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Pothole detection in bituminous road using convolutional neural network with transfer learning

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ABSTRACT

The challenges of road maintenance, particularly in detecting potholes and cracks, and the proposed method using transfer learning and convolutional neural networks (CNNs) are significant advancements in this domain. Transfer learning is particularly beneficial, as it allows leverage pre-trained models to enhance the performance of the pothole detection system. CNNs, with their ability to capture spatial hierarchies in data, are well-suited for image-based tasks like pothole detection. The potential applications of the suggested method for intelligent transportation systems (ITS) services, such as alerting drivers about real-time potholes, demonstrate we research's practical implications. This contributes to road safety and aligns with the broader goals of innovative city initiatives and infrastructure management. Achieving a 96% accuracy rate is a significant result, indicating the robustness of the proposed approach. Using this information to assess initial maintenance needs in a road management system is forward-thinking. Overall, we work is a valuable contribution to intelligent transportation and infrastructure management, showcasing the potential of advanced machine-learning techniques for addressing critical issues in road maintenance.

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1. INTRODUCTION

The presence of potholes on roads is often an indication of poor maintenance, which may suggest underlying structural issues. Potholes can cause discomfort while driving and may result in expensive. A recent survey conducted by the Asphalt Industry Alliance in 2019 in England and Wales revealed a 24% increase in filling potholes. Potholes are responsible for about one-third of the mechanical problems experienced by drivers in the United Kingdom and cost them approximately £2.8 billion each year, according to a 2013 study by the Asphalt Industry Alliance. The compensation payments of £6.9 million provided to road users in England and Wales do not cover the people costs of resolving claims, which amount to 19.8 million. Pothole damage is the primary reason for over 89% of claims made in England, marking an increase of 80% since 2018, as reported by the Asphalt Industry Alliance in 2019 [1]–[3]. While these statistics are worrying, implementing pothole detection systems can help to substantially decrease these figures by streamlining the repair process.

A 2018 study by cycling United Kingdom indicates that 56% of people would cycle more frequently if the condition of roads, including potholes, were better [4], [5]. So, it is essential to find and report potholes to let the proper authorities know how serious the problem is. This will guarantee that the necessary repairs are made on schedule. Due to recent rapid technological improvements, reliable sensors such as gyroscopes, accelerometers, global positioning system (GPS), electronic compasses, microphones, and cameras have been miniaturized and integrated into mobile devices. Due to the prevalence of mobile phones and the lack of installation requirements for specialized hardware, this method of pothole detection is the least expensive and most effective. This study used real-time data gathered from mobile devices to identify potholes. The majority of current technologies to detecting potholes are less accurate, require expensive and specialized technology, or are not reliable enough to identify potholes.

The objective of this study is to develop an efficient and accurate system for pothole identification in road infrastructure. The system should utilize image processing techniques like machine learning algorithms and deep learning algorithms to analyse road images and detect the presence of potholes. The aim is to improve road safety, facilitate timely repairs, and reduce vehicle damages by automating the process of pothole detection and enabling proactive maintenance strategies. Bitto *et al.* [6], Shaikh *et al.* [7] propose a pothole detection approach using convolutional neural network (CNN) and AlexNet, and their research focuses on detecting potholes utilizing two methods: spectral clustering (SC) and deep learning algorithms. The first approach processes the input image using SC and morphological operations. The threshold classifier is used to detect potholes. For detecting potholes, this methodology does not require any training. CNN and AlexNet use the second method of finding potholes.

Thangavel *et al.* [8] developed a method for detecting potholes on critical road infrastructure using CNNs and accelerometer data. The data has collected through a custom-designed iOS smartphone application installed on a car's dashboard. The experiment showed that they are proposed CNN approach outperformed existing solutions, but its accuracy decreased relatively for larger datasets. Yousaf *et al.* [9] developed a pothole detection system utilizing the YOLOX model and trained it for 5,000 epochs. They compared their results with other YOLO models, such as YOLOv3 and YOLOv4. While their model achieved the highest average precision (AP) value, it struggled to detect some potholes if an image contained more than one, resulting in a 55-identification rate for the total image present.

