International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 01 | January - 2024 SJIF Rating: 8.176 ISSN: 2582-3930

Survey Paper on Road Damage Detection and Reporting System Using Fully Connected CNN

[1]Prof. Nilima Pagar, [2]Yashraj Kharsade, [3]Manav Manadhane, [4]Akash Jagtap, [5]Raunak Gaikwad

Sinhgad Institute of Technology and Science, Pune 411041, Maharashtra, India.

Abstract

Many rural and metropolitan towns, as well as road authorities, encounter challenges in mapping surface damages resulting from numerous sources such strong rains, natural catastrophes, or other events that cause cracks and holes to emerge on the road surface. These organizations or private entities look out for solutions to implement automated methods of reporting damages on a surface of the road. The majority of the time, they lack the equipment needed to map the damage to the roadways. One of the main issues facing commuters is the numerous damaged road portions they must navigate. This causes riders to often reduce their pace, losing a great deal of time and energy and lengthening the time it takes them to reach their destinations. When driving at a faster speed and suddenly encountering a damaged section of the road, road damage can frequently be fatal. Furthermore, it is capable of identifying recurring bottlenecks, determining their cause, and suggesting remedies. The majority of the time, these traffic jams are brought on by road damage, which forces commuters to go far slower than is ideal.

Keywords: *Smart road damage detection, classification, Machine Learning, Image segmentation, CNN, fully connected CNNs, RDD System (Road Damage Detection System).*

1. Introduction: -

The health and safety of communities as well as the smooth operation of transportation networks depend on the preservation of safe and well-maintained roadways. However, there are several obstacles in the way of locating, documenting, and quickly fixing road damage. Potholes, cracks, debris, and other dangerous situations that can cause collisions, harm to cars, and general degradation of road infrastructure are common problems with road damage. Conventional approaches, which frequently depend on manual inspections or delayed responses to public concerns, have proven to be insufficient for detecting and reporting these problems.

Road surface damage detection and warning systems are essential for maintaining road safety, cutting down on maintenance expenses, and increasing the effectiveness of transportation as a whole. These systems are made to recognize different types of surface defects on roads, such as cracks, potholes, and deteriorations, and to alert drivers, road repair agencies, or self-driving cars in a timely manner. Systems for detecting and warning about degradation to the road surface are crucial for keeping road networks effective and safe. To identify damage and notify drivers and authorities in a timely manner, they use a mix of sensor technologies, machine learning, and communication systems. These systems are anticipated to become more crucial to the management of transportation infrastructure as technology advances. One sector that uses technology is road surface deterioration detection. The field of road surface damage detection uses technology—typically sensors and image processing—to track and evaluate the state of road surfaces. In order to identify and categorize road damages using photographs of the road surface, we are using the object detection technique. Convolutional Neural Networks (CNNs), the primary class of Deep Neural Networks (DNNs), may be used for this.

Research on road damage detection models based on artificial intelligence (AI) has received a lot of interest lately. Road damage may be automatically analyzed and tracked down, as manual damage identification is a tedious and time- consuming operation. A government agency is unable to maintain a reliable record of road conditions. The lack of experts who could assess the extent and condition of many impairments is another issue, as the evaluation is frequently quite subjective.

Among the Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs) are the primary class that can be used for image recognition and classification in most applications. CNNs are deep learning models that are especially intended for image-related tasks. Convolutional layers, pooling layers, and fully linked layers make up the structure. The CNN's first layers, which include convolutional and pooling layers, extract significant characteristics from the input pictures. These layers are in charge of identifying picture edges, forms, and patterns. The fully connected layers are located at the network's end. They take the high-level characteristics retrieved by the preceding layers and use them to produce predictions. CNN's primary advantage lies in its ability to automatically identify important elements without human oversight after training is complete. Hyperparameters, on

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 01 | January - 2024 SJIF Rating: 8.176 ISSN: 2582-3930

the other hand, are configurations that need to be established before training begins and are not learnt during training. They can significantly affect the model's performance, and choosing the best settings can improve accuracy. The procedure of hyperparameter tuning has not been covered in the majority of previous research. Metaheuristic optimization techniques are preferred since the process of fine-tuning parameters by trial and error is time-consuming.

