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Pothole detection in bituminous road using CNN with transfer learning

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ABSTRACT

Road surfaces are highly affected by climatic changes which caused potholes and cracks. Maintenance of the road is a need-of-the-hour process for preventing the physical damage caused for vehicles. The important process in road maintenance is the detection of potholes and cracks. Automatic detection of potholes in bituminous roads is a tedious task. This paper proposed the detection of potholes using transfer learning and convolution neural networks. The results are promising, and The suggested method can provide valuable information that can be used for various ITS services. One such service is alerting drivers about potholes, allowing them to be more cautious while driving. Additionally, this information can be utilized to assess the initial maintenance needs of a road management system and promptly address any repairs or maintenance required. The achieved results through the proposed method are compared with the state-of-the-art detection algorithms like Transfer Learning + Recurrent neural network, Transfer Learning + Generated adversarial network. In that, the result obtained through the proposed method (Transfer Learning + Convolutional neural networks achieves 96 % of accuracy.

1. Introduction

In modern society, the most important foundation is road infrastructure. transport is very important in interconnecting the two cities and towns for people and goods. Road networks remain the most cost-effective and efficient solution for accessing locations however the key component of roads namely asphalt, tends to deteriorate significantly due to usage and exposure to atmospheric conditions such as rain, snow, frost etc., in order to address and repair these damages effectively, it is imperative to ensure continuous and comprehensive monitoring of the road infrastructure [1]. The defects of potholes are Included the presence of excessive water retained by the underlying soil structures and frequent traffic passes over the affected areas leading to. detoration of the road due to the weight of heavy vehicles.

Climate change characterized by increased rainfall can further exacerbate the formation of potholes by contributing to pavement detoration and reducing the overall durability of road materials. Report holds pose a significant danger to road users and contribute to the number of root accidents each year, including potential fatalities. Satellites, moreover disrupt traffic flow, increase travel times and escalate vehicle operation costs, to ensure the functionality and safety of the road. Regular maintenance should be conducted to address potholes and maintain the road [2].

Over time, road surfaces naturally deteriorate, which raises important concerns regarding transportation and safety that must be effectively addressed. The current method of diagnosing pavement distress by humans is slow, expensive, and requires a lot of labour. Detecting and assessing potholes is a crucial responsibility in effectively planning for road surface repair and rehabilitation [3]. The current process of estimating road damage is time-consuming, resulting in increased expenses for materials, labour, and equipment.

To ensure cost-effectiveness in the patching process and make informed decisions for future road maintenance, it is crucial to accurately assess the extent of the damage. An automated method is needed to efficiently as the need for a fast, accurate, and unbiased assessment of road distresses continues to grow, it becomes crucial to prepare for subsequent years' levels of degradation and distribute technique funds in accordance [4].

The current approach of relying on human visual inspection for pavement distress diagnosis is inefficient, expensive, and labour-intensive. One critical aspect of effective road surface road repair and rehabilitation planning is the timely detection and assessment of potholes [5]. Unfortunately, the existing process of estimating road damage consumes considerable working hours resulting in increased material, labour, and equipment costs.Accurate damage assessment is essential for cost-effective patching and informed decision-making for future road

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Table 1
Comprehensive literature of related work.

SI·NO	TITLE	TECHNIQUE	REMARKS
1	An Automated Machine-Learning Approach for Road Pothole Detection Using Smartphone Sensor Data	YOLOv3, HOG, SSD, SVM, and Faster R–CNN	The experiment employs a pothole dataset and real-time car video., The mean a95 %, respectively. Temporal and frequency domain factors improved pothole detection. The Random Forest classifier classified potholes best with 88.5 % precision and 75 % recall.
2	Pothole Detection Using Deep Learning: A Real-Time and AI-on-the-Edge Perspective	YOLOv1, YOLOv2, YOLOv3, YOLOv4, Tiny-YOLOv4, YOLOv5, and SSD-mobilenetv2	The experiment employs a pothole dataset and real-time car video., The mean a95 %, respectively. YOLOv4 and v5 had the highest mean average precision of 80.04 %, 85.48 %, and 95 %.
3	Pothole and crack detection in the road pavement using images and RGB-D data	Deep learning	Each approach makes use of several Deep Learning approaches, and each method's performance is evaluated within the same context. image/mask pair datasets.
4	Smart Pothole Detection Using Deep Learning Based on Dilated Convolution	YOLOv5 (Large (Yl), Medium (Ym), and Small (Ys)) models with ResNet101	the pothole detection process with adequate accuracy and speed and implement the process easily and with low setup costs.
5	Pothole and crack detection in the road pavement using images and RGB-D data	Canny Edge detector and bio-inspired Contour detection method are used.	Each approach makes use of several Deep Learning approaches, and each method's performance is evaluated within the same context (that is, a single Jupyter notebook).
6	the pothole detection process with adequate accuracy and speed and implement the process easily and with low setup costs.	Yolo v4	The customized You Only Look Once (YOLO) v4 classifier achieves over 95 % accuracy
7	A Pothole Detection Using VGG16	VGG16	The results of the trial showed that the accuracy level rate had been obtained at 90 %.
8	Pothole Detection Using Deep Learning Classification Method	Deep learning	The Keras pothole picture has been trained and evaluated with the assistance of tensor flow. Our model was trained using approximately one thousand photos obtained from various internet sources to create the dataset of muddy roads, so that they may be tested using a web application.
9	Unified approach for detecting traffic signs and potholes on Indian roads	Deep learning with CNN	The purpose of this work is to establish a consistent model for recognizing the various traffic signs and potholes that can be found on Indian roads.

