A New Agent-based Solution for Bridge Lifespan Extension

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ABSTRACT

Bridges are one of the most important and useful components of the transportation infrastructure, as they are crucial to many aspects of daily life, particularly in terms of economic development. However, bridges are vulnerable to several damages, malfunctions, and collapses that may considerably reduce their lifespan. The main causes of bridge fatigue are congested areas, excessive traffic, overloads, and additional vibration brought on by vehicles crossing them over. These elements reduce a bridge's longevity and raise maintenance costs. For a bridge to last as long as possible, it must not be crossed by an excessive number of cars and big trucks at once, and traffic should be kept under control. This study proposes an intelligent and autonomous multiagent-based system that incorporates a deep learning model to improve the monitoring of a bridge's crossing traffic. The idea was to propose a novel system for monitoring autonomously crossing vehicles in real-time to prevent the hastening of a bridge's infrastructure decline. The proposed system aimed to (i) increase the safety of drivers; (ii) lower maintenance costs; (iii) lessen the likelihood of bridge collapse, and (iv) lengthen bridge lifespans. Using a sample dataset, a straightforward deep learning model (CNN) was tested to improve bridge traffic monitoring. The performance of the proposed model was compared with the VGG-19 model. The results showed that the proposed model was effective in determining traffic congestion status with a 95% accuracy. As a result, the proposed system can be deployed on any bridge and can reduce crossing traffic overloads, extending its lifespan.

Keywords-multiagent system; deep learning; convolutional neural network; decision system

I. INTRODUCTION

Any platform that enables people to go from an origin to a destination using a variety of modes, such as a car, bus, train, strolling, bicycle, etc., is referred to as a land transportation network. Besides the advantages of transportation networks for mobility and access, cities often have transportation-related problems, such as traffic congestion and air pollution, due to the growth in population and vehicle ownership [1]. One of the most important and expensive forms of transportation infrastructure is the construction of bridges. Bridges are crucial connections that cross mountain gorges, bodies of water, or other routes for cars, trains, trucks, and other vehicles and are one of the quickest, safest, and most practical ways to move from one side to the other. Bridges are also the most important elements of the transportation system for the development of economic corridors, as they help balance economic growth in deprived areas. The number of road bridges in China surpassed 870,000 by the end of 2019 [2]. The Hong Kong-Zhuhai-Macao Bridge is the longest bridge-tunnel combination route across the sea, with a total construction cost of over RMB127 billion, and was officially opened to traffic in 2018.

However, bridges experience rigorous service, primarily from external loads, which can result in several degradations and damages. Most bridge failures occur between 50 and 100 years after their first opening, according to statistics on accidents involving bridges in Europe and the US. Most bridges are currently slowly approaching the end of their design life. Traffic jams and vehicle overloads are believed to undermine bridge infrastructure, wear out bridge parts, and cause unexpected failures. So, it is critical to pay more attention to the safety of bridge structures to keep them safe, reduce maintenance requirements, and extend their lifespan. According to estimations, the lifespan of a bridge is reduced by 80% if vehicles are 50% or more overloaded. The Bohol bridge in the Philippines collapsed in 2022 because a delivery truck carrying sand and gravel passed the bridge with other vehicles, killing four people and wounding seventeen others [3]. Vehicle overloading is one of the main causes of bridge collapses throughout history. Three people were killed and two wounded after an overpass collapsed in Wuxi, Jiangsu province, China, as a result of overloaded vehicles [4].

Several studies have been conducted to ensure a specific level of service on road bridges. These studies can be divided into two categories: those attempting to strengthen the construction of a bridge [5-6] and those attempting to track its usage to improve its serviceability, mainly for bridges susceptible to vibrations caused by heavy vehicles [7]. Bridges must be regularly examined and maintained to prevent failure and collapse. Real-time monitoring of a bridge's traffic condition is crucial. Any malfunction could lead to accidents, deaths, property damage, and economic loss.

Several studies have attempted to regulate bridge traffic and subsequently improve its status [4-9]. However, none of them aimed to i) smartly monitor the traffic lights at the bridge entrance to control the intensity of crossing vehicles, ii) decrease the intensity of automobile vibrations mainly during congestion, and iii) detect any anomaly on the bridge, such as an accident that can make its status worse. This paper presents a real-time autonomous agent-based system that can: i) control and monitor traffic signals according to the total weight of vehicles on the bridge to ensure that the allowed load is not exceeded, ii) detect and identify the reason for any traffic congestion on the bridge, iii) alert authorities if the congestion is caused by anomalies, such as an accident, and iv) be deployed on any bridge regardless of its infrastructure.

