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Multiple Road Fissures Detection Using Deep Learning Algorithm

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ABSTRACT

Road infrastructure is critical in transportation systems because it ensures the safe and efficient movement of people and goods. However, the deterioration of roads over time as a result of various factors such as weather and heavy traffic poses significant maintenance and safety challenges. Early and accurate detection of road damage is critical for timely repairs and accident prevention. This paper proposes a novel approach to detecting road damage using Convolutional Neural Networks (CNNs). CNNs have demonstrated remarkable success in a variety of computer vision tasks, making them an appealing option for automated road damage detection. The goal of this research is to use deep learning and computer vision techniques to create an efficient and accurate system for detecting road damage from images. Our methodology entails gathering a diverse dataset of road images with various types of damage, such as potholes, cracks, and road surface degradation. The dataset is pre-processed to improve image quality and annotated for training and evaluation. Using this dataset, a custom CNN architecture is designed and trained to recognize and classify various types of road damage. A separate validation dataset is used to evaluate the trained model's performance in terms of accuracy, precision, recall, and F1 score. Furthermore, we investigate the model's ability to generalize to previously unseen road damage scenarios by testing it on real-world images captured under varying conditions. Our CNN-based road damage detection system achieves high accuracy in identifying and classifying road damage types, according to the results. This system can be integrated into existing infrastructure management systems, allowing for cost-effective and timely road maintenance. Furthermore, it helps to improve road safety by identifying potential hazards before they cause accidents.

Keywords : Road Crack Detection, Deep Learning, Convolutional Neural Network, Notification, Neural Networks

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I. INTRODUCTION

The detection of road cracks is an important aspect of infrastructure maintenance and safety. Cracks can form as roads deteriorate over time due to factors such as weather, traffic, and general wear and tear, posing hazards to both vehicles and pedestrians. The timely detection and repair of these cracks is critical to the longevity and dependability of road networks. Technological advancements, particularly in computer vision and image processing, have paved the way for novel road crack detection solutions in recent years. Automated systems equipped with sophisticated algorithms can analyze images of road surfaces with high accuracy, identifying and classifying various types of cracks. These systems provide a faster and more efficient alternative to traditional manual inspections, allowing authorities to quickly prioritize and address maintenance needs. The use of road crack detection technology not only improves safety but also reduces costs by preventing minor issues from escalating into major repairs. Furthermore, the information gathered by these systems can be used for predictive maintenance, allowing authorities to anticipate and address potential road issues before they become critical. This introduction sets the stage for delving into the significance and applications of road crack detection, emphasizing its role in maintaining infrastructure integrity, improving safety, and optimizing maintenance practices in today's urban environments. Fig 1 shows the road cracks.