maintenance. To address these needs, an automated method is required to anticipate future degradation rates and allocate budgets efficiently. The demand for a rapid, precise, and objective examination of road distresses is continuously growing.

Machine learning and deep learning techniques have significantly streamlined as well as decreased the complexity and expenses related to them. Investigators have suggested different approaches for pothole identification [6]. The approach utilized the Grey level Co-accurate matrices feature extraction algorithm and SVM as a classification tool to detect road potholes. The study analysed three characteristics: the contrary, connection, and disparity. Analysis showed that using a mix of transactions and disparity includes led to improved results, with a precision of 92.033 %. Furthermore, the computational time required was remarkably low at 0.0704 s per frame. Another study employed 5 binary classification models namely Navy Base, Logistic Regression, SVM, K, Nearest Neighbours, KN, and Random Forestry to compare various machine learning approaches using data collectors through smartphones and car routes [7]. Surrender Forestry and KN models achieved the highest accuracy of 0.8889 on the test set. By fine-tuning the hyper parameters of the forestry, the accuracy was further improved to 0.9444. The model showcased promising results on different loops and out-of-sample data. These advancements in machine learning and deep learning techniques of promising results for pothole detection, making the process more efficient and cost-effective [8].

Previous research has primarily focused on approaches utilizing picture classification and object recognition techniques using bounding boxes. While these methods have proved effective in identifying fractures, therefore, there is a need for a classification system that can distinguish individual pixels as crack or non-crack [9]. The backbone models underwent training on distinct datasets and functioned as an ensemble methodology utilizing the acquired knowledge from these trained models.

By employing the intersection of results to improve global search capability and by performing pixel-level segmentation on the cropped area where the crack is located to identify the extracted cracks, the proposed ensemble procedure achieves improved performance in the semantic segmentation of the crack area on the surface of the steel structure [10]. The pixel-level potential fracture locations discovered by YOLO V3 are verified by the ensemble semantic segmentation method. Using a combination of UAV flight data and SURF-based panoramic image stitching, this study was able to accurately identify and delineate the crack zones in the photos. This was accomplished by repeatedly scanning along the borders of the structure. The Urban exposition hall's structural facade in the Beijing-Tianjin Cooperation Demonstration Zone was used to verify the methodology [11].

The study proposes a method that combines convolution and dynamic feature fusion to enhance detection performance. Not with standing, these techniques are subject to the issue of loss semantic information, whereby the integration of high-level semantic information with low-level feature information results in a gradual dilution of the former, thereby impacting the ultimate performance of the model in detecting cracks. The present study introduces a deep learning model that is capable of swiftly and precisely extracting crack segments from UAV images. This model offers a technical solution for detecting road cracks across a vast expanse. The proposed model enhances the encoder and incorporates an attention module, as well as integrates the technique of fusing long and short skip connections, building upon the U-Net model.