II. RELATED WORKS

Several studies have focused on ensuring a specific level of service in bridges, and can be divided into two categories. Studies in the first category focus on how to improve bridge construction technologies to extend their lifespan. In [10], a novel bridge technology was proposed that was entirely distinct from the standards, by decreasing the weight and member size and shortening the building period. This structure addressed the problems of lifespan extension, durability improvement, and high seismic sensitivity. The webs of this bridge were made of prefabricated, high-strength, pre-stressed concrete panels that were formed like butterflies. The Bridge Weigh-in-Motion (B-WIM) system measures the weights of passing vehicles using an existing road structure such as a bridge [10]. This system was introduced in the late 1970s. The B-WIM system was improved and is now the most widely used, as it is used by more than 1000 sites in 16 different nations. By observing strain signals, the main goal of the B-WIM system is to calculate the combined weight of the passing trucks using strain gauges and strain transducers. The system offers vehicle-by-vehicle data along with other details, such as strain measurements, influence lines, load distribution factors, and dynamic loading amplification that can be used to assess the bridge's structural integrity. This system can be connected to other devices to identify overloaded cars, send warnings to heavy vehicles to reroute, and remotely monitor them by connecting WIM data to satellite tracking and wireless communication. Despite these benefits, the above solutions are expensive, difficult to integrate into existing bridges, and difficult to implement.

The second category aims to bring new ideas, based on hard and soft technologies, to existing bridges to improve their performance. In [11], a weight restriction monitoring system was described to prevent large vehicles from crossing the Cawood Swing Bridge. This system combined Clearview's M720 vehicle count classifier with the recent Automated Number Plate Recognition (ANPR) cameras. When a car crosses a bridge, the vehicle classification device measures its length, classifies it, and then turns on the ANPR cameras, which photograph any cars that do not fit the M720 standards for vehicle length. The system then notifies the offending vehicles of their infringement. Infringers shall be penalized under the national ANPR standards if the vehicle requires additional examination. The weight restriction monitoring system provides a more affordable alternative with lower maintenance costs while protecting the confidentiality of non-offending drivers. Moreover, data are delivered directly from all cars crossing the bridge to the hosted in-station, and it provides remotely accessible data for configuring counters and cameras. However, this method cannot be used to prevent a bridge from collapsing due to overweight, as the total weight of all vehicles on the bridge is unknown and an overloaded vehicle can cross it.

In recent years, computer vision-based infrastructure damage detection techniques have become increasingly popular. Surface faults like corrosion and cracks have received a lot of attention. In [12], the issue of routinely checking bridges' structural and operational status was addressed, by quantifying a bridge's displacement to analyze its structural behavior and judge its safety. This approach incorporated improved robustness to image rotation and was based on multiple-image processing bridge displacement measurements, using template matching, a homograph matrix, and the NCC function. In [13], a learning-based approach based on 1D-CNN, LSTM, and image frequency was proposed to detect concrete defects. The 1D-CNN-LSTM model was trained, validated, and tested using thousands of images of cracked and uncracked concrete bridge decks. The 1D-CNN-LSTM model proved to be 99.05%, 98.90%, and 99.25% accurate, performing better and offering a much faster training and implementation process than previously proposed CNN-based solutions. Even if the model's false positive and false negative rates were satisfactory during implementation, it could perform even better with more training data.

The Overload Vehicle Resistance System for Bridges [14] sought to prevent an overloaded vehicle from crossing it, by including a weight sensor at the start to determine the vehicle's weight before approaching the bridge. This system focused on developing a prototype that simulates a mechanism to protect the bridge from overload. The barrier closes and blocks the entry to the bridge if the weight is more than allowed. By addressing the problem of vehicle overload, this system also extends the life of roads and bridges. Moreover, it is a useful tool for boosting compliance with fundamental regulations. However, it had no control over what happens when the barrier closes on the overloaded vehicle. Without taking into account how bridge congestion affects the bridge's longevity, it solely addressed the problem of vehicle overload. The management of old bridges is one of the most difficult problems the state transportation agencies face. When deciding whether to repair or maintain a bridge, a trustworthy assessment of its status and condition is necessary. Visual inspection techniques individually analyze each component to find flaws and are extremely difficult and time-consuming. Additionally, there are times when inspectors must close bridges for security concerns.

