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Steel Defect Detection in Bridges Using Deep Encoder-Decoder Networks

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ABSTRACT

Recent major accidents related to bridges have emphasized the need for developing effective technological solutions for defect detection, which can minimize the possibility of bridge-related accidents in the future. In this respect, this research will focus towards development of automated system for the detection of defective regions within different steel parts of bridges. At present, there is no open-source image dataset, which can be used for this purpose. Consequently, the training dataset has been developed by using images acquired from bridges in Vietnam and validation was performed using images acquired from Lovelock bridge situated at Highway-80, Lovelock, NV, USA. A total of 5,500 (4,000 images for training and 1,500 for validation) images of different dimensions have been used the original dimensions of the steel bridge images have been modified 572 × 572 pixels, which have been used for the training and evaluation of the dataset on different Deep Encoder-Decoder networks. The use of diverse data from different bridges will allow the development of a robust Deep Encoder-Decoder network with considerable implications for practical systems in the future. This study will employ state-of-the-art Deep Encoder-Decoder network, which have been recently developed for other applications. However, no such study has been developed for defect detection in steel bridges. A comparative evaluation of different Deep Encoder-Decoder networks will be examined. At the same time, the performance of the system will be compared with recent advanced approaches. The results reveal the considerable potential of Deep Encoder-Decoder towards defect detection of steel bridges, which will be further exploited in the future studies.

INTRODUCTION

There has been considerable amount of attention devoted in the recent past towards developing automated systems for inspection of civil infrastructures [1-15] The existing methods for non-destructive evaluation of bridges are limited in a number of different ways. Majority of bridges are composed of different parts, which are constructed using different building block materials, such as concrete blocks, as well as steel blocks, rebars and other building structures. Some of the serious recent bridge accidents in the United States include a collapsed railroad bridge in Alabama that led to

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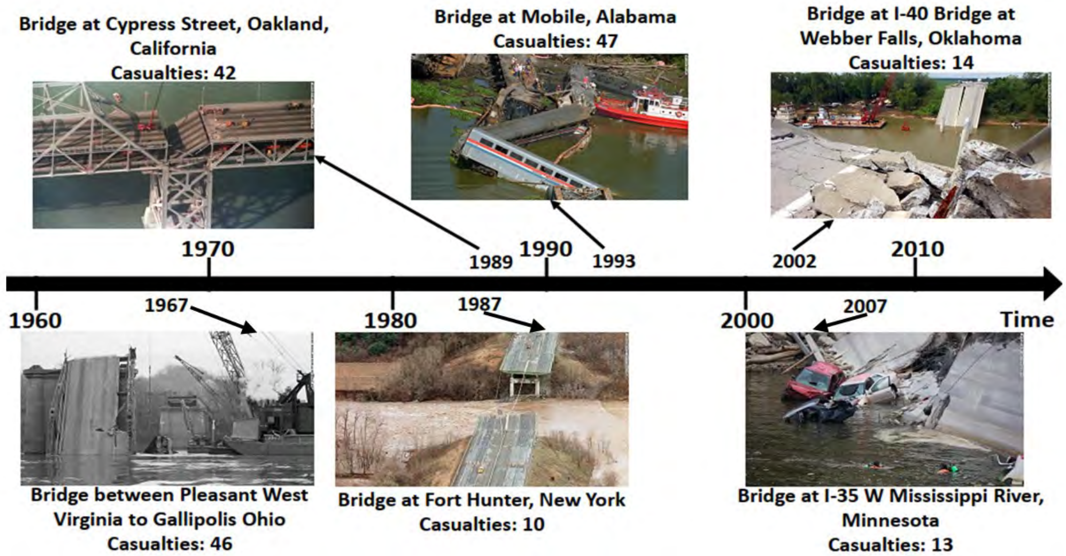

Figure I: A brief historical overview of the different bridge-related accidents that took place in the United States in the recent few decades [17].

around 47 deaths and collapsed bridge that connected Point Pleasant, West Virginia with Gallipolis, Ohio [16]. Figure 1 shows the different major bridge-related incidents that took place in the past few decades in the United States [17]. It can be seen that the bridge destruction is a recurring occurrence in the United States, which leads to devastating financial, economic, lass of lives and considerable incurred costs that could have been easily avoided with regular and effective inspection. In terms of specifically highlighting and maintaining steel structures in bridges in particular and infrastructures in general, a high level of cost is associated with repairing and maintain steel structures. It has been reported that more than 2 trillion annually is spent in this respect [18].