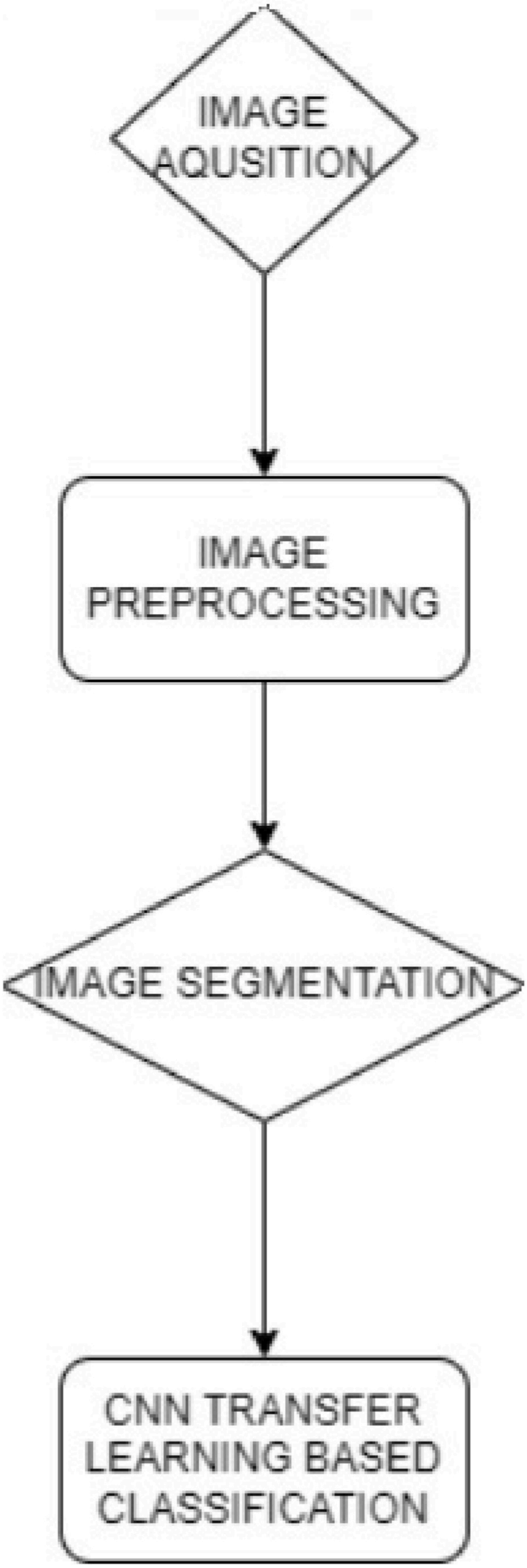

Fig. 1. Flow chart of the proposed model.

The enhanced encoder not only guarantees the efficient extraction of the crack's abstract characteristics but also minimizes the loss of information due to the down-sampling process. The utilization of an attention module results in enhanced network performance by directing its focus toward the identification of cracks in both spatial and dimensional domains. Simultaneously, the utilization of both long and short skip connections facilitates the incorporation of multiscale features, thereby enhancing the precision of crack segmentation and providing more intricate details of the crack edge. The present study validates our novel approach through the utilization of a dataset comprising 1157 unmanned aerial vehicle (UAV) images, specifically designed for the purpose of segmenting cracks on highways.

2. Related work

Automatic crack detection can identify cracks on all types of surfaces. Compared to physical inspection, automatic crack detection is a more accurate and time-saving process. In the construction industry, crack detection has been used for so long that we need some advancement and automation in that process [12]. The manual procedures are transformed into automation using this automatic crack detection, which reduces the cost of inspection and rehabilitation work. They have a multitude of capture techniques and image processing techniques that can be used in automatic crack detection, and we can also use optimization techniques and algorithms to detect and increase the accuracy of crack detection and pothole detection in structural members.

Given the limitations of the challenge at hand, there is an urgent requirement to investigate the potential of using semantic segmentation as a feature extraction technique in conjunction with Convolutional Neural Networks (CNN) for picture classification tasks. Evaluate CNN's efficacy next to that of tried-and-true methods like the Canny and Sobel algorithms. For bridge bottom crack identification, present technologies continue to rely on image processing methods, which can lessen the burden of manual inspections while saving time. However, there are a few problems with this approach [13]. Tansen is concerned about the real responsibility and impact of testing because it can be difficult to access some portions of structures during manual inspections. Manual inspection and the use of deep convolutional neural networks (CNN) are the two primary methods now used in the industry for identifying pavement faults. Due to its ability to trigger high-dimensional nonlinear processes and efficiently capture developing properties, the deep CNN methodology has emerged as the dominant method. Because of its demonstrated capacity to automatically acquire high-level characteristics and model complex nonlinear processes, CNN has gained a lot of traction in recent years.

Recent research has further emphasized the effectiveness of deep learning approaches, particularly in the direction of payment cracks in CCD images. These approaches Leverage deep learning techniques to categorize images identify objects and utilize Semantic segmentation to classify and locate cracks in the surface of the images. The study conducted by youzhi tang introduces a convolutional neural network (CNN) for the purpose of fracture detection in structures. To address the issues of imbalanced quantities between crack and non-crack pixels, a crack segmentation approach utilizing an encoder network is employed. By leveraging an autoencoder, the study effectively reduces the quantity imbalance between crack and non-crack images [14]. The achieved overall results demonstrate accuracy rates of 97.80 % and 97.82 % respectively.

Hongke Xu et al. proposed an innovative approach to enhance the effectiveness of bridge crack detection in their study. The research focused on analysing crack detection techniques using image processing methods. Government has provided an overview of the fundamental characteristics of bridge crack images and applied the theory of crack detection through image processing for initial image retreatment [15]. This paper specifically emphasizes the utilization of the grey threshold iteration technique and the clever iteration technique to achieve crack

