Design of Image Based Analysis and Classification Using Unmanned Aerial Vehicle

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Abstract— **Assessment of urban structural damage is crucial in the management of disasters like earthquakes or any structural damages, such as complete collapse, collapsed roofs, rubble piles, and sloping facets. To gather data for this assignment, high-resolution camera is installed on an unmanned aerial vehicle (UAV). Then utilize image based analysis and classification to detect and quantify any structural alterations or damage. Segmenting the photos into distinct objects based on their features, such as shape, size, and dimensions, is the process in image-based analysis and classification. Semantic reasoning involves inferring relationships between items by leveraging contextual information from the images, such as the position and orientation of the objects. In comparison to conventional visual inspection methods, image-based analysis and classification are used to identify and classify structural damage with greater accuracy and efficiency. This method uses Convolutional Neural Network for classifying images into damaged and non-damaged. Further, the identified damaged structures are classified according to the EMS-98 scale. Further, it is used to track structural changes over time and determine which maintenance and repair tasks should be prioritized.**

Keywords—Unmanned Aerial Vehicle, Image Based Analysis and Classification, Semantic reasoning, Classification, Segmentation, Structural Damage, Convolutional Neural Network

I. Introduction

Assessment of urban structural damage is crucial for post-disaster management to prioritize rescue and relief activities, support resource allocation decisions, and create plans for urban redevelopment. The last several years have seen a series of devastating urban disasters that have caused enormous losses in both lives and property. For instance, the recent 2023 Turkey-Syria Earthquake, the 2022 Indonesia Earthquake, the 2022 Great Earthquake in China, the 2022 Pakistan Floods, and so forth. Emergency responders frequently used unmanned aerial vehicles (UAV) to conduct efficient post-disaster rescue and reconnaissance during these tragic incidents. Traditional techniques of damage assessment, which mostly rely on manual surveys and ground-based inspections, are frequently time-consuming, inaccurate, and unsafe. The subjective character of human observation and measurement, limits the accuracy of traditional techniques of damage assessment, as stated in a report from the National Institute of Standards and Technology (NIST) [3,4]. The findings advise using cutting-edge imaging technology to increase damage assessment accuracy.

Drones with high-resolution cameras can offer detailed photographs of damaged structures, enabling more precise and effective damage assessment, according to research from the University of California, San Diego [3].

Although the physical inspection is not as necessary and huge areas may be assessed quickly, using UAVs for damage assessment in metropolitan areas can be cost-effective [FEMA, 2014] [7]. By blocking access to dangerous or difficult-to-reach regions, it ensures worker safety. In comparison to conventional procedures, it increases efficiency by cutting assessment times by up to 90% [5]. Yet, because of their size and intricacy, manually examining these images can be difficult.

The ability to detect structural damage features by UAV, mostly images associated with heavy damage or total collapse, or D4-D5 in the commonly used European Macroseismic scale of 1998, is made possible by the CNN model. Convolutional Neural Network (CNN), is a deep learning model commonly used in computer vision tasks, including image recognition and classification. In the context of UAV-based structural damage assessment, a CNN is used to automatically identify and classify different types of damage in buildings, bridges, or other structures.

To identify and analyze damage in metropolitan areas, a technology called image-based analysis and classification (IBAC) transforms high-resolution photos into meaningful objects based on their features. IBAC has been used in a variety of fields, including forestry, agriculture, and urban planning. IBAC is a remote sensing approach that identifies and classifies items in an image using image segmentation and classification. Building and infrastructure damage is identified and measured using IBAC. High-resolution photos are used. It produces segments of Image-based analysis and classification for subsequent analysis. It is used to assess the features that were extracted to locate structurally damaged areas. The extent and seriousness of the damage are then determined, including the size and position of significant cracks.

II. LITERATURE REVIEW

It is important to manage structural damage in urban areas. The prevention, planning for, and response to potential natural or man-made disasters that may occur in urban environments are the goals of disaster management in urban regions.

