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Damage Detection in Heritage Sites

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Abstract: Manual inspection (i.e., visual inspection and/or with professional equipment) is the most predominant approach for identifying and assessing superficial damage of masonry historic structures at present. However, this method is costly and at times difficult to apply to remote structures or components. Existing convolutional neural network (CNN)-based damage detection methods have not been specifically designed for the multiple damage identification of masonry historic structures. To overcome these limits, a deep architecture of CNN damage classification techniques for masonry historic structures is proposed in this article using a sliding window-based CNN method to identify and locate four categories of damage (intact, crack, efflorescence, and spall) with an accuracy of 94.3%. This is the first attempt to identify the multi damage of historic masonry structures based on CNN techniques and achieve excellent classification results. The data are only trained and tested from images of the Forbidden City Wall in China, and the pixel resolutions of stretcher brick images and header brick images are 480 × 105 and 210 × 105, respectively. Two CNNs (AlexNet and GoogLeNet) are both trained on a small dataset (2,000 images for training, 400 images for validation and testing) and a large dataset (20,000 images for training, 4,000 images for validation and testing). The performance of the trained model (94.3% accuracy) is examined on five new images with 1,860 × 1,260 pixel resolutions.

Keywords: Predicting the damages in the heritage sites using CNN architecture.

I. INTRODUCTION

State-of-the-art structural health monitoring (SHM) techniques have been studied and applied to historic structures because of the complexity, heterogeneity, and long tradition of existence of the structures. Masonry bricks have always been one of the key materials in historic structures, used primarily for building walls, which carry loads and provide security. The safety of masonry structures is of vital importance in the maintenance of historic architecture. As structures gradually deteriorate, they are likely to be subjected to various forms of damage, mainly resulting in the reduction of strength, stiffness, and integrity. Such damages are always reflected on the surface of structures, such as cracks, efflorescence, and spalls. Hence, it is of great significance to identify and localize the superficial damage quickly and efficiently. This work can be used as guidance for the structural repair, maintenance, and management of historic structures. The most predominant superficial damage detection method in actual practice is in situ visual inspection supplemented by professional equipment. This method has significant advantages of operation but requires extremely high levels of professional experience and is costly. For instance, in terms of crack detection, the operators must be capable of fully understanding the properties of the inspected cracks and determine whether repairs are needed. Large-scale inspection using this method is a time- and labor-intensive process. Data acquisition requires much work to acquire and record data. In big data processing, this method is based on the use of many professionals to analyze and process the collected data, which is time consuming and labor-intensive. Therefore, large-scale inspections can only be implemented with sampling detection and periodic inspection. Although manual visual inspection can achieve effective performance in most scenarios, it is sometimes unreliable because serious damage may not be detected. Hence, such methods may not provide necessary guidance for the maintenance of historic structures, which can result in a substantial increase in maintenance costs. One solution to these problems is to use sensor-based SHM systems. However, collecting data using various sensors and monitoring every historic structure in a short time require a large expense. Moreover, SHM systems that are integrated and installed into historic structures also require professionals to operate them, and the distributed devices are difficult to implement in large-scale structures. Therefore, it may not be a

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cost-effective choice. In recent years, many studies on vision-based SHM techniques have been performed with the goal of replacing conventional manual inspection. Because professionals can only speculate with visual inspection, it is possible to use computers to detect the damage based on digital image processing. However, such method requires manual feature extraction. The images of the structures are sensitive to noise such as stains, shadows, and non uniform lighting conditions. Hence, the detection results are substantially affected by this noise, and no optimal solution exists

Fig 1:- Datasets of Damaged Heritage Sites

Monuments are also the tourist destinations in any country. They even are representations of great achievements present in art and architecture. It is therefore important to preserve them for the purpose that we can continue to enjoy their majestic views and the future generations too can learn from them. They are a part of India's vast heritage because they show the historical influence of any country with respect to its citizens. These are the important and visual sourceof analyzing the history of India, very precisely. In India, there are lots of monuments which are connected with the religious feelings of the people. One example is The Sanchi Stupa- incarnating the presence of Buddhism teachings. Second example is of Khajuraho Temples- where both Hinduism andBuddhism feelings have been amalgamated.