2. Literature Survey: -

From the paper [1], a novel technique for detecting road damage based on unsupervised disparity map segmentation is presented. Instead of using intricate nonlinear optimization techniques, the algorithm modifies the disparity map by maximizing the energy function with respect to the stereo rig roll angle and the road disparity projection model. The altered map is then segmented using Otus's thresholding technique, which makes it possible to remove damaged road segments. Interestingly, the program detects road damage without requiring any settings. An evaluation of the algorithm against existing methods shows that it can reliably detect dangerous areas and that it can do it at a pace that is around 579 times faster than Cloud-based methods. Surprisingly, this performance boost requires less storage and labeling, and does not degrade user experience.

From the paper [2] the study emphasizes how crucial it is for traffic safety to identify potentially dangerous road degradation. Current cloud-based solutions need large labeled datasets and suffer from latency problems. Data augmentation strategies are applied in order to overcome data imbalances, and a mean F1-score of 0.6255 is achieved. The suggested EcRD framework offers a quick road segmentation algorithm for effective detection by fusing the benefits of the Edge and Cloud.

The paper [3] presents a novel unsupervised disparity map segmentation technique for road damage identification. It avoids the need for intricate nonlinear optimization approaches by immediately finding the numerical solution for reducing the disparity map's energy function. Using the YOLO-v4 object detector, which has been trained on a variety of road damage photos from several nations, the model exhibits good detection performance in the IEEE Global Road Damage Detection Challenge 2020. Since it is becoming more feasible to monitor urban roads using cameras—such as security, car, or smartphone cameras—the study emphasizes how crucial it is to identify road damage quickly in order to allocate repair resources wisely.

In the paper [4], road regions are identified using a segmentation algorithm, which generates a road interest map from raw photos. In order to improve maintenance and resource management, the project focuses on identifying and classifying different types of road damage by utilizing advances in computer vision. The IEEE Big Data Cup Challenge 2020 submission of the suggested ensemble model shows excellent accuracy and efficiency. The accuracy of road damage identification at the pixel level is about 97.56%. The ensemble technique achieves an F1 score of 0.6358 for the test 2 dataset and 0.628 for the test 1 dataset after thorough testing with several model versions.

The focus of the paper [5] is on recognizing damages in road photographs taken with a smartphone placed on a car. It also describes the methods used in the Road Damage Detection and Classification Challenge. The study uses a quicker R-CNN to identify and categorize different types of road damage, modifying model parameters according to size and aspect ratio analyses of the training dataset. A lightweight road damage detector is also unveiled, utilizing the Edge's Gray Level Co-occurrence Matrix capabilities for quick identification and alerting of potentially dangerous road damage. In addition, a novel image generator utilizing cycle-consistent adversarial networks is integrated into a cloud-based multi-type road damage detection model for long-term road management. This model improves detection accuracy by means of automated picture labeling.

From the paper [6], the authors, emphasizes that efficient urban road monitoring is possible with the use of contemporary technologies, such as cellphones, in-car cameras, and security cameras. This method seeks to maximize the distribution of maintenance resources according to designated regions by identifying certain forms of road damage. The research describes a method for detecting and classifying different types of road damage that took part in the 2018 IEEE Big Data Cup Challenge. Exhibiting the effectiveness of the ResNet-50 model, the study highlights how well it performs in comparison to more complex models. Testing using a Linux PC with a 1080Ti GPU and an NVIDIA consumer-grade GPU, as well as Google Collab with K80, reveals that the method relies on an object identification algorithm that was trained on a variety of photographic examples classified by the Japan Road Association.

As a part of the IEEE International Conference on Big Data 2020, the article [7] provides insights into the model selection, tuning method, and outcomes of the Global Road Damage Detection Challenge. Using popular PyTorch frameworks like Detectron 2 and Yolo v5, the study evaluates single and multi-stage network designs for object identification and creates a benchmark. Focusing on data preparation for the road damage training dataset from India, Japan, and the Czech Republic, the study includes the best 12 options offered by different teams. YOLO-based ensemble learning is notably used by the top model, which obtained an F1 score of 0.67 on test 1 and 0.66 on test 2.

The paper's [7], conclusion highlights the challenge's successful elements as well as potential areas for improvement going forward.