Janalipour, Milad & Mohammadzadeh, Ali [2] proposed finding building damage after an earthquake would aid in quick disaster relief and response. This work used a pre-event vector map and a post-event pan-sharpened high spatial resolution image to suggest an effective method for detecting building damage in an urban region following an earthquake. First, preprocessing was done on the satellite image from after the occurrence. Second, the outcomes of classifications based on objects and pixels were combined. The areas, rectangular fits and convexities of buildings' geometric attributes were retrieved in the section that follows. To determine the degree of building damage, a decision-making system based on these characteristics and the adaptive network-based fuzzy inference system (ANFIS) model was developed. To determine the ANFIS model's optimal parameters that would produce reliable damage estimates, a thorough sensitivity analysis was conducted. J. Fernandez Galarreta et al. [1] constructed model which uses 3-D points cloud to identify D4-D5 building damage and then using OBIA model to analyze the damage.

Assessing post-earthquake damages of building using UAV imagery Huang et al. [3] presented method using OBIA. The result shown higher accuracy than traditional method. Alon Oring [4] used the approach of a deep convolutional neural network to do picture pre-processing, segmentation, and feature extraction (CNN). A support vector machine (SVM) classifier is then trained using the collected characteristics to differentiate between the building's damaged and undamaged areas.

Norman Kerle et al. [5] focused on 3D point clouds and geometric derivatives when used UAV photos for structural damage assessment and used OBIA to extract structural damage features. For Real-Time Mapping of building with low-cost solutions Francesco Nex et al. [6] proposed study that showed how low-cost, commercial UAVs can produce building damage maps in real time. But, only tiny datasets with mature data processing demonstrate real-time possibilities. A larger dataset is processed with longer orientation delays.

Christopher Reardon constructed a deep learning-based method for classifying and identifying objects in UAV data. They identify and categorise items in the photos using a convolutional neural network (CNN), attaining high accuracy rates. The suggested strategy might be used in urban planning and catastrophe response. Similarly, Yuhao Kang et al. presented a method for neural network-based object detection and classification with data augmentation. The scientists achieved high accuracy rates in object detection and classification by training their model using aerial pictures. They contrast the effectiveness of their model with other cutting-edge techniques for object recognition and classification.

Wu et al. [8] constructed model for earthquake damage assessment of urban buildings using OBIA and semantic reasoning. It uses deep learning-based semantic segmentation approach to identify damaged areas and rule-based expert system to classify damage severity.

III.PROPOSED METHODOLOGY

The goal of this study is to use a UAV to gather high-resolution imagery. To determine the amount of damage, CNN will be employed, which enable the professional to classify into levels D0, D1, D2, D3, D4, and D5 damage. The majority of the data is collected from a UAV, with some data also coming from a camera mounted on a pole. Levels D0 indicates Zero damage, D1 indicates mild damage, D2-D3 indicates moderate to heavy damage, and levels D4 and D5 indicates tremendous damage respectively. It made it simple for experts to pinpoint D4 and D5 as the most impacted structures. IBAC will then be used to evaluate the photos of buildings' roofs and facades that cannot be recognised.

Table 1. levels of Structural Damages

Damage Features	**EMS-98**
Zero Damage	D0
Mild Damage	D1
Moderate to Heavy damage	D2-D3
Tremendous damage	D4-D5

Data Collection

The AiBot X6 V.1 UAV, which has a camera mounted on a 7-meter pole, was used to gather the high definition photos used in this investigation. The major applications of AiBot X6 V.1 include surveying and mapping structural damage. At a flying height of 7 metres, the UAV is used with a Canon 600D and an 80mm fixed zoom length provides a Ground sample distance (GSD) of almost 70mm. A straightforward

Canon Powershot S100 is mounted to the pole. It was positioned at a damaged structure about 15 metres away, and the ground sample distance was close to 1 centimetre. Pictures are collected from the Turkish provinces of Adana, Adiyaman, Hatay, Kilis, and the cities of Nurdagi and Gaziantep, which are immediately outside the provincial capital and will experience a magnitude 7.8 earthquake in 2023 that will cause significant structural damage.