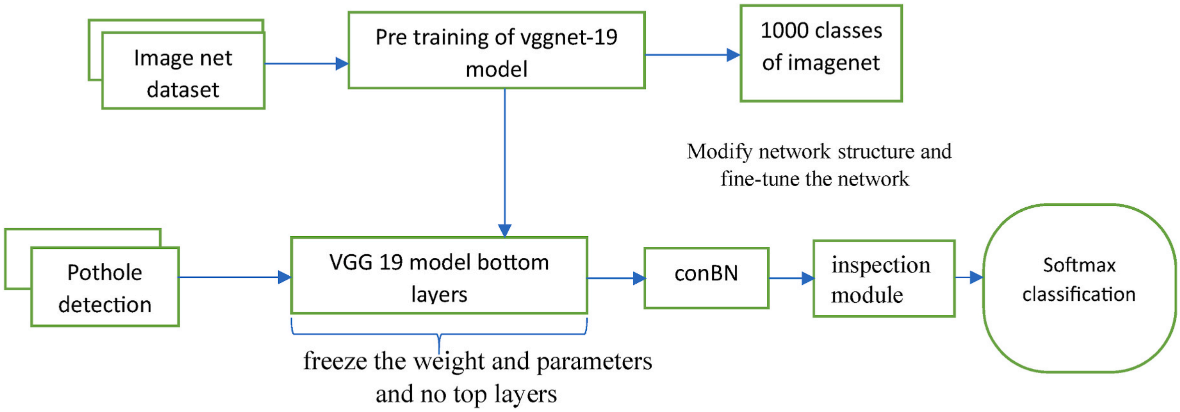

Fig. 2. Flow representation for Transfer Learning With CNN.

extraction, while also improving the filter parameters of the clever uniform algorithm the main contribution of this paper is the successful extraction of cracks on the concrete bridge surface using image processing techniques at a significantly low cost [16]. The study investigates the image pre-processing techniques suitable for crack extraction by considering the characteristics of crack images and the crack target especially, the paper addresses the crack image greying algorithm histogram enhancements and mathematician filtering algorithms. The proposed approach demonstrates higher accuracy compared to the grayscale uniform threshold segmentation algorithm.

The present study centers on the identification of fractures in the pavement at the pixel level, which yields information regarding the precise boundaries and dimensions of the cracks. The technology facilitates the detailed characterization of cracks, thereby enabling the provision of more crucial data for the analysis of pavement distress [17]. The precise identification of pavement cracks enables the attainment of precise outcomes for diverse categories of road pores, such as longitudinal, diagonal, parallel, and obstacle.

The research endeavors to examine the detection of road damage through the utilization of road images that were captured by the researchers. Therefore, the comparison of the performance of the methods presented in the studies is challenging. Despite demonstrating satisfactory levels of recall and precision, the current pothole detection algorithms have the potential for further enhancement, as their networks tend to prioritize a global context over discriminative regions. In contrast to the techniques, the present investigation is specifically directed towards enhancing efficacy through the utilization of a location-sensitive framework that concentrates on the distinctive areas within the roadway, rather than the overall context. Furthermore, the utilization of a publicly available dataset is demonstrated, and it is shown that potholes can be detected with a significantly high level of accuracy [18].

Furthermore, a variety of road surfaces exist, including but not limited to concrete panels, cobblestones, asphalt, and dirt roads. Typically, such road surfaces tend to induce instability in the vehicle through various means. Hence, possessing knowledge regarding the road surface over which the vehicle is traversing holds significant importance. If a vehicle experiences destabilization while traversing a cobblestone road, it may be categorized as a pothole if the same destabilization is observed on asphalt road. Furthermore, the operator has the ability to perform manoeuvres that may impact the accurate perception of the roadway. As an illustration, the operator has the ability to relocate the handheld device in order to respond to an incoming call or compose a message [19]. Table 1 shows the comprehensive existing work done in the proposed area.

3. Methodology

The process of detecting and classifying potholes is outlined in Fig. 1. Initially, images capturing the identified code holds already acquired. Next, the data set undergoes various image pre-processing techniques such as background removal and noise reduction. Subsequently, a mission learning approach is employed to select relevant features from the images. Finally, our proposed method is used to classify the potholes in the normal bituminous road (see Fig. 2).

CNN shorted for convolutional neural networks, is an artificial neural network (ANN) known for its exceptional performance in various categorization and sensing tasks, such as feature sensing, object sensing, and image object sensing. The experiment employs a pothole dataset and real-time car video., The mean a95 %, respectively.A chromatic image with five two-dimensional arrays of pixel intensity values over three colour channels is handled well by the approach.The CNN employs discrete convolutional filters to extract pertinent features from the image. The first layer of the network detects edges, while the following layers capture distinct components. Ultimately, the final layers identify the entire object. The design of CNN is effective due to the incorporation of various layers such as convolutional, max-pooling, and SoftMax classification layers, among others.

The convolutional layer is a crucial component in the planning as it performed the foundational step of processing input images. At this phase, the input image undergoes the application of a filter kernel and its corresponding weight value. The process of generating feature maps involves the multiplication of the kernel with the corresponding pixel values, followed by the summation of the resulting values. The aforementioned feature maps depict distinct patterns or characteristics that are discernible within the image and the result of initial feature mapping process. The input for the following map is provided by the initial stage, and this sequence persists with a growing quantity of interlinked neurons.