RELATED WORKS

This research area has not properly been defined and explored in the past. There have been studies, but reputable and sincere efforts by researchers remains missing at present. It is only recently that some studies have tried to work on the research problem of detecting steel defects to some extent. For the major part, there are very few main credible recent studies that can be reported in this section [19-21]. The algorithm developed for corrosion detection attempts to exploit some physical and visual features, such that the surface of the corroded region differs from non-corroded regions in terms of hue [20]. In [19], the method proposed for visual inspection of the steel structures using two basic features, namely roughness and color to locate the corrosion pixels from normal, un-corroded pixels in images. Another study towards corrosion detection in metal and steel structures made use of texture-based features for differentiating between non-corroded and corroded regions in images containing steel structures [21]. Due to the lack of effective examination of this research problem, this study will attempt to contribute in terms of improving the overall performance as well as extending the state-of-the-art for defect detection in bridge steel structures. The existing literature does not properly highlight the performance of the steel defect detection systems and the manner in which Deep Learning frameworks can contribute towards improving the overall

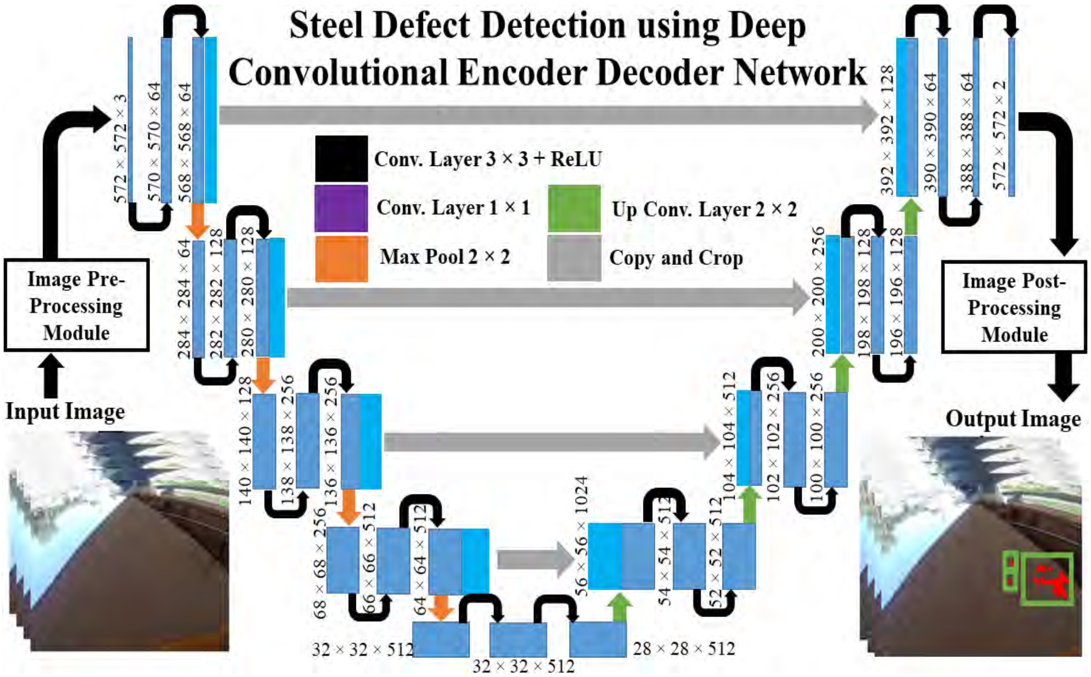

Figure II: The proposed model for steel defect detection, which is based on image pre- and post-processing modules. At the center is given the Deep Encoder-Decoder architecture for UNet with different layer, input and output information.

performance of such systems in practical settings. The next section will shed light on the method proposed for steel defect detection.

METHODOLOGY

The complete block diagram of the proposed system for steel defect detection has been given in figure 2. As it can be seen in figure 2, there are five steps of the proposed system. Starting from the input video frames, which are individually pre-processed using a number of steps, e.g. the Region-of-Interest (ROI) selection. The original size of the high-resolution image frame is very large, due to which, a selected region is separated out. This ensures that the background regions are separated and majority of the steel region close to the robot can be cropped, resized and saved separately. The image ROI is resized to 572 × 572 × 3, which is the input size permitted for the validation of the input video frames using Deep Encoder Decoder Networks. These networks are pre-trained on Vietnam bridge dataset. A state-of-the-art Deep Encoder-Decoder Network architecture has been used in this study, namely U-Net [22], which has found considerable application in the field of medical imaging and other research fields in the recent past. A number of different Encoders modules are leveraged to examine and compare the performance of the different Architecture-Encoder pairs. Some of the Encoders used in this study include the ResNet-18 [23], ResNet-34 [23], EfficientNet-B0 [24], EfficientNet-B2 [24], and RegNet-X2 [25]. One of the prime focus was towards selecting Encoder modules that are not very large in terms of number of layers and parameters. The output image from this stage in the video processing pipeline contains pixel-level masks highlighting steel defect locations. This output is modified to ensure that the predicted defect locations are highlighted using red pixels

TABLE I. THE DIFFERENT SYSTEM-LEVEL SPECIFICATION INFORMATION FOR THE TWO SYSTEMS USED IN THIS STUDY FOR ASSESSING THE VALIDATION PERFORMANCE OF THE PROPOSED MODEL FOR STEEL DEFECT DETECTION.