Fig 1 . Unmanned Aerial Vehicle AiBot X6 V.1

Data Preprocessing

Preprocessing data is a crucial step in any machine learning application, and structural damage assessment using unmanned aerial vehicles is no exception. For image processing tasks like the evaluation of structural damage from UAV photos, convolutional neural networks (CNNs) are a common option. In order to ensure that the UAV photos are uniform in size, have consistent illumination, and are free of noise or distortion, they are first preprocessed by resizing, cropping, normalising, and/or standardising. For better results, this dataset was later converted from png to jpg format. The dataset has been manually labelled according to the degree of structural damage, which can be divided into classes like mild, moderate, or severe. Using image-based analysis and classification, the significant features are further extracted. Edge detection, texture analysis, color-based segmentation, and convolutional neural networks for image classification are some of the techniques used to spot structural damage in images. Moreover, training and testing sets have been separated from the dataset.

Convolutional Neural Network

The CNN model enables us to identify structural damage patterns, primarily linked to severe damage or catastrophic collapse, or D4-D5 in the widely used European Macroseismic scale from 1998. Deep learning model known as Convolutional Neural Network (CNN) is frequently used in computer vision applications including picture recognition and categorization. A CNN is used to automatically recognise and classify various types of damage in buildings, bridges, or other structures in the context of UAV-based structural damage assessment. High-resolution pictures of the target structure are taken from a variety of perspectives and angles using a UAV. The CNN then uses these images as input data. High-resolution pictures of the target structure are taken from a variety of perspectives and angles using a UAV. The CNN then uses these images as input data. Following collection, the images are preprocessed to improve their quality and eliminate any noise or artefacts that would make it difficult for CNN to correctly identify damage. The preprocessed images are used to train the CNN, which entails feeding the network a lot of labelled data (such as pictures of damaged and undamaged structures) and letting it discover the characteristics that set the two apart. After training, the CNN is put to the test on a collection of photos it has never seen before to gauge. The speed and accuracy of damage detection can be increased by utilising a CNN in UAV-based structural damage assessment, enabling more effective and efficient inspections of buildings following catastrophes or other potentially damaging occurrences.

IBAC feature extraction

The Aim of this stage is to thoroughly inspect the building roofs and facades that had not previously shown any symptoms of D4-D5 damage[1,3]. In order to identify different sorts of damage, such as fractures, debris piles, slanted facades, holes, and misplaced roof tiles, The IBAC is used to analyse photos of roofs and facades. In order to extract valuable information, Image Based Analysis and classification (IBAC) entails segmenting a picture into meaningful items and classifying these objects[3]. In the field of remote sensing, IBAC has become a potent tool that allows for efficient image processing by applying feature or process knowledge in a way that provides manual or visual analysis.

Damage-feature extraction can be divided in multiple steps: first, image segmentation is used to spot different features in the image, and then object classification is used to assign labels to these features depending on their properties. Following completion of this, the data obtained will be used for accuracy assessment [3]

The technique of segmenting an image involves breaking it up into homogeneous areas or objects based on its spectral, spatial, and contextual characteristics. After collecting high-resolution photographs from UAVs, preprocessing will be carried out to remove noise, fix geometric errors, and improve image contrast. To achieve correct segmentation, this step is essential[3]. In this case, a multi-resolution segmentation using a small scale parameter to create small (oversegmented) objects was used as the first phase in a two-step segmentation process, which was then followed by a particular difference segmentation. This method made sure that huge, unitary objects, like facades, were created from segments that were mostly spectrally homogenous, but minor, clearly defined or heterogenous elements, like cracks or holes, were left as separate segments. Following that, the

Fig 2. No Structural Damage Images

classification of damage and non-damage object types wasdone based on typical topological, topographical, and size features.