The Max pooling layer plays a crucial role in deep learning by providing position in variants and down sampling the input image based on a specified kernel size. This layer operates by identifying the highest activation value within non-overlapping regions defined by the kernel size is shown in Fig. 3. Selecting the maximum value, it captures the most dominant features present in the local region.

The Max pooling process helps to achieve position invariance by considering larger local regions. By downscaling the input image according to the kernel size in each direction, it reduces the spatial dimension while preserving the most salient information. The utilization of max pooling with its max selection pooling mechanism contributes to improved invariance and enhances overall performance this technique also accelerates the convergence state which is shown in Fig. 4.

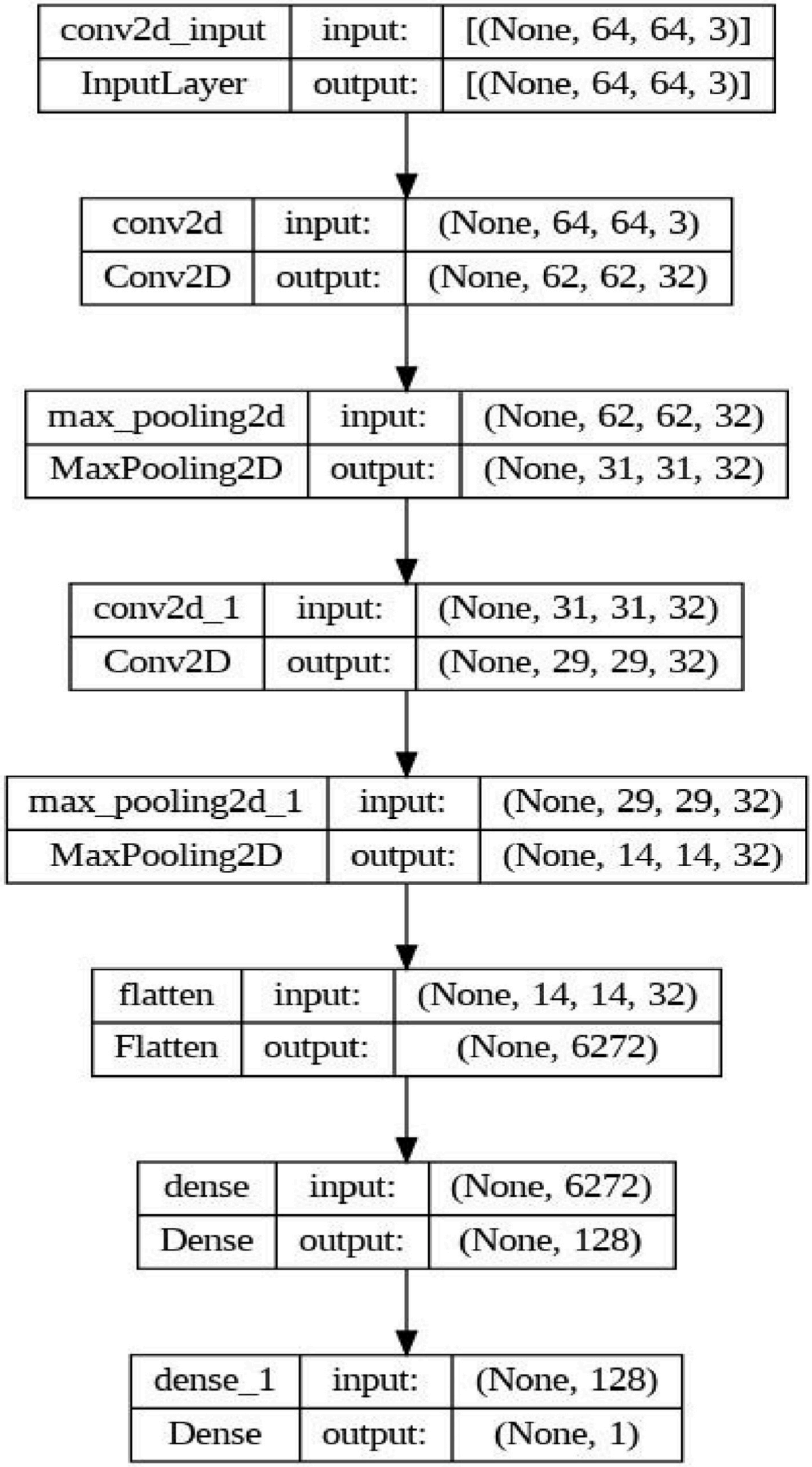

Fig. 3. Layers for the purposed model.

12	3	8	4
10	21	24	6
34	2	10	30
6	15	4	5

21	24
34	30

Fig. 4. Process of max-pooling.