Additionally, the model produced an average confidence threshold of 81.3%. The author present by combining information from different sensors, the method aims to enhance the accuracy and efficiency of pothole detection [8], [9]. The precision of 94.7, recall of 90, and accuracy of 88% respectively, achieved demonstrate the effectiveness of the proposed approach in accurately identifying potholes. Precision, recall, and accuracy are commonly used metrics in classification tasks, and these results suggest a good balance between correctly identifying potholes (precision and recall) and overall correctness (accuracy). The extraction of pothole shapes with a mean error percentage of 12.8% and a standard deviation of 6.5% provides insights into the method's accuracy in delineating the actual form of potholes. These error percentages give a sense of the deviation from the ground truth, and the relatively low values indicate a promising level of accuracy in shape extraction. This approach highlights the importance of leveraging the strengths of each sensor in a complementary manner, leading to more robust and comprehensive data processing. Valuing the proposed approach through 50 experiments adds credibility to the study. Testing the method across various scenarios is essential to ensure its robustness and generalizability [10], [11].

The stereo vision-based system proposed by the author for pothole detection using a quadratic road surface fitting algorithm is an exciting approach [11]–[14]. Using stereo vision allows for calculating the distance by providing valuable information on pothole size, volume, and position. This data can be crucial for prioritizing repairs based on the severity of potholes. Incorporating an efficient disparity calculation algorithm is a crucial aspect of the proposed system. Disparity calculation is fundamental in stereo vision, as it helps determine the depth of information in a scene. Masad [15] work, the proposal of a real-time system for pothole detection and road condition assessment using sensor data and an support vector machine (SVM) model is another valuable contribution. Achieving a classification accuracy of 93% for road conditions and pothole detection is commendable, indicating the effectiveness of the chosen approach. The real-time nature of the system is essential for timely intervention and maintenance. The use of SVM for classification suggests a robust machine-learning model for handling the complex task of distinguishing between road conditions and identifying potholes. In future work, it could be beneficial for the authors to explore the scalability of their systems to different road types and environmental conditions. Additionally, considerations related to the computational resources required for real-time processing and potential challenges faced during system deployment could provide insights for further refinement.

The author proposed the paper is a notable advancement in road maintenance and intelligent transportation systems (ITS) services [16]. Leveraging 2D photographs for pothole detection has practical implications for scalability and ease of implementation in existing infrastructure. The utilization of 2D road photos captured by a survey truck for evaluating the proposed model adds a real-world dimension to the study. This approach allows for assessing the model's performance. Evaluating the model under various scenarios is crucial to ensuring its robustness and adaptability to other real-world situations. The positive results obtained from the study indicate the efficacy of the proposed model. The ability to identify potholes from 2D photographs suggests a practical and cost-effective solution that can be integrated into existing road network management systems. The data obtained from this model can play a significant role in preventive maintenance strategies. By identifying potholes early on, road authorities can take prompt action to restore and preserve roadways, potentially reducing the overall cost of repairs and minimizing disruptions to traffic. Furthermore, providing real-time information to drivers enables them to be more cautious and proactive, contributing to overall road safety.

In summary, introducing a pothole identification method using 2D photographs is a promising contribution with positive results. The potential applications in ITS services and road network management, coupled with the practicality of using 2D images, make it a noteworthy advancement in the ongoing efforts to enhance road maintenance and safety. Vinodhini and Sidhaarth [17], Arya *et al.* [18] presents an innovative approach, where users actively contribute to data collection, is an exciting methodology that taps into the widespread use of smartphones. The study's examination of participatory sensing for gathering information about road irregularities adds a crowd sourced element to the data collection process. This can provide a large volume of real-time data from various locations, offering a comprehensive view of road conditions. The use of specific data processing algorithms for evaluation is a critical aspect of the study. This high accuracy is promising for the practical implementation of the mobile sensing system. Identifying optimal parameters for these algorithms is valuable, as it helps fine-tune the system for better performance.

