8. Functional Comparison

Feature	Conventional AI Models	Proposed ASHM
Crack Detection	Yes	Yes
Crack Segmentation	Yes	Yes
Crack Area Measurement	Limited	Yes
Crack Length Estimation	Limited	Yes
Crack Width Estimation	Limited	Yes
Severity Classification	Limited	Yes
Maintenance Recommendation	No	Yes
Automatic PDF Report	No	Yes
Batch Image Inspection	No	Yes
Static Camera Inspection	No	Yes
Live Infrastructure Inspection	No	Yes

F. Sample Inspection Results

ASHM also developed the graphical interface that was used to create an interactive environment for infrastructure inspection. The three inspection modes are available for users based on the inspection scenario. Once acquired, the AI engine automatically identifies cracks, creates the segmentation mask, calculates geometric features of the cracks, assesses the severity of the structure and generates a professional inspection report.

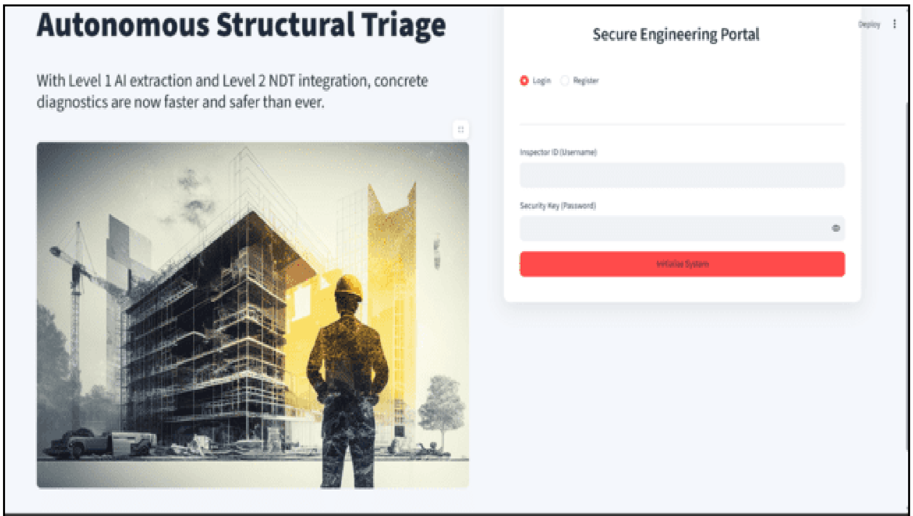
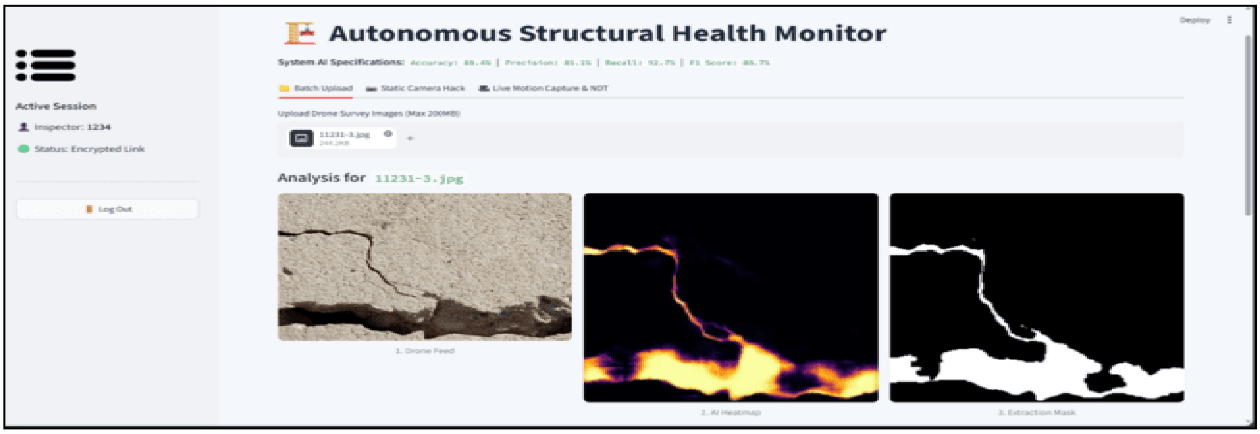


Figure 6. ASHM Login Page



ISSN: 2456-9348 (Online)
SJIF Impact Factor: 8.232

iJETRM

INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

Figure 7. Batch Image Inspection, Static Camera Inspection, and Live Infrastructure Inspection.