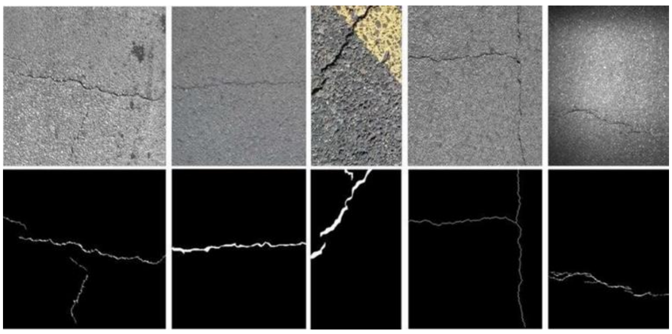

Fig 1 : Road crack with segmented results

II. RELATED WORK

Jiangpeng shu, et.al,…[1] improved a model's performance while annotating as few samples as possible. Active learning can be used to reduce the cost of sample annotations while retaining deep learning's powerful learning capabilities. Semi-supervised learning and active learning in machine learning use labelled and unlabeled samples on autonomous label engineering. Semi-supervised learning, in general, does not require manual intervention and can automatically label unlabeled samples using a benchmark classifier with a certain classification accuracy. One difference between active learning and semi-supervised learning is that the selected high-value samples must be marked manually and accurately. Semisupervised learning replaces manual labeling with automatic or semi-automatic labeling by computer. Although the labeling cost is effectively reduced, the labeling results depend on the classification accuracy of the benchmark classifier trained with some labeled samples, so the labeling results cannot be guaranteed to be completely correct. In contrast, active learning selects samples manually and does not introduce error class labels. In this study, a difficulty- learning active learning method to select the most informative crack images is proposed, aiming at promoting crack segmentation dataset construction. An acquisition function that is combined with difficulty and traditional uncertainty maps is utilized to measure the informativeness of crack images in our method. A steel box girder crack image dataset containing 500 images of 320 × 320 pixels for training, 100 for validation, and 190 for testing is used for our experiments. Four common segmentation networks, including U-Net, DeepLabV3, FPN, and PSPNet, are applied to segment cracks. A comparison study between our acquisition function and traditional acquisition functions, including Random, QBC, Entropy, and Core-set, is conducted on the four networks. The role of probability attention module

(PAM) that is used in our method is evaluated by experiments through removing this module.

Yalong yang, et.al,…[2] presented the system for the detection of pavement crack mainly depends on manual inspection in practice, which is not only expensive inefficient and labor- intensive, but also has subjective. It may lead to missed detection or wrong classification due to bad physical condition or lack of concentration. Therefore, how to automatically detect pavement crack accuratelly has become one of the current research hotspots. Aiming at the segmentation inaccuracy caused by complex background and fuzzy crack edge in asphalt pavement image, an improved pavement crack segmentation method based on deep convolutional neural network model is proposed in this paper, which combines the idea of semantic segmentation with image detection. Experimental results show the proposed method is superior to the classical threshold segmentation iterative segmentation method and the traditional semantic segmentation method UNet in terms of F1 score,Precision,and Recall, and has better segmentation effect. The proposed method is expected to solve the problem of crack detection in complex asphalt pavement images. Therefore, the methods presented in this paper can be applied to crack detection of highway pavement to a certain extent, and better assist the maintenance of highway traffic safety Eleni vrochidou, et.al,…[3] provided dense pixel-level data that can be used to fully comprehend a scene. However, due to a lack of sufficient spatial information, the majority of the backbones used in segmentation models for feature extraction resulting from pretrained models may result in poor performance, particularly in small categories such as marble cracks. As a result, efficient model architecture combinations must be investigated for the problem at hand. In this paper, four deep convolutional neural network models (all layers) are fully trained, and 28 feature extraction backbone architectures are tested for marble crack semantic segmentation. The need to fully train the models stems from the previously mentioned weakness of pretrained models in extracting meaningful spatial features from new image samples for the problem under consideration. Furthermore, to strengthen this decision, a pretrained baseline model is also examined for comparative reasons. Cracks can occur on different surfaces such as buildings, roads, aircrafts, etc. The manual inspection of cracks is time-consuming and prone to human error. Machine vision has been used for decades to detect defects in materials in production lines. However, the detection or segmentation of cracks on a randomly textured surface, such as marble, has not been sufficiently investigated. This work provides an up-to-date systematic and exhaustive study on marble crack segmentation with color images based on deep learning (DL) techniques. The results indicate the importance of selecting the appropriate Loss function and backbone network, underline the challenges related to the marble crack segmentation problem, and pose an important step towards the robotic automation of crack segmentation and simultaneous resin application to heal cracks in marble-processing plants Vaughn, Peter Golding, et.al,…[4] used a dataset of 40,000 images to investigate the effects of image preprocessing on the performance of DL crack detection. According to the findings, using a pretrained model with RGB weights and grayscale images has no effect on the performance of a CNN model for detecting cracks in a concrete structure. The other IP methods (thresholding and edge detection) had a negative impact on performance. Grayscale was discovered to be promising in reducing image noise without removing relevant features. The CNN was built using the Keras Python package and pretrained VGG16. The original image dataset was converted into four sets to compare using the SciKit Image Python package: RGB (control), luminance (grayscale), Otsu method (thresholding), and Sobel filter (edge detection). This was promising, as colour images are larger, and decreasing image data size could increase processing speed and decrease the data size needed for storage. These results may be misleading due to the RGB weights in the pretrained model. The weights for the pretrained models are only available in three-channel (RGB). This was performed due to a lack of time and the greater knowledge needed to execute. Further research should either train the models from scratch on their respective images or obtain one- channel (grayscale) pretrained weights. Infrastructure, such as buildings, bridges, pavement, etc., needs to be examined periodically to maintain its reliability and structural health. Visual signs of cracks and depressions indicate stress and wear and tear over time, leading to failure/collapse if these cracks are located at critical locations, such as in load-bearing joints.