II. PROBLEM DEFINITION

Compared with manual inspection ,damage monitoring of large scale historic buildings is efficient and provides powerful supplement for manual inspection.Especially in some cases that cannot be easily reached by manual workers,the camera images are used for automatic damage detection so a lot of time anf manpower can be saved.

Damage detection in heritage sites is a critical issue that needs to be addressed in order to ensure the preservation of cultural heritage. Many heritage sites around the world are susceptible to damage due to various factors such as natural disasters, environmental factors, and human activities. Damage detection is crucial for the timely identification of any structural defects, which can lead to the implementation of effective repair and maintenance measures, thereby safeguarding the heritage site for future generations. However, the process of damage detection in heritage sites is often challenging due to the unique nature of these structures and the limitations of existing detection technologies. Therefore, there is a need for innovative approaches to address this problem and ensure the long-term preservation of cultural heritage.

2.1 Objectives

Early Detection: The primary objective is to detect damage as early as possible so that appropriate measures can be taken to prevent further damage.

Preservation of Heritage Sites: The preservation of heritage sites is of utmost importance. The objective is to detect damage and preserve the heritage site for future generations.

Structural Assessment: The objective is to assess the structural integrity of the heritage site and identify any structural deficiencies that require attention.

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Preventative Maintenance: The objective is to identify potential areas of damage and perform maintenance before it becomes a major issue.

Minimize Risk: The objective is to minimize the risk of damage to the heritage site and ensure the safety of visitors.

Sustainability: The objective is to ensure the sustainability of the heritage site by implementing long-term solutions for maintenance and preservation.

Use of Advanced Technology: The objective is to use advanced technology such as remote sensing, drones, and artificial intelligence to improve the accuracy and efficiency of damage detection in heritage sites.

III. LITERATURE SURVEY

Paper [1] "Damage detection in heritage structures: State of the art review and future directions" by A. İlkay and E. Safak, published in Engineering Structures, 2017.

This review paper provides a comprehensive analysis of the various techniques and methods used for damage detection in heritage structures. The paper covers the different types of damage, the challenges of damage detection, and the various technologies and approaches used for damage detection in heritage structures.

Paper[2]"Damage assessment of historical buildings: A review of existing approaches" by M. Roca-Pardiñas, R. Cao, and F.J. Rodríguez-Pérez, published in Engineering Failure Analysis, 2014.

This paper provides a detailed overview of the different approaches used for damage assessment in historical buildings. The paper covers the various types of damage, the importance of damage assessment, and the different techniques used for damage assessment in historical buildings.

Paper[3]"Application of Infrared Thermography for the Evaluation of Historic Building Envelopes: A Review" by M. Ioannou and T. Theodosiou, published in Sustainability, 2021.

This paper provides a review of the use of infrared thermography for the evaluation of historic building envelopes. The paper covers the basic principles of infrared thermography, the applications of infrared thermography in heritage buildings, and the benefits and limitations of using this technology.

Paper[4]"Non-destructive testing and structural health monitoring for the conservation of cultural heritage buildings" by R. Oliveira, C. Ribeiro, and R. Veloso, published in Construction and Building Materials, 2015.

This paper provides an overview of the use of non-destructive testing and structural health monitoring for the conservation of cultural heritage buildings. The paper covers the different techniques used for non-destructive testing and structural health monitoring, their benefits, and limitations.

Paper[5]"Remote sensing and GIS applications for cultural heritage conservation" by S. Chaudhuri and S. Ghosh, published in Journal of Cultural Heritage, 2015.

This paper provides an overview of the use of remote sensing and GIS applications for cultural heritage conservation. The paper covers the different types of remote sensing technologies, their applications in cultural heritage conservation, and the benefits of using GIS for cultural heritage conservation.