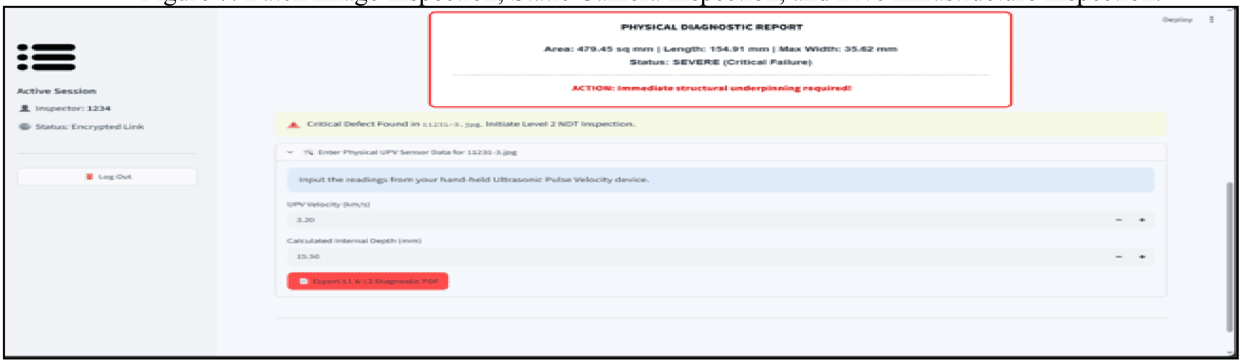


Figure 8. Generated inspection report

Discussion

The experimental evaluation shows that ASHM is able to use image analysis, but also includes engineering-based inspection functions to add to conventional deep learning-based crack detection. The system will recognize crack areas, and provide a quantitative characterization of the cracks, as well as a configurable rule-based assessment of structural severity, and a reporting of the results in standardized format. The following are some of their capabilities that make the inspection process easier while also cutting down manpower during infrastructure condition assessment.

The current implementation is based on image-based inspection of surface, but is expandable for the future integration with drone-based image inspection, with IoT-based monitoring and with physical non-destructive testing (NDT) methods. This flexibility enables ASHM to be the basis for future structural health monitoring applications that can be scaled up.

ACKNOWLEDGEMENT

The authors are grateful to Master of Computer Applications Department of Andhra University, Visakhapatnam, for their academic environment and facilities provided to conduct this research work. The authors are also thankful to the project guide, Mrs. K. S. S. Soujanya Kumari, Assistant Professor, for her valuable guidance, encouragement and constant support throughout the development of this work.

CONCLUSION

This paper proposed the design and realization of the Autonomous Structural Health Monitor (ASHM), a multi-modal intelligent software platform to provide automated civil infrastructure inspection with the help of Artificial Intelligence and Computer Vision technology. The proposed platform combines the capabilities of crack detection, quantification, rule based structural assessment, maintenance recommendation and automated report generation in a single inspection workflow, which differs from conventional crack detection systems mainly focusing on classification and segmentation.

The platform can be used in three modes, Batch Image Inspection, Static Camera Inspection and Live Infrastructure Inspection, allowing for flexibility in various inspection situations. A deep learning model using ResNet50 and U-Net were combined for both crack classification and pixel-level segmentation.

The image processing technique based on OpenCV was used for the estimation of the normalized crack area, crack length, and estimated maximum crack width from the segmented crack areas. These measurements were then analysed through engineering rules that can be configured to suit each specific crack and make a maintenance recommendation.