Junhua Ren, et.al,…[5] examined pavement cracks as a significant indicator of potential damage and degradation in pavement performance and functionality. In general, pavement cracks can be caused by heavy traffic, drastic temperature changes, reflection from the base layers, and other factors. These cracks have a negative impact on the pavement structure, significantly reducing pavement performance. When cracks form, the entire road structure can be influenced. The road's safety and service life can be reduced to some extent. A regular inspection is required to prevent the formation of cracks. The corresponding strategies and in-depth analysis can be made by collecting various types of data for pavement conditions. According to the analysis results, timely and appropriate maintenance can be employed to repair the pavement and prevent its failure at an early stage of crack development. In this way, as for the pavement, the service life can be prolonged, and the performance and functionality can be maintained in a good condition. As most previous studies have stated, collecting and analyzing the images of cracks is a primary way to realize the detection and classification of pavement cracks. Generally, the pavement crack detection methods can be divided into two types based on whether the deep learning method is applied. They are the traditional methods and deep learning methods. However, in Mosaic, four pictures are randomly selected to join together through random rotation, random scaling, and random distribution. In sum, there were three advantages to employing Mosaic. Firstly, the background of the detected object becomes rich. Secondly, a better model can be more easily trained with fewer GPU resources due to the combination of four pictures. Lastly, by applying random rotation, random scaling, and random distribution to generate the data, the number of small samples is increased. All of the advantages were beneficial to enhance the robustness of the crack detection model Senthan Mathavan, et.al,…[6] offered a faster, more accurate, and objective alternative to manual inspection surveys. Furthermore, automated surveys can provide a quantitative analysis of the condition of a pavement, adding another dimension to traditional surveys, which are predominantly qualitative. When combined with intelligent data analysis and digital storage techniques, automated surveys can provide the foundation for a comprehensive pavement maintenance strategy based on both spatial and temporal trends. There are several pavement distresses. Cracking, rutting, loss of texture, and poor skid resistance are all common road surface distresses. Distresses such as cracks have much larger depths when compared to their dimensions on the plane of the road and present a unique challenge to an imaging system. Spelling has the same order of magnitude when it comes to its size in 3D. Hence, the imaging system that is specifically designed to measure spelling will preferably have similar imaging performances in the lateral and depth directions. Potholes are considerably large on the road plane, usually requiring a high-resolution imaging setup for the horizontal plane. Rutting is extremely shallow in the depth direction making it measurable by a system with very high accuracy in the depth direction. Defects such as shoving exhibit a small bump on the road surface, making their profiling with some imagers difficult.