The paper [8] uses segmentation to identify road regions and create a road-interest map from raw photos, and then uses deep learning models for effective road damage identification. In order to achieve an F1 score of 0.58 using an ensemble model with TTA, the article [8] presents the solution using YOLO in the IEEE Big Data Cup Challenge 2020. It highlights the lightweight and quick YOLO v5x-based strategy with impressive accuracy. The suggested model has potential for detecting road deterioration in real time. For thorough detection, the study also incorporates cutting-edge deep objective detection models like YOLOv4 and Faster-RCNN. Image processing-based technologies, such as security cameras, in-vehicle cameras, and smartphones, offer practical options for identifying and categorizing road problems given the requirement for automated monitoring systems to expedite road repair.

In the mentioned study [9], a novel deep neural network approach for road-surface-damage object recognition is presented, with a move toward semantic segmentation as the detection strategy. This modification tackles issues related to precisely extracting damaged parts when utilizing bounding boxes, which frequently include superfluous bigger picture sections. In order to provide the foundation for a recently developed semantic segmentation method, a new picture dataset consisting of 1,650 sets is created for training and validation purposes. The enhancement of accuracy and computational speed is achieved by surmounting the computational inefficiencies of auto-encoding procedures through the implementation of an encoder-type semantic segmentation. Based on four performance indicators, performance evaluation shows that the ProposedNet model outperforms auto-encoder-based deep neural networks in terms of efficacy. In addition, the model achieves a notable decrease in the number of parameters and an increase in operating speed. The encoder-type technique outperforms auto-encoder-based competitors in accuracy, according to experimental results on a generic set of road-surface damage photos. The strategy correlates well with ground truth.

The mentioned study [10] describes deep learning-based image analysis for detecting and classifying road damage. The 2020 IEEE Big Data Global Road Damage Detection Challenge Dataset was used to comprehensively examine the suggested ensemble learning algorithms with test time augmentation. Our strategies were able to obtain an F1 score of up to 0.67, according to experimental data, which allowed us to win the Challenge. The 2020 IEEE Big Data Global Road Damage Detection Challenge Dataset was used to comprehensively examine the suggested ensemble learning algorithms with test time augmentation. Based on experimental data, the author was able to win the Challenge since this technique was able to attain an F1 score of up to 0.67.

3. Gap Analysis: -

The survey article emphasized the necessity for improvements in semantic segmentation techniques for precise identification, as well as the relevance of the suggested deep neural network approach for road-surface-damage object recognition. The survey paper's shortcomings pertain to the difficulties encountered by conventional bounding box-based detection algorithms, which find it difficult to identify specific damaged areas because of the presence of wider, unnecessary picture portions. The areas for improvement are:

1. **Semantic Segmentation Techniques**: In order to guarantee the precise identification and isolation of damaged regions in road-surface photographs, the study highlights the necessity for more research into improving semantic segmentation approaches.
2. **Computational Efficiency:** There is a need to overcome the shortcomings of current auto-encoding methodologies, which are frequently sluggish when processing big datasets, by developing quicker computing techniques while maintaining high accuracy**.**
3. **Standardization and Benchmarking:** The lack of established benchmarks and performance metrics related to road-surface-damage object detection creates a gap in the evaluation and comparison of different algorithms, impeding the formation of a uniform performance standard.
4. **Real-World Application Validation:** To verify the ProposedNet model's usefulness and resilience in actual applications, more research is required to validate it in real-world scenarios and different environmental circumstances.
5. **Dataset Diversity:** Improving the diversity and volume of the datasets used for training and validation might close the gap in terms of complete data representation, allowing for more accurate and dependable model performance over a wide range of road-surface conditions.

4. Problem Statement: -

To create a model that can segment the road surface from the images. It should utilize the Fully Convolutional Neural Networks to perform semantic segmentation for road surface identification and damage detection. To create an application which can detect the road damage, and can acquire the geographic location through the GPS and save the related data to visualize it in application.

5. Motivation: -

Potholes and speed bumps are the most frequent causes of traffic accidents. It ought to be observed and reported. The primary form of public transportation is the city road system. Roads have to be inspected often. Road condition inspections in urban areas are often performed by human resources, which is a labor-and time-intensive activity. The motivation for the Road Damage Detection project stems from a shared desire to make our roads safer and more robust. Every day, numerous people use these critical modes of transportation, and the initiative aims to give them with a useful tool to help improve their communities. We hope to decrease accidents, car damage, and traffic interruptions by encouraging citizen involvement and facilitating the rapid detection and resolution of road damage.