2. PROPOSED SYSTEM

Pothole detection devices help to prevent and mitigate various accidents that occur around the world. Many methods for detecting potholes have been proposed. The strategy proposed here employs two approaches. CNN, a deep learning model, and random forest, a machine learning model. They are trained on multiple datasets and their performance is evaluated. The paper aims to compare the performance of two different models, the random forest model [19] and the CNN model [20], specifically in the context of pothole identification. Evaluating the accuracy and other performance metrics across various datasets is a valuable approach to understand how well each model performs under different conditions.

The detailed steps involved in the proposed model are depicted by Figure 1:

- Data splitting: divide the pre-processed dataset into training, validation, and testing subsets. The training set is used to train the model, the validation set is employed for hyperparameter tuning, and the testing set evaluates the final model performance.
- Feature extraction: extract relevant features from the images to represent them in a more compact and meaningful format. This step may involve techniques like edge detection, color histograms, or texture analysis to capture important characteristics related to potholes.
- Feature scaling: this is essential in pothole detection to ensure that features are on a similar scale. Techniques like standardization (Z-score) or min-max scaling are commonly used. Scaling prevents features with larger magnitudes from dominating the learning process. The choice depends on data characteristics and algorithm requirements. Scaling should be applied after data splitting to avoid leakage. It enables the machine learning model to learn effectively and make accurate predictions.

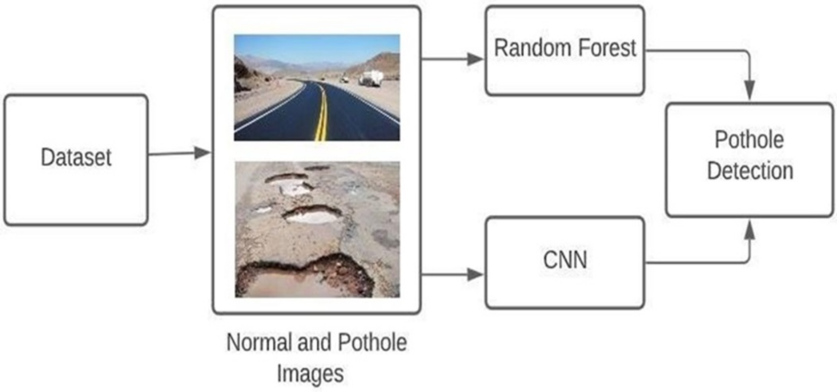

Figure 1. Flow diagram of the proposed model

3. METHOD

The study employed a comprehensive approach to evaluating the performance of ensemble learning classifiers, considering various validation techniques, handling dataset imbalance, and fine-tuning model. Using bagging and boosting methods allows for a balanced exploration of bias-variance trade-offs. Two different learning classifiers were chosen for the review such as random forest and CCNNs.

3.1. Random forest

Random forest is an ensemble learning algorithm that operates by constructing many decision trees during training and outputs the class, that is, the mode of the categories (classification) or the mean prediction (regression) of the individual trees [21], [22]. The base models in a random forest are decision trees depicted in Figure 2. Decision trees are simple models that recursively split the data based on features to make predictions. Random forest employs bootstrapping, where multiple random samples (with replacement) are drawn from the training dataset. These samples are used to train individual decision trees. In addition to using different subsets of data for training, random forest introduces feature randomization. Instead of using all features for splitting at each node, a random subset of features is considered. This helps to decorate the trees and makes the model more robust. Random forest is a powerful and widely used algorithm for its simplicity, flexibility, and excellent application performance.