IV. PROPOSED SYSTEM

The surface damage detection methods proposed in this article regard a single brick in the structures as a unit, which implies that the detection seeks to find damaged bricks in the structures. The classification technology is a powerful supplement to the health monitoring of the historic masonry structures and must be integrated with other, possibly multidisciplinary, information to determine safety measures. Periodic and efficient surface inspection can provide necessary guidance for the damage diagnosis and management of historic buildings, which is of great significance.

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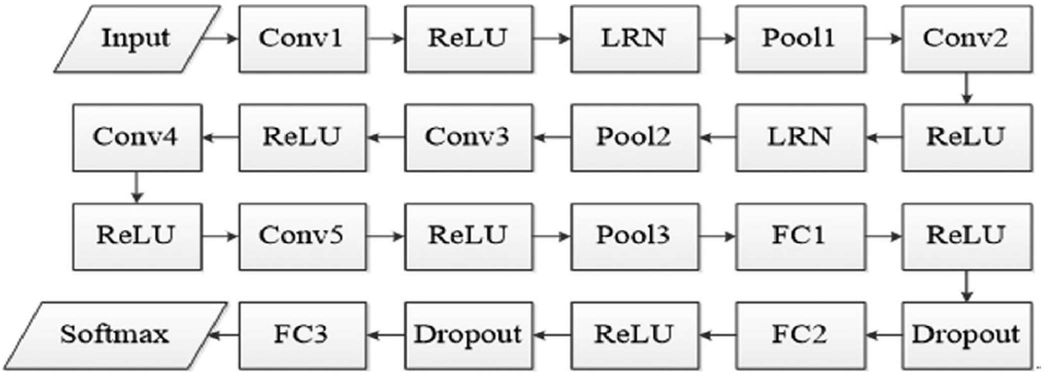
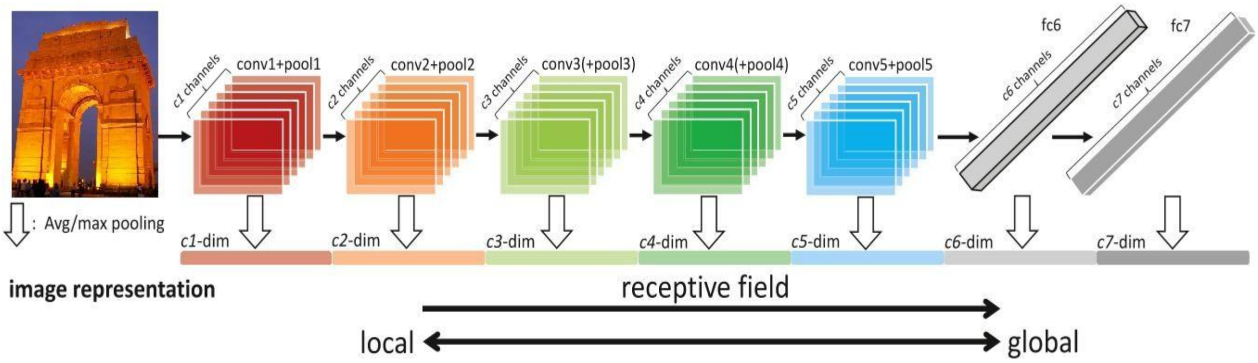


Fig2:-CNNArchitecture

V. METHODOLOGY



1.**Convolutional Layers**: These layers apply convolution operations to input data to extract local patterns or features. Convolution involves sliding a small filter or kernel across the input data and computing dot products between the filter and the overlapping regions of the input. This process helps the network learn to detect features such as edges, corners, and textures from the input data.

2. **Pooling Layers**: These layers down sample the feature maps generated by the convolutional layers, reducing the spatial dimensions while retaining important features. Common types of pooling operations include max pooling and average pooling.

3. **Activation Functions**: These functions introduce non-linearity into the network, allowing it to learn complex non-linear relationships in the data. Common activation functions used in CNNs include ReLU (Rectified Linear Unit), sigmoid, and tanh.

