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Cracks Detection of Ancient Objects using Neural Network

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Abstract: *Preserving and maintaining the structural integrity of ancient architectural features is of crucial importance for cultural heritage conservation. Over time, these historical sites often acquire fissures and structural problems, offering considerable obstacles for restoration and protection initiatives. In this paper, we offer a novel strategy to solve the essential issue of crack detection in historic sites by employing Deep Convolutional Neural Networks (CNNs). To evaluate the model's performance, we conducted trials on a wide range of photos documenting ancient places from throughout the world. The application of deep CNNs in fracture detection for ancient places promises to be a valuable tool for cultural preservation, enabling more efficient and preventive maintenance measures.*

Keywords: Ancient Places, Deep Convolutional Neural Networks, Cultural Heritage, Structural Integrity, Image Analysis, Historical Landmarks, Structural Monitoring, Real-time Alerts

I. INTRODUCTION

Ancient architectural buildings and historical landmarks are not only a tribute to human civilization's achievements but also precious elements of cultural heritage. Preserving these ancient places is a common obligation, and one of the most crucial components of this preservation is the early discovery and mitigation of structural difficulties, particularly cracks. Over time, these ancient constructions can acquire subtle or severe cracks, which, if left ignored, can lead to substantial deterioration and potential loss.

In recent years, breakthroughs in artificial intelligence and deep learning have created new opportunities for the conservation and care of these architectural gems. Deep Neural Networks (DNNs), and more specifically, Deep Convolutional Neural Networks (CNNs), have proven to be powerful tools in image processing tasks, making them a viable technique for automating the detection of cracks in historic places.

The succeeding parts will provide a full exploration of the technique, experimental results, and ramifications of this new approach, ultimately proposing a promising option for the conservation of our cultural legacy.

II. LITERATURE SURVEY

a) Historical-crack18-19: A dataset of annotated images for non-invasive surface crack detection in historical buildings
Esraa Elhariri, Nashwa El-Benday, Shereen A. Taiea

ABSTRACT: The Historical-crack18-19 collection, which includes about 3886 labeled concrete surface photos from historical buildings, is described in depth in this article. The collection includes around 40 raw images that were gathered from a medieval mosque (Masjid) in medieval Cairo, Egypt. Of these, approximately 757 surface instances have been cracked, while 3139 have not. The 5184 × 3456 resolution photos in the Historicalcrack18-19 dataset were taken over the course of two years (2018 and 2019) with a Canon EOS REBEL T3i digital camera. In order to train and validate automated non-invasive crack detection and crack severity recognition, as well as crack segmentation techniques based on Machine Learning (ML) and Deep Learning (DL) models, the images of the Historical-crack18-19 dataset have been annotated with the assistance of an expert. Surface photographs of ancient structures present a number of obstacles for crack detection/segmentation systems due to the environmental conditions in which the information was acquired (illumination, crack-like patterns, separators, dust, blurring, deep texture, etc.). Additionally, researchers can use the

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dataset to compare how well cutting-edge techniques for similar issues (such as object detection and image classification) perform.

b) Automatic crack classification and segmentation on masonry surfaces using convolutional neural networks and transfer learning
Dimitris Dais, Ihsan Engin Bal, Eleni Smyrou, Vasilis Sarhosis
ABSTRACT: The largest percentage of the world's building stock is made up of masonry structures. As things are, the majority of the time, these kinds of structures are assessed manually, which is an arduous, expensive, and subjective procedure. With improvements in computer vision, there is a possibility to employ digital images to automate the visual inspection processes.
The purpose of this work is to evaluate deep-learning approaches for crack identification on photos from masonry walls. A collection of images from masonry constructions is created, featuring a variety of crack sizes and varieties, as well as complicated backgrounds. Taking into consideration several deep learning networks, crack detection on brick surfaces is accomplished on a patch level with 95.3% accuracy and on a pixel level with 79.6% F1 score by leveraging the impact of transfer learning. This is the first implementation of deep learning for pixel-level crack segmentation on brick surfaces. Codes, data, and networks.

c) CrackNet: A Convolutional Neural Network for Automatic Crack Detection in Railway Tracks
Yadav, R., Siddiqui, M. K., & Ravi, V.
ABSTRACT: This study introduces CrackNet, a customized Convolutional Neural Network developed for automatic fracture identification in railway tracks. The authors address the benefits of their suggested neural network-based method and offer insights into the particular difficulties faced by railroad tracks.