Even with these advantages, most of these approaches: i) are expensive, ii) are challenging to integrate and deploy into existing bridges, iii) do not take into account the longevity consequences of bridge congestion, iv) use computer vision only to detect real-time concrete cracks or bridge displacements, and v) do not take into account the total weight of vehicles on the bridge. Therefore, more investigation is still required to determine how to prevent vehicular damage to bridges. The available solutions are insufficient for a comprehensive protection system. The major goal of the current study was to propose a new autonomous and intelligent system based on learning agents to recognize bridge conjunctions, identify their causes, and make the best decisions. To accomplish these goals, this solution aimed to i) smartly monitor the traffic lights at the bridge's entrance according to the number and the total load of vehicles crossing, ii) identify any traffic congestion on the bridge and make the appropriate decision in real-time, and iii) notify the appropriate authorities if an anomaly, such as an accident, is detected on the bridge.

III. PROPOSED SYSTEM DESCRIPTION

The proposed system consists of both hardware and software components. Its hardware components are shown in Figure 1.

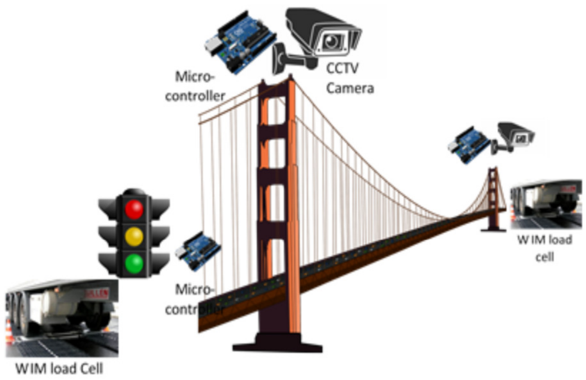

Fig. 1. Proposed system's hardware architecture.

A. *System's Hardware Architecture*

The proposed autonomous system consists of:

- Two weight sensors such as Weigh-in-Motion (WIM) load cells placed at the bridge entrance and exit. A WIM sensor is a piezoelectric polymer sensor that generates a voltage proportional to the applied pressure or load. This system is used primarily to measure the weight and speed of vehicles in motion [15]. The instant total weight of the vehicles on the bridge can be calculated based on the weight of each vehicle entering and exiting the bridge.
- Closed Circuit Television (CCTV) cameras installed along the entire bridge. This system consists of video cameras, display monitors, and wired or wireless data networks. This system is used to capture an image of the current traffic on the bridge and send it for processing. The field of view for CCTV cameras ranges between 40-120 feet [16], depending on various variables. The number of cameras to be deployed is based on the length of the bridge.
- Some microcontroller boards, such as the Arduino UNO. Arduino is an open-source prototype platform built on simple hardware and software [17]. These devices can be used to collect the necessary data from the sensors/camera and carry out the required computations for managing and manipulating the bridge traffic lights.
- A server for displaying the instant status of the bridge, i.e. a dashboard.

B. *System Software Components*

The proposed system's multi-agent global dynamic includes two different kinds of agents:

- The first is the Traffic agent, who is responsible for monitoring the traffic lights. Based on the instantaneous detected traffic, its task is to decide when to change the traffic lights from green to red (and inversely). This agent can be installed on the traffic lights' microcontroller at the bridge entrance and is in charge of providing the server with the data required to update the dashboard with the status of the entire bridge. It has also the duty to report any irregularity found on the bridge to the authorities.
- Crowd agents are responsible for detecting any anomalies on the bridge, such as normal congestion or congestion brought on by accidents, etc. These agents are placed at each camera's microcontroller across the bridge, and they are in charge of turning on the corresponding camera and analyzing the status of the bridge according to the taken bridge picture. Each crowd agent can assess the condition of a specific section of the bridge and inform the Traffic agent to update the traffic lights appropriately.

These agents communicate by sending messages to prevent the bridge from traffic congestion. This dynamic includes three main processes:

1. A Negotiation process between these agents according to the current status of the bridge to take the right decision. When the Traffic agent requests it, the Crowd agents are in charge of checking the status of their respective bridge segments. The subsequent duty is to monitor the traffic light following the data gathered from the Crowd agents and the knowledge of the bridge status.
2. A Prediction process, using a supervised learning model (regression model). This model is trained based on historical data on previous bridge traffic, such as those in Table I. These records detail the total weights of the vehicles that crossed the bridge every time interval, every day, and every month. The trained model is employed to determine the initial schedule for the traffic light switching per time, day, month, etc. This schedule is flexible and subject to change depending on the situation.
3. A Detection process that uses a Convolutional Neural Network (CNN) to identify any irregularities on the bridge that necessitates an urgent adjustment to the timetable for switching the lights. This process is used to determine whether there is congestion on the bridge, classify it according to normal or abnormal, and determine whether or not it is related to an accident.