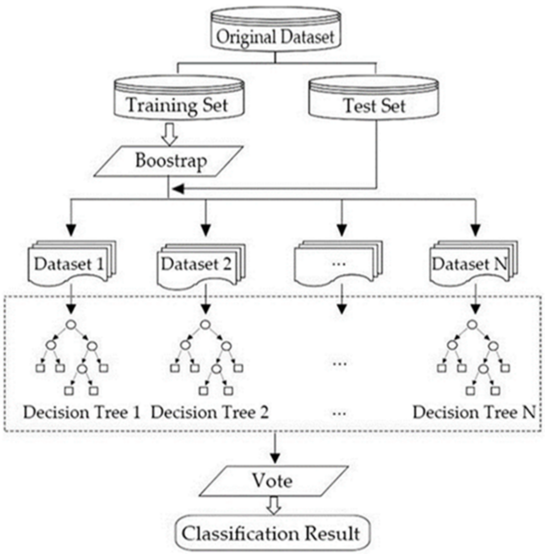

Figure 2. Random forest architecture

3.2. Convolutional neural networks

CNNs are a type of artificial neural network (ANN) renowned for their exceptional performance in tasks related to categorization and sensing, particularly in the domains of feature sensing, object sensing, and image object sensing [23], [24]. The experiment conducted in our study involves the use of a pothole dataset and real-time car video. This suggests a practical application, likely related to detecting potholes in road conditions. The input data for the CNN consists of chromatic images, each represented by five two-dimensional arrays of pixel intensity values over three-color channels (presumably red, green, and blue). The CNN employs discrete convolutional filters to extract relevant features from the input image. The architecture of the CNN typically consists of multiple layers as shown in Figure 3. The first layer is designed to detect edges in the image, and subsequent layers capture more complex and abstract features. The final layers of the network are responsible for identifying the entire object, in this case, potholes. The effectiveness of the CNN design is attributed to incorporating various layers and reducing spatial dimensions, and SoftMax classification layers for making predictions. Each layer plays a specific role in the network's ability to learn hierarchical representations from the input data. The information provided gives a high-level overview of how CNNs are utilized for pothole detection in real-time car videos.

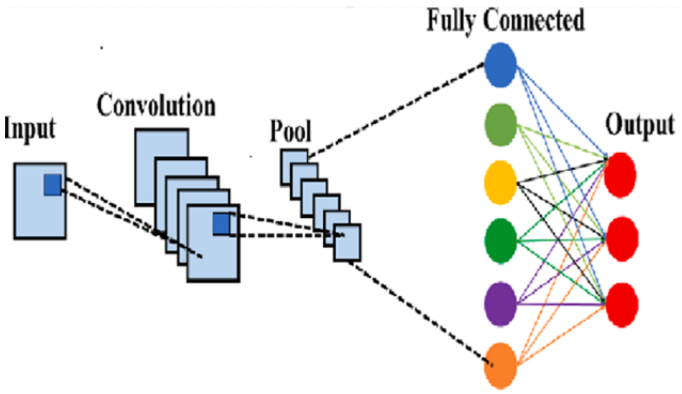

Figure 3. Convolutional neural networks architecture

4. RESULTS AND DISCUSSION

The findings highlight a necessary trade-off between the performance and efficiency of the two models, random forest and CNN, in the context of pothole detection. CNN exhibits considerably higher accuracy compared to random forest. This suggests that CNN is more effective in capturing intricate patterns and features in the datasets related to pothole detection. CNN requires more training time than random forest. This is a crucial consideration, especially in scenarios where computational resources are limited or when there is a need for quick model training and deployment [25]. Random forest performs well in classifying potholes and non-potholes while requiring less training time and resources. This efficiency makes it a viable option when computational resources are a limiting factor. Choosing between CNN and Random Forest depends on the context and available resources. If high accuracy is the primary concern and computational resources are sufficient, CNN might be the preferred choice. On the other hand, if efficiency in terms of training time and resource utilization is a priority, random forest could be the more practical option. Depending on the application, weighing the trade-off between model accuracy and resource efficiency may be beneficial. For instance, in real-time applications or environments with limited computational power, the efficiency of random forest may outweigh the slightly lower accuracy compared to CNN.