The ability to transport passengers and goods is one of the critical points that limits a country's level of economic activity, and thus its wealth and welfare, according to Roberto Medina et al. [7]. Because the use of road transportation has increased significantly in recent decades, the state of a country's road network has a significant impact on its economic activity. In this context, the use of road management systems is becoming more common. These systems work by comparing current road conditions to the desired state. Periodic road surveys are conducted on a regular basis, and they play an important role in measuring pavement surface distress. Human visual inspection of the road surface is the most common method for evaluating the surface distress, but high-speed cameras on board vehicles have recently been introduced to automate these inspections. One of the critical points that limits the level of economic activity in a country, and therefore its wealth and welfare, is the ability to transport passengers and goods. The use of road transport has increased considerably in recent decades; thus, the conditions of a country’s road network have a great influence on its economic activity.

Aggelos Katsaliros, et.al,…[8] compare the results of image classification and segmentation CNN architectures with their respective quaternionic counterparts in the task of road crack detection. We specifically replace standard layers with quaternion-valued versions and compare the accuracy, precision, and number of parameters required by the new models. To assess network performance in conditions where training data is not readily available, a reduced- data training regime is devised in which new datasets are produced by sampling from a large source dataset of road crack images. The timely detection and repair of road damage is critical for the safety of drivers and passengers. In this work, we explored the applicability of quaternion- valued layers in deep CNNs for the task of road crack detection. We proposed quaternion models that are able to accurately detect cracks in images and perform on par with real-valued ones while requiring significantly fewer parameters. In fact, utilizing all quaternionic layers leads to a parameter reduction of 75%, compared to using standard layers. We conclude that quaternion- valued networks are a promising alternative to real-valued ones, since they are able to effectively reduce model size without lowering performance, even when trained on a very low amount of samples. Consequently, quaternionic models are ideal for deployment in scenarios where hardware requirements are low or the available data are scarce.

Efstathios Branikas, et.al,…[9] used CycleGAN, a cyclic-consistency GAN, to augment crack detection datasets on a wide range of applications, such as nuclear reactor fuel channel surfaces, concrete roads, and stone surfaces, to obtain realistic examples of cracks that are under-represented in the original datasets. To the best of our knowledge, this proposed model is the first to perform style transfer on structural crack data. Because the original images are already annotated, extra training material is created for the respective datasets without any additional manual annotation. This allows a plug- and-play approach that poses no model restrictions to the subsequent defect detection process. Extensive experiments are carried out to demonstrate the additional data generated by our approach contributes to superior image segmentation results, both on the nuclear industrial case, and the public datasets used for exploring generalization. To this end, various data combinations between real and artificial images are explored.

B.G. Pantoja-Rosero et al. [10] demonstrated the importance of accurately representing crack topology in assessing the mechanical properties of cracked structures. Unfortunately, popular U-Net-like architectures are accurate at segmenting cracks but fail to preserve their topology. We show how the TOPO loss function can be used to improve U-Net's performance in those areas. We demonstrated this through qualitative and quantitative results, for which we proposed the CPP, a novel metric. Furthermore, TOPO avoids the use of precise labels, significantly reducing the time required for the annotation process, which is one of the limitations of supervised deep learning techniques. Additionally, we showed that a deep network trained with a combination of TOPO and MSE yields convincing results when applied to images showing cracked buildings in the context of entire urban scenes. To facilitate future experimental comparisons, we released the Wild dataset and the code from work.

III. EXISTING METHODOLOGIES

By introducing a novel approach to feature extraction and learning, the IGCNN-RCD (Intelligent Graph Convolution Neural Network for Road Crack Detection) proposes a significant improvement to the existing road crack detection system. In the traditional system, features are most likely extracted using traditional image processing or standard deep learning methods, and these features are typically represented in vector or matrix form. For feature extraction, the IGCNN-RCD uses the Scale-Invariant Feature Transform (SIFT) algorithm, which provides scale and rotation-invariant features. This integration allows the system to capture more distinct key points and descriptors, resulting in a more complete representation of the road surface, especially in the context of intricate crack patterns. Furthermore, the IGCNN-RCD introduces a graph-based representation, which builds graphs to depict relationships between key points extracted by the SIFT algorithm. This graph-based approach allows the system to capture spatial relationships and similarities between features, allowing for a more nuanced understanding of road surface characteristics. The final layer of enhancement includes the use of a Graph Convolutional Neural Network (GCNN) to learn from road image graph representations. GCNNs excel at learning from complex relationships within graph structures, allowing the system to detect defects such as road cracks with greater accuracy and efficiency.