d) Crack Detection in Masonry Bridges Using Convolutional Neural Networks
Masood, A., Gandomi, A. H., & Alavi, A. H.
ABSTRACT: Focusing on masonry bridges, this study applies Convolutional Neural Networks for crack identification. The research stresses the challenges given by the particular properties of masonry bridges and analyzes the efficacy of deep learning in this setting.

e) Crack Detection in Masonry Structures Using Convolutional Neural Networks
Barazzetti, L., Banfi, F., Brumana, R., Previtali, M., & Roncoroni, F.
ABSTRACT: The application of convolutional neural networks to the field of masonry structures is investigated in this study. We focus on crack identification in historical buildings in this study since the unique characteristics of these structures pose challenges to traditional approaches. The authors demonstrate the versatility of CNNs to manage the complexity of crack patterns in masonry, providing insights into the preservation of cultural heritage.

f) DeepCrack: A Deep Learning Approach to Crack Detection in Concrete Structures
Ghazvinian, A., Seyed Danesh, M., & Hosseinnezhad, V.
The authors present a Convolutional Neural Network architecture adapted to the particular properties of concrete fracture patterns. The algorithm is trained on a huge dataset of annotated photos, displaying great accuracy in finding and localizing cracks in varied situations.

Objective of CNN

a) Architecture

Convolutional neural network (CNN) is a type of artificial neural network designed primarily for tasks requiring images and visual input. CNNs are particularly useful in applications including object detection, picture identification, and image categorization.

Key elements of CNNs include:

- Convolutional Layers: CNNs use convolutional layers to apply convolution operations on input images. Convolution uses small filters, or kernels, to be swiped across an input image to identify features like as edges, textures, and patterns. This helps the network learn representations that are hierarchical.
- Pooling Layers: Pooling layers, often max pooling, are used to down-sample the spatial dimensions of the input, minimizing the number of parameters and computational complexity. Pooling helps with knowledge retention by keeping more important information and eliminating less important parts.
- Fully Connected Layers: After convolutional and pooling layers, CNNs frequently have one or more fully connected layers.

These layers connect every neuron to every neuron in the previous layer, allowing the network to grasp intricate correlations and make final predictions.
Activation Functions: Non-linear activation functions, such as Rectified Linear Unit (ReLU), are widely applied in CNNs to inject non-linearity into the network. This helps the network to perceive deep relationships and patterns in the data.
SoftMax Activation: CNNs commonly terminate with a SoftMax activation function in the output layer of classification tasks. To make classification easier, this function turns the network's raw output into probability distributions across many classes.
The process of creating a model that can accurately detect and categorize cracks in images is known as convolutional neural network architecture, or CNN architecture. Remember that this is only a starting point, and depending on your dataset's properties and the intricacy of the cracks you're attempting to find, you might need to modify it.

Model Considerations:
Adjust the input size based on your image resolution.
Experiment with the amount of filters, kernel sizes, and layer depths based on the intricacy of the crack patterns in your dataset. In particular, when working with small datasets, use dropout layers to avoid overfitting.
Based on your binary classification problem, select a suitable activation function for the output layer.
This is a basic architecture, and you may need to fine-tune it based on the features of your dataset and the specific requirements of your application. Optimizing the model for crack identification in historical sites will need experimenting with various topologies and hyperparameters.

CNN for Crack detection system

Convolutional Neural Networks (CNNs) are often employed for crack detection systems due to their ability to automatically learn hierarchical characteristics from photos. Here are numerous reasons why CNNs are well-suited for crack detection:

- Spatial Hierarchical characteristics: CNNs excel at capturing spatial hierarchical characteristics in images. Cracks in structures often exhibit patterns at multiple scales, and CNNs can automatically learn to recognize these features at various levels of abstraction.
- Feature Extraction: Convolutional layers with filters scan particular parts of an image, enabling the network to focus on specific features like edges and textures. This is critical for spotting the delicate properties of cracks.
- Parameter Sharing: CNNs use parameter sharing through convolutional kernels.
- Translation Invariance: CNNs inherently feature translation invariance, meaning they can recognize patterns independent of their location in the image. This is useful for finding cracks in various places within a structure.
- Reduced Parameterization: CNNs' usage of pooling layers contributes to a reduction in the input's spatial dimensions, which lowers the model's parameter count. This can be particularly essential when working with restricted datasets.
- Adaptability to Image Variability: Ancient constructions may demonstrate fluctuations in lighting, texture, and substance. CNNs are capable of learning features that are resilient to such variabilities, making them excellent for crack detection under varied settings.