3.1. Softmax classification

Both the convolutional and the Max pooling layers have their skipping factors—the kernel size and stride—decided upon. to control the downscaling and feature extraction process. The aim is to reduce the spatial dimensions of the output feature maps boiled capturing important patterns and maintaining relevant information.

In the case of the convolutional layer. The kernel size determines the respective field of each neuron. Specifying the region it covers in the input image. The weights are associated with the kernel or multiplied with the corresponding pixel value in the respective field. And the sum of this multiplication produces the future map. For the Max pooling layers, the kernel size defines the size of the non-overlapping region. The maximum activation value is identified by downsampling the future map. Based on the kernel size, the spatula dimensions are reduced.

Once the future extraction and down-sampling stages are complete, a fully connected layer is introduced. This layer connects every neuron to every activation instance in the president levels. The purpose of this layer is to combine the results obtained from the latest convolutional layer into a one-dimensional feature vector. Vector represents the extracted features and serves as an input for the subsequent Classification stages. The final step involves a software classification layer. The process of assigning classes to images is accomplished by this layer, which relies on the extracted features as its basis. Each neuron in this layer is associated with a specific class and the soft max function is applied to calculate the probability distribution over the classes. By employing a fully connected layer and software classification, the neural network can effectively classify portfolio deductions based on the discovered features and make predictions based on the learned patterns in the data.

3.2. Transfer learning VGG NET

Transfer learning is a powerful technique in supervised learning barrier model train to 41 taxis leverage to 4 subsequent related tasks. In this is the government used to improve and optimize performance in different settings. In other research, we focus on the outing architectural topology of CNN for image Classification and aim to develop a suitable model through transfer learning. Through experimentation with network parameters and dataset properties, we aim to identify the variables that have a positive impact on classification accuracy, while taking into consideration the limitations imposed by computing resources and time constraints. The methodology employed entails the alteration of said factors in order to determine the most advantageous configurations.

To implement transfer learning we utilize the VGG NET CNN which is pre-trained on the image dataset along with the inspection module. These pre-trained models save as the starting point for ever research work. Then we fine-tune these networks using our own data sets specifically tailored to our classification task. The primary procedures employed in our strategy of depicted in Figs. 5 and 6. It outlines the key step involved in applying the CM transfer learning techniques. We follow a multi-step methodology to adapt the pre-trained models to our specific classification problem. By employing transfer learning and systematically exploring different configurations, PM develops a highly effective and efficient model for image classification tasks within the given constraints of computing resources and time (see Fig. 7).

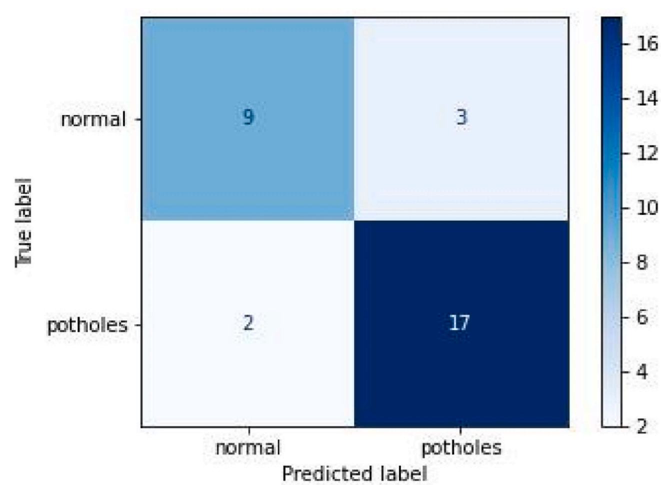

Fig. 6. Confusion matrix.