4. **Fully Connected Layers**: These layers are typically used at the end of the CNN architecture and are responsible for making the final decision based on the extracted features. Fully connected layers connect every neuron to every other neuron in the previous and subsequent layers, allowing the network to learn global patterns and make predictions.

5. Dencovn layer :- Deconvolution is to regenerating the image from the convolution output layer, by doing this we can be sure that the convolution is extracting the correct features from the image.

6. **Dropout:** Dropout is a regularization technique commonly used in CNNs to prevent overfitting. It randomly sets a fraction of the neuron outputs to zero during training, which helps improve the network's generalization performance and robustness.

7. **Softmax Layer**: The softmax layer is typically used for multi-class classification tasks, where the network needs to assign input data to one of several possible classes. The softmax function converts the output of the fully connected layers into a probability distribution over the classes, allowing the network to make class predictions.

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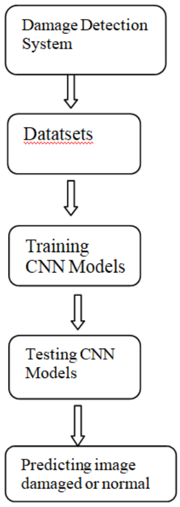
Block Diagram

Block Diagram



Building new CNNs for damage identification and classification requires time and effort, especially in hyper parameter optimization. A hyper parameter search can take weeks or even months for deep networks. The validation performance should be checked after every epoch in the training process to configure and optimize the hyper parameters. Cross-validation is usually required when choosing the best parameters and a large number of checkpoints must be recorded. Hence, building a new CNN from the very beginning is challenging; however, it is not the focus of this study. Fortunately, the best CNN models of the LSVRC in recent years are available to use and fine-tune. The optimal network architecture for this brick damage detection must be explored using trial-and-error and guided by checking the validation set error.

VI. CONCLUSION

This article presents a damage identification technology for masonry historic structures based on deep learning. The technology is based on deep CNNs. Based on the AlexNet and GoogLeNet models, this article develops AlexNet-for-MHSD and GoogLeNet-for-MHSD models to detect the surface damage of masonry historic structures. Then, the recognition classifier for three categories of masonry damage is identified by network training. More importantly, based on the high-accuracy model a sliding window algorithm suitable for historic structures is developed to perform rapid identification and locating of masonry historic structural damage. Using Beijing' Forbidden City wall structure as the research object, the training and verification of the four-category model are performed. Based on the sliding window algorithm,the wall samples are tested and three types of damage: spall, crack, and efflorescence, are quickly and effectively identified.

VII. RESULT

In the results part the cnn model is used in which the model accuracy, loss and the roc curve plot also plotting in the results part in which the results are displayed in the python shell window in which the accuracy of the model is displayed. In testing damaged heritage will be in percentage wise grading is assigned and the output is displayed in which preprocessing, feature extraction, segmentation and classification all this commands are used and by using the grading the damaged image the results will be shown by undergoing the process of preprocessing, feature extraction and segmentation process then the classification or the result of given image is damaged means percentage of detection in which percentage of damaged image in grading or whether it is a normal image it will be predicted by using the damaged means there three grading for damaged image and normal heritage images also there in which the results will be predicted and displayed.