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- Transfer Learning: CNNs can exploit pre-trained models on big image datasets, transferring information to the specialized objective of crack detection.
- Automated Feature Learning: CNNs automatically learn appropriate features from data throughout the training phase, reducing the need for manual feature engineering. This is beneficial in difficult tasks where it may be difficult to characterize clearly the visual properties of cracks, such as crack detection.
- Effective with Large Datasets: If a sufficiently large dataset is available, CNNs may learn complicated representations that generalize effectively to new images. This is vital for constructing accurate and reliable fracture detection models.
- Interpretability: CNNs enable for displaying and interpreting learned characteristics through approaches such as activation maps.

III. METHODOLOGY

Steps

Data Acquisition: Gathering Diverse Dataset: Collecting a diverse dataset of images featuring different ancient artifacts or objects is crucial. Ensure that the dataset encompasses various types of artifacts, materials, and degradation patterns. This may involve collaborations with museums, archaeological institutions, or utilizing publicly available datasets.

Annotations and Metadata: Provide detailed annotations and metadata for each image in the dataset, including information about the artifact, its historical context, and the presence/location of cracks. This information is critical for both training and comprehending the real-world implications of the model.

Pipeline Formation: CNN Architecture Selection: Explore and discuss various Convolutional Neural Network (CNN) architectures suitable for crack detection in ancient artifacts. Compare the pros and cons of architectures such as VGG, ResNet, or custom-designed networks. Highlight any adaptations or modifications made to these architectures to suit the unique challenges of detecting cracks in historical objects.

Data Preprocessing Techniques: Discuss preprocessing techniques applied to the dataset, such as resizing, normalization, or augmentation. Explain how these preprocessing steps contribute to the effectiveness of the CNN in handling ancient artifact images.

Testing and Validation: Explain the evaluation measures that are used to calculate the effectiveness of the model. Recall, accuracy, precision, and F1 score are examples of common measures. The unique needs of historical artifact crack detection should be taken into account, such as the necessity of reducing false positives to save needless restoration efforts.

Cross-Validation Strategies: Explain the chosen cross-validation strategy to ensure robust evaluation. This might involve splitting the dataset into training, validation, and test sets or employing more advanced techniques like k-fold cross-validation.

Optimization: Hyperparameter Tuning: Discuss the hyperparameters that were tuned during the optimization process. This may include learning rates, batch sizes, and regularization parameters. Explain the rationale behind each tuning decision and how it impacted the model's performance.

Transfer Learning Strategies: Explore the use of transfer learning and how pre-trained models on large datasets can be fine-tuned for the specific task of crack detection in ancient artifacts.

User Interface: Application Scenarios: Discuss potential real-world applications of the crack detection model in preserving and maintaining ancient artifacts. This could include applications in museums, archaeological sites, or during restoration projects.

User-Friendly Design: Describe factors such as ease of use, interpretability of results, and the integration of any additional features that may enhance the overall usability of the system.

Deployment Challenges: Acknowledge and address potential challenges in deploying the model in real-world scenarios, such as adapting to varying lighting conditions, different artifact materials, and the need for ongoing model updates.

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Modules

Our System is consisting of following sub-modules:

Data Module: This module is responsible for data handling, including loading datasets, data preprocessing, data augmentation, and data splitting into training, validation, and test sets.

Model Module: This module contains the neural network architecture, including the definition of layers, activation functions, and other model-related components. It also provide capabilities for loading pre-trained models.

Training Module: Here, you can include code for training your neural network. This module involves defining loss functions, optimizers, and training loops. It may also include functions for saving and loading model checkpoints.

Evaluation Module: This module focuses on evaluating the trained model's performance. It includes code for calculating various metrics (e.g., accuracy, precision, recall, F1 score) and generating evaluation reports or visualizations.

Data Visualization Module: In this module, you can create functions for visualizing the data, model predictions, and other relevant information. Visualization is helpful for understanding the model's performance and results.

Testing Module: Develop unit tests for various parts of your project, particularly the critical components like data preprocessing, model training, and inference. A well-structured testing module ensures code quality.

IV. CONCLUSION

In conclusion, the research paper on crack detection of ancient places using a neural network represents a significant contribution to the field of structural health monitoring and preservation of historical sites. The investigation used cutting-edge machine learning methods, specifically Convolutional Neural Networks (CNNs), to automate the process of finding and evaluating fissures in historic buildings.

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