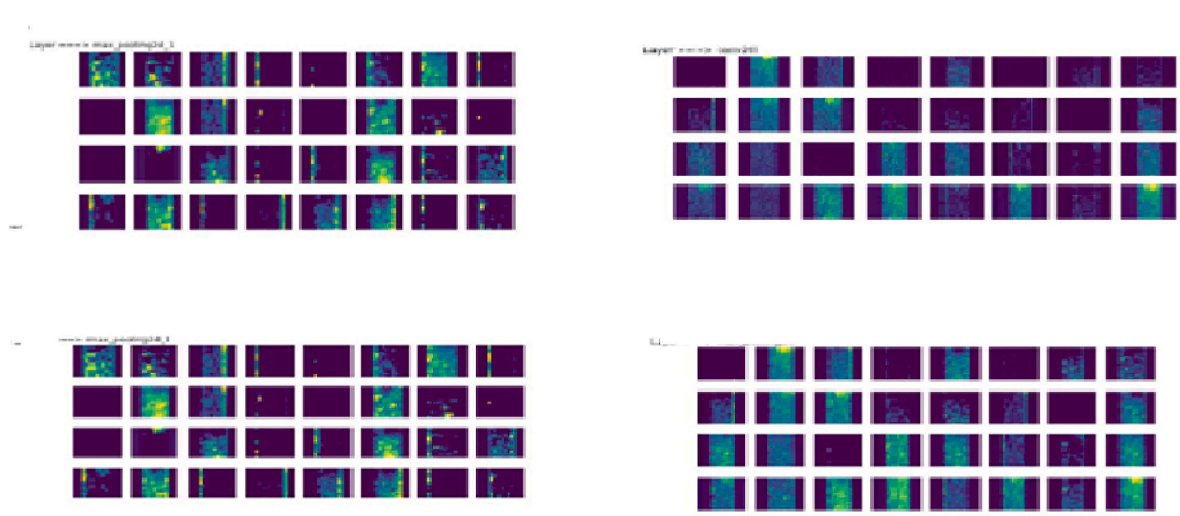

Fig. 5. Sample output obtained through purposed mode.

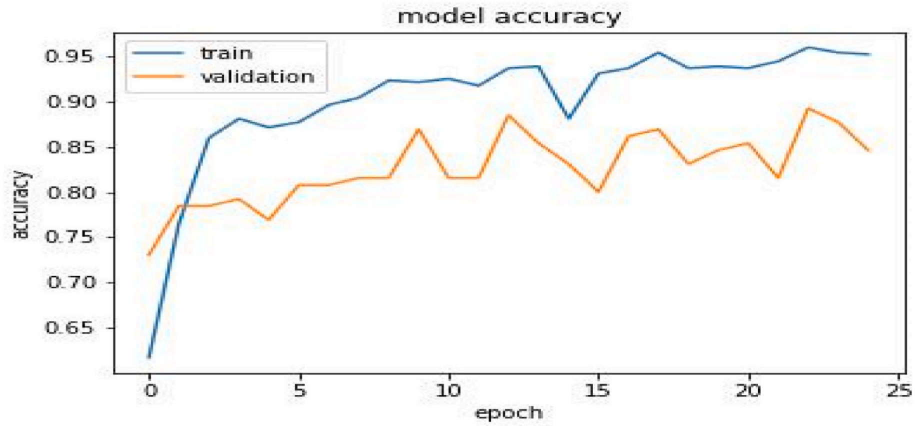

Fig. 7. Accuracy of the model.

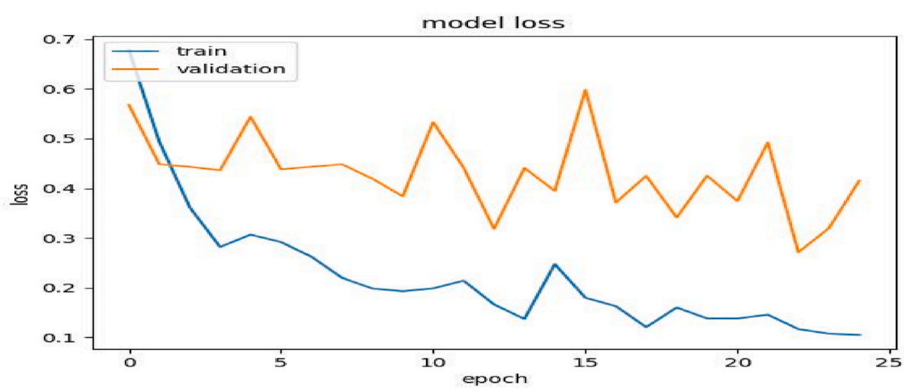

Fig. 8. Loss of the model.

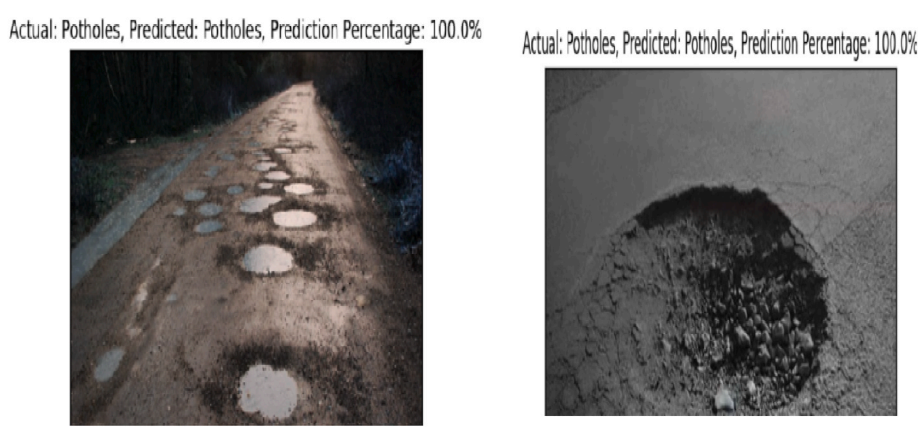

Fig. 9. Real time results obtained from proposed model.

Table 2
Comparison of the accuracy of the purposed model and state of art.