Furthermore, this effort demonstrates the potential of technology in uniting individuals to address real-world issues. The motivation is strongly rooted in the conviction that by collaborating and using new ideas, we can lead the path for safer and more efficient road networks that benefit everyone. The motivation for the Road Damage Detection project stems from a shared desire to make our roads safer and more robust.

6. Proposed Methodology: -

The proposed method incorporates a complete approach to developing an efficient and accurate road damage detection system utilizing a fully connected Convolutional Neural Network (CNN). The technique begins with a thorough examination of the literature and the gathering of datasets, followed by the creation and modification of the CNN model architecture adapted particularly for road damage detection.

Advanced backpropagation techniques are used to train and refine the model, and its performance is measured using important metrics such as accuracy, precision, recall, and F1 score. The trained CNN model is incorporated smoothly into a Flutter application, allowing users to contribute real-time road photos for fast damage prediction. The Flask-based backend infrastructure guarantees smooth communication between the application and the CNN model. The solution also includes geo-location data processing and database connectivity to securely store and manage the gathered road damage data. A specialized website is built for local governments to view and update the status of maintenance and repaired places, allowing for more efficient communication and collaboration. To assure the system's functioning and dependability, rigorous testing and validation processes are carried out. The detailed reporting and documentation of the whole development process further explain the methodology, technical requirements, and system architecture, stressing the project's contribution to efficient road maintenance and management methods.

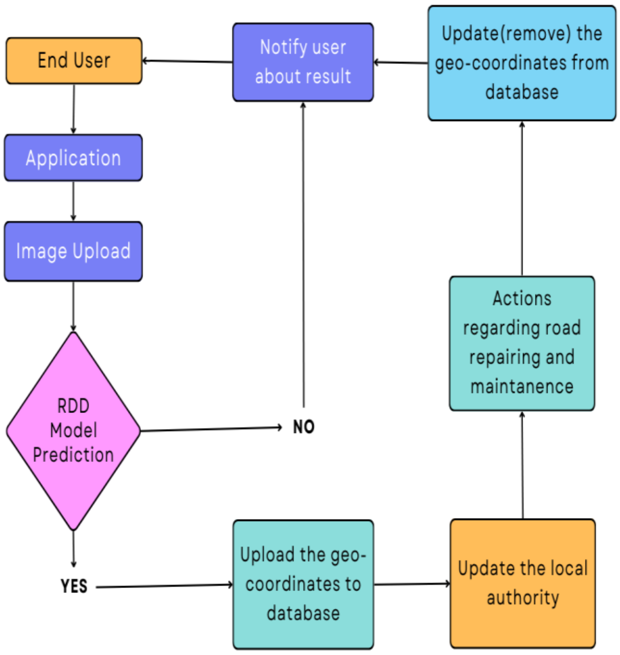

Figure 1: System Architecture of RDD System.

Moreover, the suggested approach highlights the CNN model's careful architecture, which incorporates essential architectural components to improve its ability to detect road damage accurately. The CNN model is designed to extract complex characteristics and patterns from a variety of road photos by carefully configuring its numerous convolutional layers. Efficient feature extraction with minimal computing cost is possible with the use of suitable activation functions and pooling layers.

Furthermore, the presence of fully linked layers enables thorough learning of intricate correlations within the retrieved characteristics, enabling the model to identify minute differences between various kinds of road damage. To reduce overfitting and improve the model's capacity for generalization, the methodology makes use of regularization strategies such batch normalization and dropout. The survey paper aims to provide a thorough understanding of the model's architecture and its crucial role in the accurate identification and classification of road damages for effective and timely road maintenance practices by going into detail about the CNN model design within the proposed methodology.