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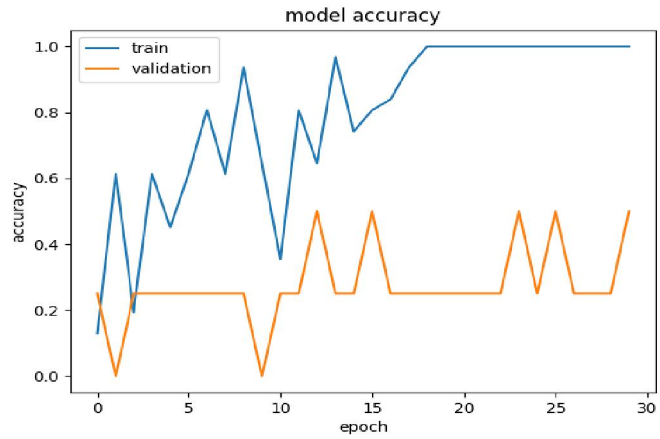
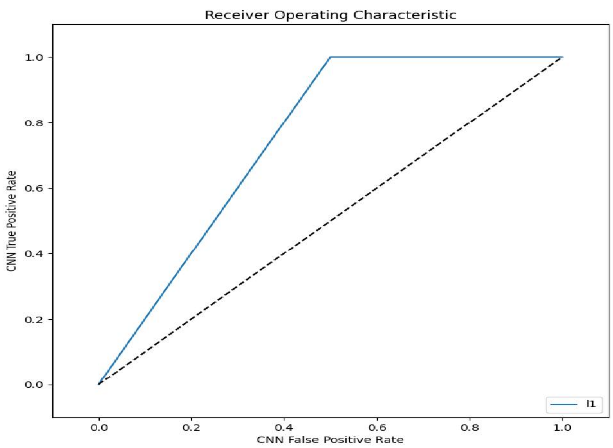
Accuracy plot:



Loss plot:

Roc curve plot:



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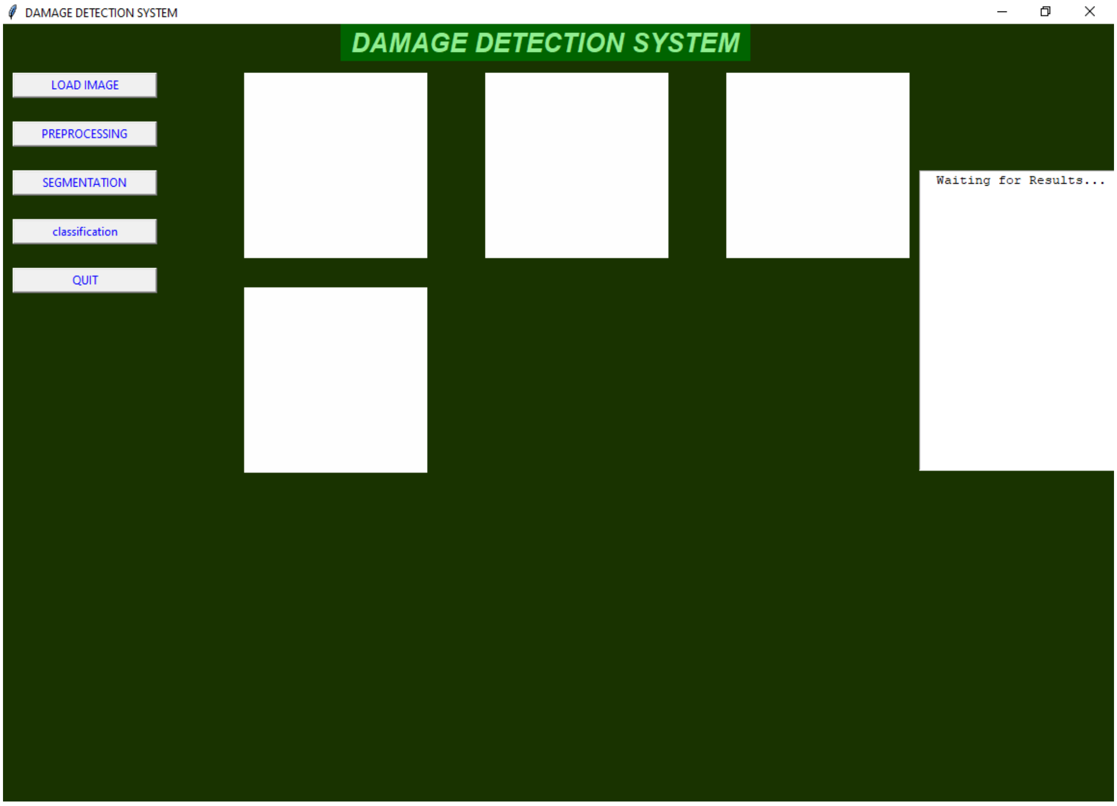
GUI Form:



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