Pothole detection	Transfer Learning + RNN	Transfer Learning + GNN	Transfer Learning + CNN
	92	90	95
	95	90	96
	95	90.2	96

3.2.1. Determination of the base networks

To perform transfer learning, we begin by identifying the base networks that will serve as the foundation for our model. These base networks consist of pre-trained. Convolutional Neural Network models come with pre-determined network weights [W1, W2, and Wn]. The next step involves setting up behind new neural network by taking into account the bottom layers of the pre-trained model. These bottom layers are typically responsible for capturing low-level fractures such as textures and basic shapes. When constructing the new neural network we have the flexibility to modify the network structure. By adding, deleting, or replacing layers based on these bottom layers. This process allows us to customize the network architecture to fit our specific tasks and requirements. By leveraging the pre-trained-based network and incorporating changes to the network structure, we can adapt the model to the target problem more effectively. This way we can benefit from the learned representations from the basic network while tailoring the network to our specific means.

The recently established network is enhanced by training them on a data set A along with its corresponding labels B. The goal of training is to minimize the loss of function C, which is defined as follows:

The given equation involves the variables 'n' and 'W', which respectively represent the training data index (I), the class index (K), the number of training samples, and the weighting matrices of the convolutional and fully connected layers.

The training process iteratively adjusts the network weights (W) to minimize the overall loss by updating the network's parameters through techniques like backpropagation and gradient descent.

$$A(W) = -\frac{1}{n}\sum_{xi}^{n}\sum_{k=1}^{k}[clog\ p(xi=\mathrm{b}) + (1\text{-cib})\log\ (1\text{-p}(\mathrm{xi}=\mathrm{b}))]$$

By optimizing the loss function c, the networks are trained to accurately classify the input data from data security and assign probabilities to each class. The network is then able to anticipate the likely classifications of new, unknown data using this instrumentation.

4. Results and discussion

During the training phase of our system prototype their children impressive 96 % accuracy on the test data file. Leverage leveraging transfer learning with a Convolutional Neural Network. [CNN] Specifically using the pre-trained Alex net model initially we stored the data set and divided it into 2 categories, 70 % of training data and 30 % of validation data.

To adopt the pre-trained network. two specific tasks we replaced the final layer of the AlexNet model. Subsequently, we loaded the pre-trained network and prepared the data for training. The training process utilizes the available training data while the final player back is replaced by various settings and layers such as the activation function (Example Sigmoid), minimum batch sizes (1, 5, 10, 15), and maximum. Epochs were specified to optimize the training process. Once the network was trained. Once the network was trying to be proceed. We proceed with predicting and evolving meeting its performance. This involved assessing the accuracy of the network's predictions and further evaluating the effectiveness of our chosen classification algorithm using a confusion matrix. The confusion matrix provides a comprehensive analysis of the model's performance in terms of current and incorrectly classified instances across different classes. The accuracy and model loss of the proposed model is shown in Figs. 8 and 9.

By the following steps, we successfully developed a system prototype that incorporates transfer learning with a pre-trained Alex Net CNN. Through extensive training, prediction, and evaluation mission achieved an impressive 96 % accuracy on her test data set demonstrating the effectiveness of our approach. These figures provide a visual presentation of the curiosity secured by our approach across various batch sizes, allowing us to analyze any patterns or trends in the results. The confusion matrix is a size of n × n, where n represents the total number of classes that are being targeted. It provides a consolidated summary of both correct and incorrect predictions made by the classification technique.

In one scenario, the target classes are related to pothole detection. We evaluated the framework using different batch sizes of 1, 5, 10, 15. By examining the confusion matrix, we can gain valuable insights into the framework's performance across the various batch sizes. In the confusion matrix, TP refers to true positives. FP refers to false positives (Incorrectly predicted instances). The values within each indicate the count of instances falling into these categories. By analyzing the confusion matrix for different batch sizes, we can assess the impact of varying batch sizes on the framework's performance, and identify any trends or patterns in classification results. Table 2 shows the precision of the classification model, which serves as the primary performance metric. Accuracy is calculated by dividing the total number of correct predictions by the total number of predictions made. Each classifier's accuracy is displayed in the table. To construct the models we utilized pre-trained weights from the image net and adjusted the top layers. The top layers were modified to include A novel fully connected softmax layer that has been proposed with a specified number of particles for classification purposes.

5. Conclusion

Bituminous roads are used all over the world for safe transportation of vehicles. The accident and injuries are happening due to potholes in the bituminous roads. The numerous researches is carried on this area of automatic detection of potholes through different methods. The proposed approach can help road maintenance authorities to formulate rapid and optimized actions for road infrastructure repairs. A Global Positioning System can be used to detect the potholes in the different locations. This work can contribute to self-driving applications and the automation industry. In this paper, transfer learning is used with three different deep learning algorithms such as CNN, RNN and GNN. In that transfer learning + CNN outperforms state of art other algorithms with 96 %. This work can further be extended to detect other pavement distresses, road depressions, classify roads as per quality, and depth estimation of potholes.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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