The experimental results showed that the proposed platform is capable of detecting cracks with high reliability and offers engineering-oriented inspection capabilities beyond the traditional AI-based methods. Documentation consistency is further enhanced with the automated generation of standardised PDF inspection reports and the manual effort involved in infrastructure assessment is reduced.

iJETRM
INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

Overall, ASHM shows that the combination of deep learning and a rule-based engineering assessment is a promising way to enhance the efficiency and usability of infrastructure assessment. The envisioned platform will offer a flexible software backbone that can help engineers carry out consistent, repeatable, and well documented structural inspect for various categories of civil infrastructure.

FUTURE WORK

The platform proposed by ASHM is able to successfully incorporate the AI-powered crack inspection feature into the automated structural assessment, however there are some features that could be added to enhance the platform's capabilities

Further studies could involve:

- Installation of the platform on Unmanned Aerial Vehicles (UAVs) for large-scale inspections of bridges, highways and hig- rise buildings.
- Incorporation of real Non-Destructive Testing (NDT) techniques to assist internal structural assessment, including Ultrasonic Pulse Velocity (UPV), Ground Penetrating Radar (GPR) and Infrared Thermography.
- Seamless interoperability with IoT (Internet of Things) sensors to monitor the structure's health and condition in real time.
- Camera calibration methods for converting pixel-based crack measurements into accurate physical dimensions (millimetres).
- Cloud-based inspection databases, for long-term monitoring and comparison of infrastructure condition, across multiple inspection cycles.
- Modelling of predictive maintenance to predict future crack propagation from the historical inspection data and machine learning.

These improvements would further expand the use of ASHM to a fully-fledged ecosystem for SHM.

REFERENCES

1)] K. X. Zhang, S. Ren, J. Sun, and He, *"Deep Residual Learning for Image Recognition," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, pp. 770–778, 2016.*
2) O. Ronneberger, P. Fischer and T. Brox, *"U-Net: Convolutional Networks for Biomedical Image Segmentation," Medical Image Computing and Computer-Assisted Intervention (MICCAI), LNCS 9351, Springer, pp. 234–241, 2015.*
3) S. Dorafshan, R. J. Thomas and M. Maguire, *"SDNET2018: An Annotated Image Dataset for Non-Contact Concrete Crack Detection Using Deep Convolutional Neural Networks", Data in Brief, vol. 21, pp. 1664–1668, 2018.*
4) S. Dorafshan and M. Maguire, *"Autonomous Detection of Concrete Cracks on Bridge Decks Using Deep Learning," Proceedings of Digital Imaging, 2017.*
5) A. Zhang, K. C. P. Wang, B. Li, E. Yang, X. Dai, Y. Peng and others, *"Automated Pixel-Level Pavement Crack Detection on 3D Asphalt Surfaces Using a Deep-Learning Network", Computer-Aided Civil and Infrastructure Engineering, vol. 32, no. 10, pp. 805–819, 2017.*
6) J. Long, E. Shelhamer, and T. Darrell, *"Fully Convolutional Networks for Semantic Segmentation," in Proceedings of CVPR, pp. 3431–3440, 2015.*
7) G. Bradski, "The OpenCV Library,*" Dr. Dobb's Journal of Software Tools, 2000.*
8) D. P. Kingma, J. Ba: Adam: *A Method for Stochastic Optimization, International Conference on Learning Representations (ICLR), 2015.*
9) I. Goodfellow, Y. Bengio and A. Courville, Deep Learning, MIT Press, Cambridge, MA, USA, 2016The Manila Times (2018, April 26). *At a glance: The Philippine Health Care System*
10) R. Szeliski, Computer Vision: *Algorithms and Applications, 2nd Ed., Springer, 2022*.
11) S. Shomal Zadeh, S. Aalipour Birgani, M. Khorshidi, and F. Kooban, *"Concrete Surface Crack Detection with Convolutional Based Deep Learning Models," 2024*
12) R. C. Gonzalez and R. E. Woods, *Digital Image Processing, 4th ed., Pearson, 2018.*
13) Y. LeCun, Y. Bengio, and G. Hinton, *"Deep Learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015.*
14) TensorFlow Developers, *TensorFlow*: *Large-Scale Machine Learning on Heterogeneous Systems, Google, 2015.*

INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY RESEARCH & MANAGEMENT (IJETRM)
Peer-Reviewed | Open Access | International Journal
https://ijetrm.com/

15) F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