System Specifications	System 1	System 2
Processor	Intel® NUC10i7FNH1 Core i7 with 1.10 GHz clock speed	Intel® Core i7–8700 CPU with 3.2 GHz clock Speed
RAM	16GB SDRAM	32GB SDRAM
ROM	256GB SSD	N/A
Hard Disk	1 TB HDD	350 GB HDD
Operating System	Ubuntu 20.04	Ubuntu 18.04
GPU	Intel® Integrated UHD Graphics	NVIDIA® GeForce® GTX 1080 TI GPU

and green color bounding box surrounding each of these pixel regions.

Two different types of systems were used to examine the performance of the proposed model for Steel Defect Detection. The training process was conducted offline on System 2, which is equipped with on-board GPU with details given in table I. The different Deep Learning models trained for varying Architecture-Encoder pairs were saved and the validation process was performed on two separate systems to examine whether the validation process could be performed in real-time for the two different PCs with varying system configurations. Table I highlights the different aspects of the two different types of PCs that have been used to examine the performance of pre-trained models in terms of providing real-time steel defect detection. It can be seen from table I that system 1 has *Intel* ® Integrated UHD Graphics Card, which is not supported by *Nvidia* ® *CUDA* ® libraries leading to slower validation time. In comparison, the onboard GPU within system 2 had full support from the *Nvidia* ® *CUDA* ® libraries, which allowed a faster training and validation processing time, which will be elaborated in the next section.

RESULTS AND DISCUSSION

Table 2 outline statistical evaluation for the different Architecture-Encoder pairs in terms of the different metrics, such as Dice Loss, mIoU, Precision, and Recall. For the metrics such as mIoU, Precision and Recall, higher values reflect better performance. Each metric and encoder module has the highest, lowest and average values specified, as it allows the exploration of level of variance as well as upper and lower bounds on the different metrics. For Dice Loss, the opposite rule has to be applied; the smaller values reflect better performance of the system. The bold values in tables 2 specify the highest value for a particular Architecture. The bold values with an underline specify the highest value in comparison to all the different Architecture-Encoder pairs. For performance regarding UNet [22] Architecture, EfficientNet-B0 [24] outperforms other Encoder modules with best performance for two out of four metrics, namely Dice Loss (a.k.a. F1-score) and mIoU. For the case of Precision, the best results are highlighted by ResNet-18 encoder module with UNet architecture. Whereas, the encoder module RegNet-X2 is able provide the highest performance in terms of Recall. Since, most of the studies pertaining to the deployment of Deep Encoder-Decoder

TABLE. II: A COMPARISON BETWEEN THE DIFFERENT ENCODER-ARCHITECTURE PAIRS IN TERMS OF THE DIFFERENT PERFORMANCE METRICS UTILIZED IN THIS STUDY.

UNet Architecture					
Encoder		**Dice Loss**	**mIOU**	**Precision**	**Recall**
ResNet-18 [35]	Max.	31.80	91.86	**99.92**	91.59
	Min.	4.37	54.87	99.54	54.86
	Avg.	12.59	80.88	99.73	81.02
ResNet-34 [35]	Max.	28.11	96.40	99.83	96.57
	Min.	1.96	59.40	99.56	59.43
	Avg.	11.11	83.47	99.72	82.13
RegNet-X-2 [37]	Max.	18.81	97.13	99.78	**99.35**
	Min.	1.59	71.56	99.55	71.71
	Avg.	7.26	88.01	99.65	87.06
Efficient-b0 [36]	Max.	32.17	**97.33**	99.80	97.53
	Min.	**1.41**	55.85	99.53	55.92
	Avg.	11.44	83.26	99.61	83.46
Efficient-b2 [36]	Max.	47.25	96.06	99.75	96.36
	Min.	2.18	43.56	99.56	43.60
	Avg.	14.39	69.84	99.65	81.87

networks for different applications leverage F1-score and mIoU as the most reliable metrics, the most optimal performance can be obtained by using UNet architecture with EfficientNet-B0 encoder module.