It is commendable that Modle achieved a notable accuracy of 96%, considering the challenges posed by a small dataset. Working with limited data significantly hinders training robust machine learning models. Augmenting our existing dataset can artificially increase its size and diversity. Combining predictions from multiple models (ensemble methods) can improve overall performance. If there is a significant class imbalance (i.e., more images of one class than the other), consider techniques to balance the classes or use algorithms that are robust to imbalanced. In addition to resizing, consider applying data augmentation techniques during training. This can include random rotations, flips, and other transformations, further diversifying dataset and improving model generalization. While sharpening and cubic convolution have shown positive results, consider experimenting with different image enhancement techniques, such as contrast adjustment, histogram equalization, or filtering methods, to see if they provide additional benefits. The results indicate that CNN yielded superior performance compared to random forest. This implies that, for the specific task of pothole detection in our study, the deep learning model CNN outperformed the machine learning model random forest, depicted in Figures 4 and 5, respectively; it's highlighted that the observations were made considering small datasets. This is an essential acknowledgement as the performance of machine learning and deep learning models can be influenced by the size and diversity of the dataset. With an increase in dataset size, random forest might yield better results.

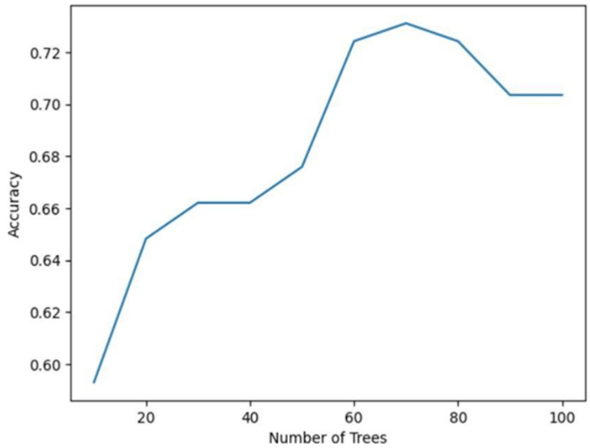

Figure 4. Number of trees vs accuracy

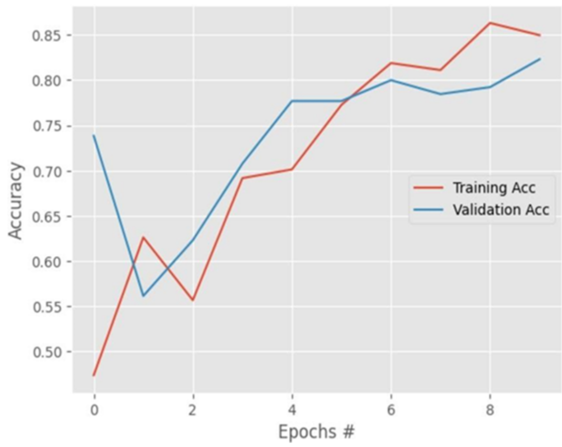

Figure 5. CNN: epochs vs accuracy

5. CONCLUSION

The paper provides a concise overview of the importance of pothole detection and presents a comparative analysis between random forest and CNN for this task. This paper emphasizes the significance of pothole detection for preventing accidents and vehicle damages, setting the context for the study. The primary objective is to conduct a comparative analysis between random forest and CNN for pothole detection. Methodology describes using two machine learning models, random forest, and CNN, for pothole detection. Results Highlights the key findings, stating that CNN demonstrated faster speed and superior results compared to random forest. This reflects an awareness of the impact of dataset size on model performance. The performance of the proposed indicates that the current results are promising, suggesting that both speed and accuracy are considered positive outcomes. In conclusion, this paper provides valuable insights into the comparative analysis of random forest and CNN for pothole detection. Acknowledging variations in performance and the potential for improvement through increased dataset size adds depth to findings and encourages further exploration in this critical area.

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