TABLE I. DATA SAMPLE OF VEHICLES CROSSING THE BRIDGE

Date	Time	Total weight	Number of cars	Camera result	Traffic lights status
2023/02/12	8:08:48	4486	3	0	1
2023/02/12	8:08:54	4485	3	1	0
2023/02/12	8:08:59	4483	4	1	0
2023/02/12	8:09:04	4481	5	1	1
2023/02/12	8:09:10	4480	6	1	0
2023/02/12	8:09:16	4478	7	1	0
2023/02/12	8:09:21	4476	8	1	1
2023/02/12	8:09:27	4476	8	1	0
2023/02/12	8:09:33	4476	8	1	0
2023/02/12	8:09:39	4475	8	1	1
2023/02/12	8:09:44	4474	8	1	0
2023/02/12	8:09:50	4473	8	1	0
2023/02/13	8:24:12	4500	1	0	1
2023/02/13	8:24:17	4500	1	0	1
2023/02/13	8:24:23	4499	1	0	1
2023/02/13	8:24:28	4499	1	0	1
2023/02/13	8:24:34	4498	1	0	1
2023/02/13	8:24:39	4498	1	0	1
2023/02/13	8:24:45	4498	1	0	1
2023/02/13	8:24:51	4498	1	0	1
2023/02/13	8:24:56	4498	1	0	1
2023/02/13	8:25:02	4497	1	0	1

C. System's Global Dynamic

The global dynamic of this system can be divided into two phases: an initialization and a decision phase.

- During the Initialization phase, the Traffic agent employs a regression model to predict the weights of oncoming traffic on the bridge for the upcoming days. The time/duration schedule of traffic light switching is decided based on the acquired estimates. When this phase is over, the second begins.
- Using the aforementioned schedule, the Traffic agent adjusts the traffic signal during the Decision phase as shown by the flow diagram in Figure 3. The agent updates the overall weight over the bridge at each instant using the information obtained from the weight sensors and the WIM load cells. This value will be compared to the estimated one to determine whether there is any congestion on the bridge and to ensure that the maximum load permitted is not being exceeded. There could be several cases.

The first case is when the calculated total weight is much less than or very close to both the estimated and the permitted weights, respectively. Then, the timetable for the traffic light is maintained.

Fig. 2. Crowded road detection.

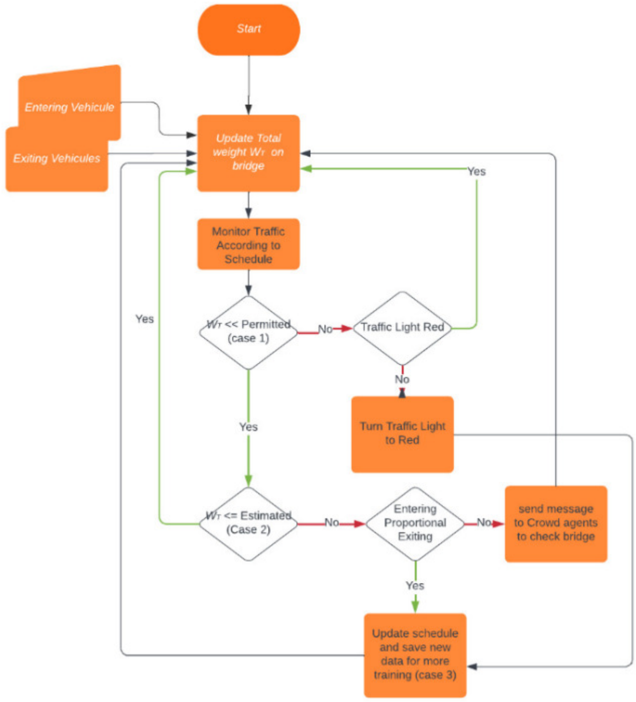

Fig. 3. Decision phase flowchart.