Additionally, the incorporation of the CNN model into the suggested technique highlights its flexibility and scalability, enabling the effective analysis of various road photos in a range of geographical locations and climatic circumstances. With the use of deep learning, the CNN model is able to identify and classify many sorts of defects, such as cracks, potholes, and surface deformations, with accuracy. It also shows a strong capacity to detect subtle patterns and abnormalities within the road photos. The CNN model's practical applicability in real-world scenarios is highlighted by its seamless integration with user-friendly applications and backend infrastructures. This facilitates seamless communication between end users and local authorities, resulting in streamlined data collection, analysis, and timely decision-making. This survey paper highlights the potential of advanced deep learning techniques in revolutionizing the field of road infrastructure management, paving the way for safer and more resilient transportation networks globally. It does this by clarifying the complex interactions between the CNN model and the larger system architecture.

7. Proposed Algorithm: -

The steps of the CNN model are given below:

1. Initialize the CNN model with the required parameters and architecture specifications.
2. Perform the following steps for each input image:
   a. Apply the convolution operation with a set of learnable filters to extract features.
   b. Apply the ReLU activation function to introduce non-linearity.
   c. Perform pooling operations (e.g., max-pooling) to downsample the feature maps.
   d. Repeat the convolution and pooling steps to further extract hierarchical features.
3. Flatten the final feature maps into a one-dimensional vector.
4. Connect the flattened features to a fully connected layer.
   a. Apply the ReLU activation function for non-linearity.
   b. Incorporate dropout regularization for preventing overfitting.
5. Implement the output layer with appropriate activation (e.g., softmax) for multi-class classification.
6. Define the loss function (e.g., categorical cross-entropy) to measure the model's performance.
7. Employ an optimization algorithm (e.g., stochastic gradient descent) to minimize the loss function.
8. Iterate through multiple epochs of training to update the model's parameters and improve performance.
9. Validate the model using a separate validation dataset to assess generalization capability and prevent overfitting.
10. Once the model achieves satisfactory performance, evaluate it on the test dataset for final performance analysis.
11. Fine-tune the model's hyperparameters and architecture based on the evaluation results for optimal road damage detection accuracy.

The algorithm is further extended for the depth detection of the pothole with these steps:

1. Depth Estimation: Utilizing depth estimation algorithms, such as stereo vision or monocular depth estimation, to calculate the depth of identified potholes within the road images.
2. Depth Analysis: Analyzing the estimated depths of the potholes, categorizing them based on predefined depth thresholds to determine the severity of the road damage.
3. Prioritization: Assigning repair priorities to road segments based on the analyzed depths of the potholes, with deeper potholes receiving higher priority for immediate maintenance.
4. Validation and Calibration: Regularly validate and calibrate the depth analysis system to ensure accurate and reliable depth estimations, maintaining the system's effectiveness in prioritizing road repairs.

8. Conclusion: -

The study report concludes by offering a thorough summary of the state of road damage detection systems today and highlighting the value and effectiveness of applying cutting edge deep learning techniques, especially fully linked Convolutional Neural Networks (CNNs). This survey paper highlights the critical role of CNN models in accurately identifying and classifying various types of road damages, thereby improving road maintenance practices and overall transportation infrastructure management. It does this by thoroughly examining existing methodologies and thoroughly exploring the proposed methodology. The thorough approach taken by the suggested methodology—which includes the careful construction of the CNN model, smooth integration with user-friendly applications, and effective database management—reflects its potential to expedite the process of quickly identifying, reporting, and resolving road damage. This survey paper emphasizes the critical role of cutting-edge deep learning technologies in fostering safer and more resilient road networks, ultimately paving the way for improved road safety and sustainable transportation systems. It does so by shedding light on the real-world applications and promising results of the suggested methodology.

The Road Damage detection and Reporting System is a unique system that combines Convolutional Neural Networks (CNNs) for automatic identification of various forms of road damage with a user-friendly mobile app and a web-based interface for local authorities. The system intends to improve overall road safety and infrastructure management by streamlining the process of reporting road damage and facilitating timely repairs and maintenance activities. Using CNNs' more accurate capabilities, the system can effectively recognize and categorize various types of road damage, such as potholes, fractures, and debris, from visual inputs. The smartphone application offers users a streamlined interface for shooting and sending photographs of road damage, as well as geo-location details, enabling effective and quick reporting. The incorporation of a strong backend server allows for good communication between end users and local authorities, assuring quick response and management of reported damage incidents. Local governments may efficiently analyze and prioritize reported issues, easing the scheduling and coordination of repair actions to resolve detected road damage as soon as possible.