IV. PROPOSED METHODOLOGIES

The proposed road damage detection system makes use of the capabilities of Convolutional Neural Networks (CNNs) to improve the precision and effectiveness of identifying different types of road damages. The first step is to collect a large dataset of diverse road images encompassing various damage scenarios such as cracks, potholes, and surface deterioration. This dataset is critical for accurately training the CNN to recognize and classify various types of road damage. Following that, a series of preprocessing steps are performed on the collected images to ensure uniformity and optimize model performance. Preprocessing may include resizing images, normalizing pixel values, and using data augmentation techniques to increase the dataset's diversity. The proposed system is built around the design of a dedicated CNN architecture tailored for road damage detection. Convolutional layers are typically responsible for feature extraction, pooling layers for downsampling, and fully connected layers for classification in the CNN architecture. The convolutional layers allow the model to automatically learn and extract relevant features from the input images, while the pooling layers contribute to spatial down-sampling and thus reduce computational complexity. The extracted features are then processed by the fully connected layers to make predictions about the presence and nature of road damages.

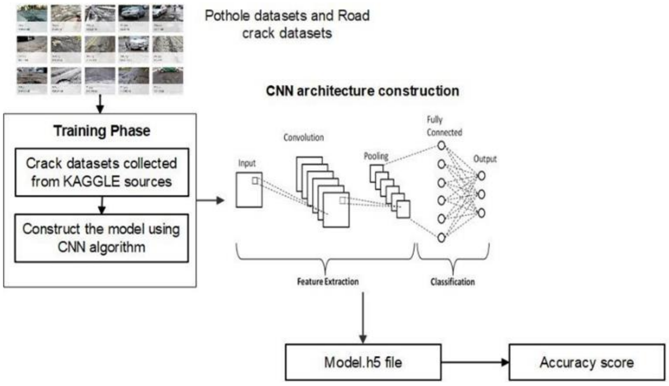

Fig 2 : Proposed architecture

CNNs' architecture tries to mimic the structure of neurons in the human visual system composed of multiple layers, where each one is responsible for detecting a specific feature in the data. As illustrated in the image below, the typical CNN is made of a combination of four main layers:

- Convolutional layers
- Rectified Linear Unit (ReLU for short)
- Pooling layers
- Fully connected layers

Convolution layers

This is the first building block of a CNN. As the name suggests, the main mathematical task performed is called convolution, which is the application of a sliding window function to a matrix of pixels representing an image. The sliding function applied to the matrix is called kernel or filter, and both can be used interchangeably.

In the convolution layer, several filters of equal size are applied, and each filter is used to recognize a specific pattern from the image,

Activation function

A ReLU activation function is applied after each convolution operation. This function helps the network learn non-linear relationships between the features in the image, hence making the network more robust for identifying different patterns. It also helps to mitigate the vanishing gradient problems.

Pooling layer

The goal of the pooling layer is to pull the most significant features from the convoluted matrix. This is done by applying some aggregation operations, which reduces the dimension of the feature map (convoluted matrix), hence reducing the memory used while training the network. Pooling is also relevant for mitigating overfitting.

The most common aggregation functions that can be applied are:

- Max pooling which is the maximum value of the feature map
- Sum pooling corresponds to the sum of all the values of the feature map
- Average pooling is the average of all the values.

Fully connected layers

These layers are in the last layer of the convolutional neural network, and their inputs correspond to the flattened one-dimensional matrix generated by the last pooling layer. ReLU activations functions are applied to them for non- linearity.

Finally, a softmax prediction layer is used to generate probability values for each of the possible output labels, and the final label predicted is the one with the highest probability score.