Fig 3. Structural Damage Images

The classification strategy for both roofs and facades attempted to imitate field surveyors' methods. Before moving on to the smaller, more geometrically distinct classifications, such as windows, columns, cracks, holes, and dislocated tiles, it was necessary to first classify the bigger objects, such as undamaged roof and façade objects. With the use of different object picture features, these were located. Following the classification of the basic damage features, their topological relationships were employed to ascertain each feature's semantic dimension as well as to spot connected and crossing cracks.

Create a damage assessment report using the information gleaned from the OBIA analysis. The location, scope, and severity of the damage are determined using the classification results.

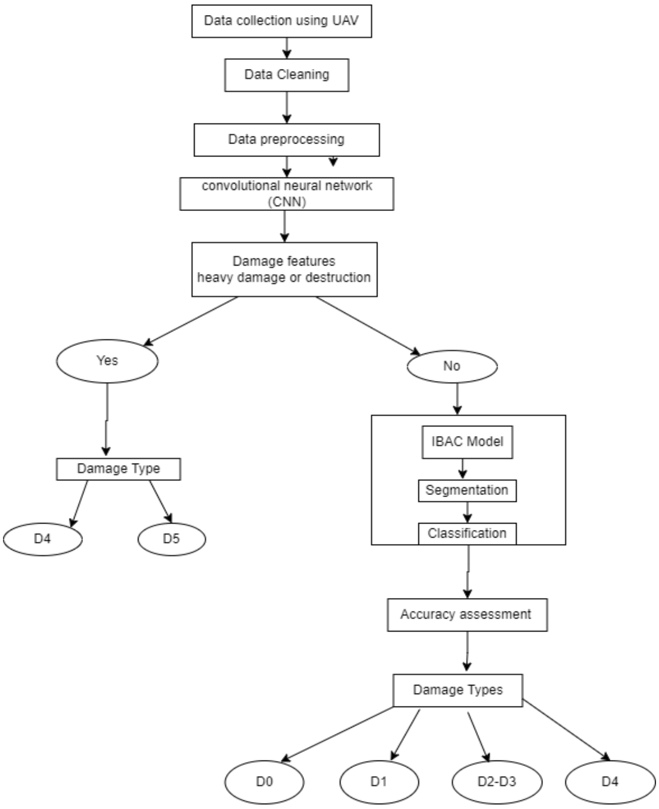

Fig 4. Overview of the methodology

IV. RESULTS

AiBot X6 was used to collect data from UAVs, and this data was then further examined. The primary goal is to categorise structural damage using the EMS-98 scale, which is used to analyse and assess the correctness of urban structural damage. Firstly, images are converted to the png image to the jpg image, and then by using Elbow method value of k has been calculated as shown in fig. 5. Elbow method is a technique used in K-means clustering to determine the optimal number of clusters to use for a given dataset. The K-means clustering is used to separate the photos into damaged and non-damaged categories which is depicted in fig. 6 and fig. 7

Subsequently, with a batch size of 32 and an epoch of 5, The CNN model is utilized to classify the dataset into damaged and undamaged structures. The accuracy of the damaged and undamaged image datasets has then been assessed which is depicted in fig. 8

Then, with a batch size of 64 and an epoch of 10, damaged images have been further categorised into D0, D1, D2-D3, and D4-D5 levels. Also, the categorised level is utilised for accuracy assessment which is depicted in the fig. 9