There are some relevant studies, which have presented their own approach towards steel corrosion detection. For example, study by [19] make use of roughness analysis and color comparison on image patches to separate corrosion patches for steel images. The recall and precision levels computed by the study range between 5% and 100% and 25% and 30% respectively, which is much lower than results obtained in this study. Another study [21] made use of texture analysis with variables such as contrast, correlation and energy. Since, these variables do not correlate with the metrics used in this study, no comparison can be possible. Study by [26] is used for crack and corrosion detection, which made use of a supervised classification method with code-word dictionary consisting of stacked RGB histograms for image patches symmetric gray-level co-occurrence matrix for each patch. The metrics used by this study [26] are also different from our study. The study [26] reports that the false positive rate ranges from 1 pixel (0.2 percent of image patches), 25% (0.1 percent of image patches) and 100% (very low percent) When comparing the results in the other studies [19-21, 26] in terms of depth of evaluation and the metrics used within this study, the performance of the proposed system far surpasses other study highlighted with demonstrable high-performance using quantitative and qualitative analysis.

Figure 3 highlights a side-by-side comparison between the validation time between System 1 and System 2 with values for each Architecture-Encoder Pair highlighted on top of each bar plot. For system 1, lowest value for validation time is outlined by UNet architecture [22] with RegNet-X2 encoder module. For system 2, the lowest values for validation time have been reported by UNet [22] architecture with ResNet-18 encoder module. The EfficientNet-B0 encoder module, which provided the optimal performance has significantly higher validation time in comparison to other encoder modules selected. It can be seen here that there is always a trade-off between the best validation time and best performance, as improving one variable leads to decrease in another and vice versa. For obvious reasons, the validation time values for

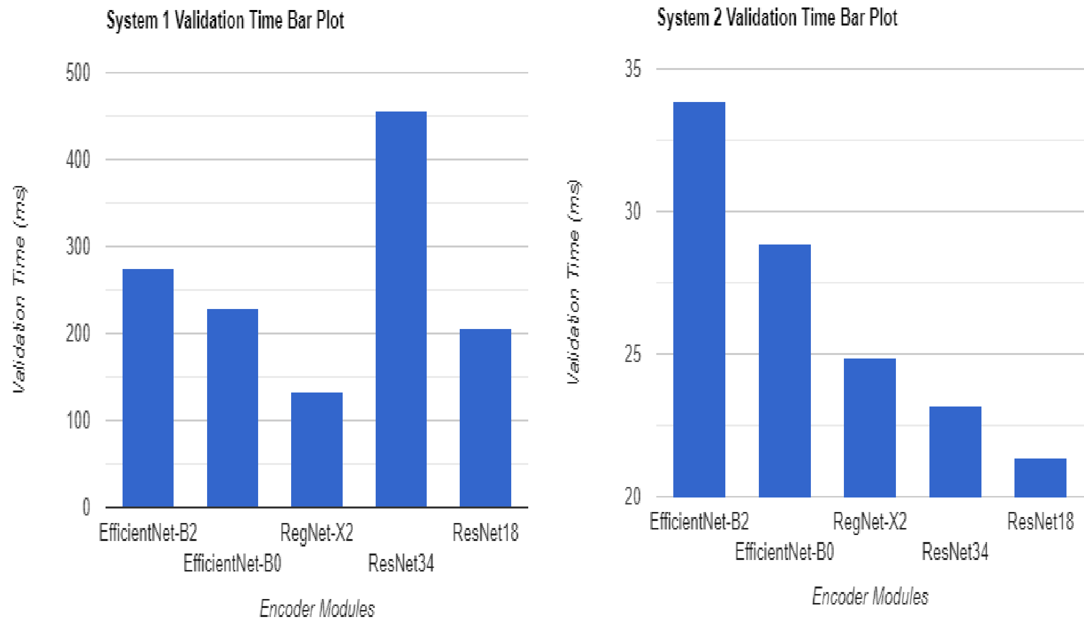

Figure III: A side-by-side comparison between the validation time for System 1 and System 2, which is mentioned in table I.

GPU are considerably lower than their counterparts leveraging CPU computational capabilities alone. The difference in validation time between system 1 and 2 is significant, where the system 2 is able to provide real-time performance if it is implemented on an actual robot with GPU resources to compute defect detection algorithm for bridge inspection.

CONCLUSION AND FUTURE WORKS

This paper presents the development of a novel defect detection system, which can be introduced as one part of the overall suite for automated system for bridge inspection. Two novel dataset containing data from two separate set of bridges were used in this study; one set was used for system training and the other was used for validation of the system. The first set was developed using bridge image information from Vietnam and the second set was developed from data collection at Highway-80, Lovelock, NV, USA. The proposed system was able to leverage the Deep Encoder-Decoder architecture, namely UNet, along with different encoder modules. The different modules were used to create Architecture-Encoder pairs and compare their performance for steel defect detection. The quantitative results demonstrate considerable promise of the proposed system for real-time processing with reliable performance for different Architecture-Encoder pairs. Future work will focus towards on-board implementation on an actual robotic platform to provide real-time performance for steel defect detection on actual bridges.

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