Dropout

Dropout is a regularization technic applied to improve the generalization capability of the neural networks with a large number of parameters. It consists of randomly dropping some neurons during the training process, which forces the remaining neurons to learn new features from the input data.

V. EXPERIMENTAL RESULTS

The simulation can be done in python and model file can be generated using CNN algorithm using Tensorflow library. Then can evaluate the performance using accuracy metrics. The accuracy metric is evaluated as

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} * 100$$

Where as,

TP – True positive rate TN- True negative rate FP – False positive rate FN- False negative rate

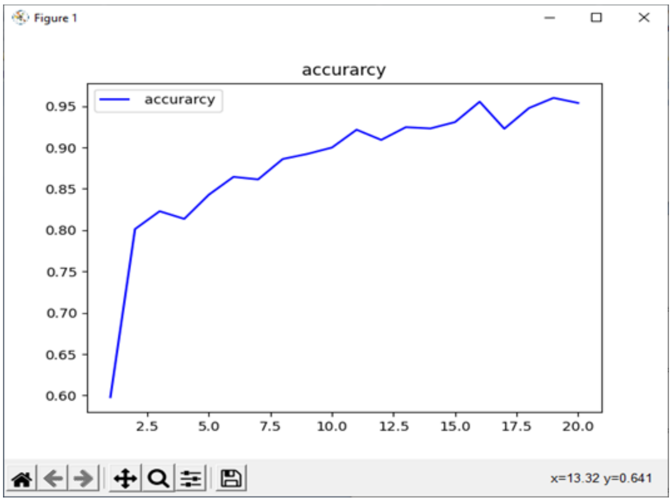

Fig 3 : Training accuracy

A confusion matrix is a table that is often used to evaluate the performance of a classification algorithm. It provides a summary of the predicted and actual class labels for a set of instances. The matrix has four entries: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These elements are arranged in a 2x2 grid, and the matrix can be used to calculate various performance metrics

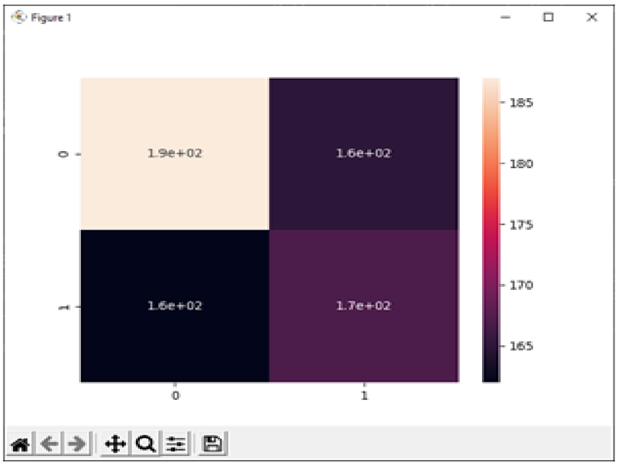

Fig 4 : Confusion matrix

VI. CONCLUSION

To summarize, the use of Convolutional Neural Networks (CNNs) for road crack detection represents a powerful and promising solution to the challenges of automated infrastructure maintenance. The use of CNNs in this context has several benefits, including the ability to learn intricate patterns and features indicative of road cracks from diverse datasets. CNNs can improve their ability to accurately identify and classify various types of road damage by incorporating sophisticated architectures such as those that incorporate graph convolutional layers and advanced feature extraction methods. The proposed CNN algorithm takes a methodical approach that includes data collection, preprocessing, model architecture design, training, and evaluation. Using techniques such as data augmentation increases the model's robustness, allowing it to generalize well to a variety of road conditions and environmental factors. The iterative process of fine-tuning and validation ensures that the CNN is performance optimized, striking a balance between accuracy and generalization. The importance of using CNNs to detect road cracks stems from its potential to revolutionize infrastructure maintenance practices.

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