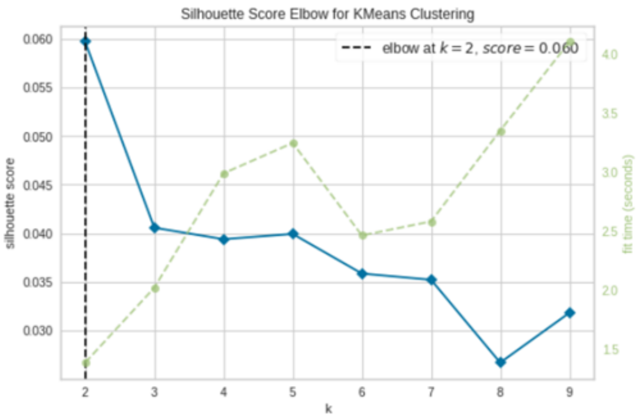

Fig 5. K-means clustering (k=2) for damaged & non-damaged

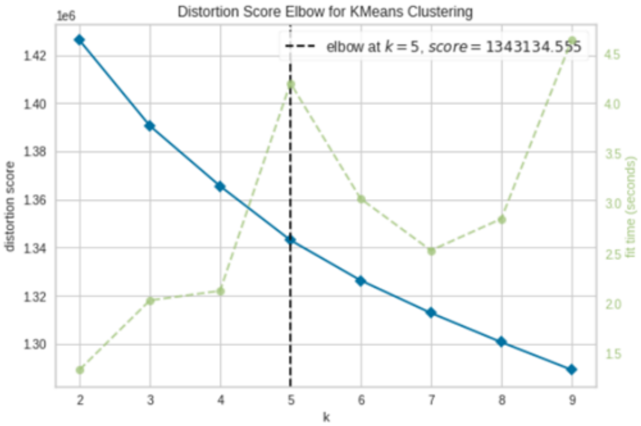

Fig 6. K-means clustering (k=5) for damaged & non-damaged

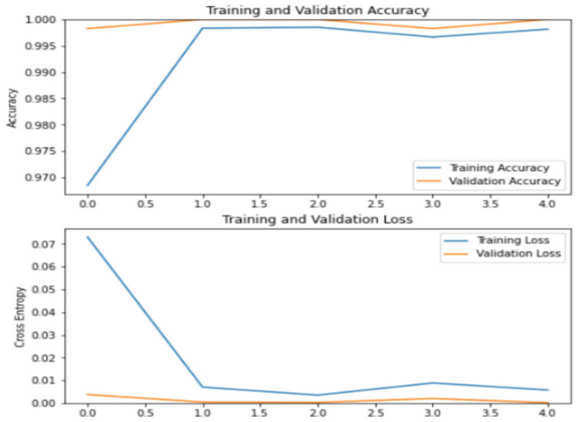

Fig 7. Accuracy assessment of training and testing phase for damaged and non-damaged images

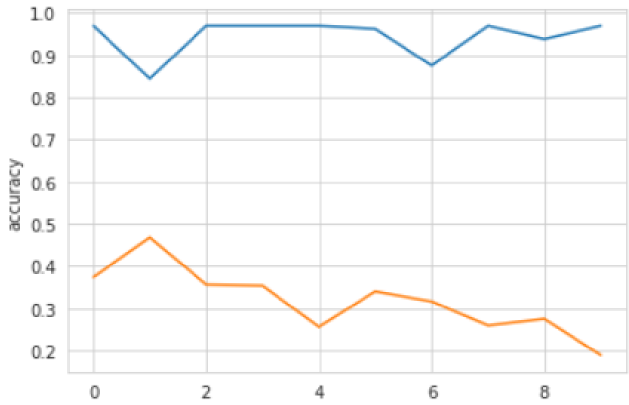

Fig 8. Accuracy assessment of damaged levels

V. CONCLUSION

The objective of this model is to capture the high resolution images from UAV. Unmanned aerial vehicles (UAVs) analyse urban structural damage utilising the sophisticated techniques of object-based image analysis (OBIA) and semantic reasoning. Building footprints and rooftop structures are two examples of the pertinent aspects that may be effectively extracted from UAV data by OBIA and then evaluated and categorised using semantic reasoning methods.

UAV-based damage assessment can be carried out quickly and accurately by combining OBIA and semantic reasoning, providing crucial data for disaster response and recovery activities. By eliminating the need for ground-based evaluations in dangerous regions, the deployment of UAVs also improves safety. Then use this images for classification firstly into damaged and non-damaged and then classifying it into D0, D1, D2-D3 and D4-D5 levels.

The implementation of OBIA and semantic reasoning for UAV-based damage assessment still faces challenges related to the need for high-quality photos and the development of precise classification models. Nonetheless, given the benefits of this approach, additional research and use in disaster management could be profitable

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