9. Future Scope: -

Looking ahead, a number of directions for further study and development offer good chances to enhance the capabilities of the suggested road damage detecting system. Future research might look at integrating sophisticated image processing methods and sensor fusion techniques to improve the system's capacity to identify intricate and subtle road damage with increased accuracy and precision. Furthermore, the integration of sophisticated deep learning algorithms, such as attention mechanisms and recurrent neural networks (RNNs), has the potential to enhance the system's temporal context awareness and predictive powers, allowing for more accurate and dynamic road damage forecasts. Furthermore, the system's proactive monitoring and early detection capabilities might be strengthened with the addition of real-time anomaly detection algorithms and anomaly localization techniques, enabling timely intervention and preventative maintenance procedures. In addition, the combination of cutting-edge geospatial analytics and predictive modeling techniques may provide insightful information about the long-term trends and patterns of road deterioration, equipping stakeholders with proactive infrastructure management procedures and predictive maintenance plans. The project is to contribute to the ongoing innovation and improvement in the field of road infrastructure maintenance and management by exploring these prospective directions for future research, hence promoting safer, more robust, and sustainable transportation networks in the future.

References: -

[1] L. A. Silva, V. R. Q. Leithardt, V. F. L. Batista, G. Villarrubia González, and J. F. De Paz Santana, "Automated Road Damage Detection Using UAV Images and Deep Learning Techniques," *IEEE Access*, vol. 11, pp. 62918–62931, 2023, doi: 10.1109/access.2023.3287770.

[2] M. Alamgeer *et al.*, "Optimal Fuzzy Wavelet Neural Network Based Road Damage Detection," *IEEE Access*, vol. 11, pp. 61986–61994, 2023, doi: 10.1109/access.2023.3283299.

[3] K. Zhao, J. Liu, Q. Wang, X. Wu, and J. Tu, "Road Damage Detection from Post-Disaster High-Resolution Remote Sensing Images Based on TLD Framework," *IEEE Access*, vol. 10, pp. 43552–43561, 2022, doi: 10.1109/access.2022.3169031.

[4] S. Karimzadeh, M. Ghasemi, M. Matsuoka, K. Yagi, and A. C. Zulfikar, "A Deep Learning Model for Road Damage Detection After an Earthquake Based on Synthetic Aperture Radar (SAR) and Field Datasets," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 5753–5765, 2022, doi: 10.1109/jstars.2022.3189875.

[5] Md. M. Hasan, S. Sakib, and K. Deb, "Road Damage Detection and Classification using Deep Neural Network," *2022 4th International Conference on Electrical, Computer & Telecommunication Engineering (ICECTE)*, Dec. 2022, Published, doi: 10.1109/icecte57896.2022.10114508.

[6] Q. Wang, J. Mao, X. Zhai, J. Gui, W. Shen, and Y. Liu, "Improvements of YoloV3 for road damage detection," *Journal of Physics: Conference Series*, vol. 1903, no. 1, p. 012008, Apr. 2021, doi: 10.1088/1742-6596/1903/1/012008.

[7] H. Samma, S. A. Suandi, N. A. Ismail, S. Sulaiman, and L. L. Ping, "Evolving Pre-Trained CNN Using Two-Layers Optimizer for Road Damage Detection from Drone Images," *IEEE Access*, vol. 9, pp. 158215–158226, 2021, doi: 10.1109/access.2021.3131231.

[8] S. Shim and G.-C. Cho, "Lightweight Semantic Segmentation for Road-Surface Damage Recognition Based on Multiscale Learning," *IEEE Access*, vol. 8, pp. 102680–102690, 2020, doi: 10.1109/access.2020.2998427.

[9] S. Shim, J. Kim, S.-W. Lee, and G.-C. Cho, "Road surface damage detection based on hierarchical architecture using lightweight auto-encoder network," *Automation in Construction*, vol. 130, p. 103833, Oct. 2021, doi: 10.1016/j.autcon.2021.103833.

[10] H. Maeda, Y. Sekimoto, T. Seto, T. Kashiyama, and H. Omata, "Road Damage Detection and Classification Using Deep Neural Networks with Smartphone Images," *Computer-Aided Civil and Infrastructure Engineering*, vol. 33, no. 12, pp. 1127–1141, Jun. 2018, doi: 10.1111/mice.12387.