The second case occurs if the calculated total weight is greater than the estimated but is still less than the permitted. The traffic agent determines whether the excess weight is the result of accident-related or regular congestion. The timetable for the traffic lights should be adjusted, depending on the congestion type:

- A bridge anomaly exists if there is a large proportion of vehicles arriving relative to those leaving. The closest and farthest (two extremities) Crowd agents will receive a message from the Traffic agent asking them to investigate any anomalies in their section of the bridge.
- If the number of vehicles entering is proportional to those departing, there is normal congestion, and the traffic signal schedule should be modified following these new findings. The Traffic lights should be turned red until the traffic jam is alleviated.

Each Crowd agent should turn on its camera after receiving a message from a Traffic agent to capture a photo of the bridge before starting the detection procedure. The Traffic agent determines whether to examine additional Crowd agents based on the results or whether to alert the police of the accident's position on the bridge.

The third case occurs if the calculated total weight is larger than the estimated total weight, less than the permitted one, and there is no accident on the bridge. In this case, the traffic signal schedule will be maintained. These new records will be used for further training of the supervised model to improve its performance. All discoveries must be submitted to the server to be preserved for later use or to be exhibited in the dashboard, as shown in Figure 4.

Fig. 4. Example of the dashboard content.

IV. EXPERIMENTAL EVALUATION

A simplified version of a CNN model for binary image classification was designed and implemented to test the feasibility and possible deployment of the system, as shown in Figures 2 and 5. A binary classification was used since only the two classes of congested and not-congested were taken into account in this initial version of the model.

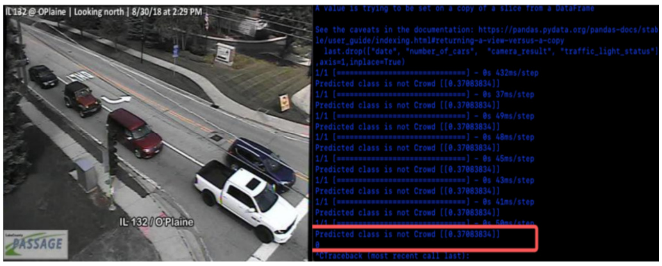

Fig. 5. Not crowed road detection.

The Google Images platform was used to obtain a dataset of road congestion levels for the training of the CNN, and 1168 total photos were collected. The dataset included two traffic congestion classes: Crowded (418 images) and Not Crowded (750 images). The implemented network consists of three convolutional layers with a Relu activation function, each followed by a Maxpoling layer and two fully connected layers. As it is easy to recognize the crowded (or not) features within an image, only a few deep layers were needed for testing the model. The last layer was based on the Sigmoid activation function. The used filters had a size of 3×3×3 for RBG images (256×256×3) and a stride of 1. The first layer was a convolutional layer with 16 filters, the second used 32 filters, and the last used 16 filters. The performance of the traffic detection models was evaluated using three metrics: Precision, Recall, and Accuracy. The results of this model were compared to VGG-19, as shown in Table II.

TABLE II. CNN VS. VGG-19

	Precision	**Recall**	**Accuracy**
CNN	0.9062	0.9354	0.9545
VGG-19	0.9722	0.8139	0.9181

The accuracy, precision, and recall of the CNN model were 95%, 91%, and 93%, respectively. On the other hand, the accuracy, precision, and recall of the VGG-19 model were 92%, 97%, and 81%, respectively. VGG-19 classified 91% of the instances accurately, however, only 97% of the events classified as positive were genuinely positive. In addition, only 81% of all positive events were accurately detected by the model. These findings imply that the proposed CNN model could be a preferable option due to its simplicity, higher accuracy, and better ability to balance precision and recall.

V. CONCLUSION

Bridges are crucial components of the transportation system, and their collapse can have serious repercussions. It is essential to have a regular, real-time, autonomous controlling and monitoring system to protect against bridge damages caused by excessive traffic and traffic jams, particularly from overloaded vehicles. This study presented a novel autonomous and intelligent bridge protection system that uses an autonomous real-time decision-making system. This system was designed to increase a bridge's usage by protecting it from overload and traffic congestion. The hardware component of this solution, which included WIM load cells, microcontrollers, and CCTV cameras, was supported by a multi-agent system for autonomous decision-making that used deep and machine learning models. Using a road dataset, a limited version of the deep learning model was developed, trained, and tested. A straightforward CNN was used to demonstrate the viability of the suggested system. Despite its usefulness, this system had some limitations in preventing overloaded vehicles from crossing the bridge and identifying the type of anomalies. In future work, the CNN model will be expanded to detect overloaded vehicles, identify the cause of an anomaly, such as the occurrence of an accident among congestion, and will be evaluated based on real data cases.

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