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Classification of Potholes using Convolutional Neural Network Model

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KEYWORDS

Pothole Detection, Deep Learning, Convolutional Neural Network (CNN), Image Processing, Road Damage Classification

ABSTRACT

Road surface damage, particularly potholes, is a major concern in transportation systems as it leads to vehicle damage, traffic disruptions, and road accidents. In countries with extensive road networks such as India, manual road inspection is time-consuming, labour-intensive, and prone to human error. The increasing number of vehicles and the effects of weather conditions, especially during the rainy season, further accelerate road deterioration and increase the occurrence of potholes. Therefore, there is a need for an efficient and automated system to detect and analyse road surface damage in order to improve road maintenance and public safety. This study proposes automated pothole detection and classification system using image processing and deep learning techniques. The system utilizes road images captured through cameras and applies image pre-processing methods to enhance image quality and remove noise. After pre-processing, pothole regions are identified through segmentation techniques, and the surface area of the detected potholes is calculated. A Convolutional Neural Network (CNN) model is then used to classify potholes into different categories such as small, medium, and large based on their surface area and spatial features. Experimental results demonstrate that the CNN-based model effectively learns distinguishing features from road images and achieves high classification accuracy under varying lighting and environmental conditions. The proposed system enables automatic monitoring of road conditions and can provide valuable data to government authorities for timely road maintenance and repair. By implementing this intelligent detection system, road safety can be improved, maintenance costs can be optimized, and the risk of accidents caused by damaged roads can be significantly reduced.

I. INTRODUCTION

In recent years, due to advancement in transportation, poorly maintained highways and roads results in traffic and also leads to accidents. This can be reduced by properly maintaining the roads and filling the potholes regularly which also reduces the maintenance cost. As road inspection is done manually, it becomes a time-consuming job and it also requires human labour and it is also subjected to errors. Due to the damaged roads, traffic jams occur which is indirectly responsible for economic losses. Also, if these damaged roads are not repaired timely the conditions of the roads may become worse and the cost of repairing these roads also increases immensely. But it is difficult to monitor the road conditions by visiting all the roads and checking for the damages manually as it is a labor-intensive process and it also involves high inspection cost. In order the solve these problems modern techniques can be used. In the proposed system, first the images of the roads are collected after which the images are then being processed using various deep learning algorithms. The dataset used in this model for the purpose training, testing and for validation is collected from various websites such as Kaggle ,etc .Then the dataset collected is divided into three smaller datasets in which one is used for training purpose, the other dataset is used for the purpose of testing and the third set is used after the model is trained and tested, for the purpose of validation. After the process of training, testing and validation, the algorithm with the most accuracy is used to develop an application in which the video of the road is processed and is converted into images after which the images are processed using the algorithm with the best accuracy and the potholes are found. These reports can then be sent to the concerned department to look into the matter and repairing the damaged roads thus reducing the traffic and accidents.

The aim of the work is to develop system captures road images using a camera and processes them through deep learning algorithms to detect and classify potholes present on the road surface. By analyzing image features such as texture, shape, and depth patterns, the CNN model identifies potholes and differentiates them from normal road surfaces. The objective is to provide an efficient and accurate method for detecting road damage, which can assist authorities in road maintenance and improve transportation safety by enabling timely detection and repair of potholes.

Objective

- Objective is to design a system that can automatically detect and classify potholes on road surfaces using image processing and a Convolutional Neural Network (CNN) model. The system analyses road images captured through a camera and identifies damaged areas accurately. This helps reduce manual inspection and improves the efficiency of road monitoring.
- Objective is to assist road authorities in identifying potholes quickly so that repairs can be carried out on time. Early detection of road damage helps prevent accidents and ensures smoother transportation. The system can support smart city infrastructure by providing reliable information about road conditions.

Roads are an essential part of transportation infrastructure, but over time they develop damages such as potholes due to heavy traffic, weather conditions, and poor maintenance. Potholes can cause serious problems including vehicle damage, traffic congestion, and road accidents. In many areas, pothole detection is still carried out manually by road inspection teams, which is time-consuming, costly, and sometimes inefficient. Human inspection may also miss small or newly formed potholes, leading to delays in road maintenance.

The smart system designed to automatically detect and classify potholes on road surfaces using image processing and artificial intelligence techniques. Road damage such as potholes is a major problem that affects transportation safety and vehicle performance. Manual inspection of roads is time-consuming and may not always provide accurate or timely information. Therefore, an automated detection system can greatly improve road monitoring and maintenance. In this project, a camera or image dataset is used to capture images of road surfaces. These images are then processed and analysed using a CNN-based deep learning model. The CNN model learns important features such as texture, edges, and patterns from the images to distinguish between normal road surfaces and potholes. During the training phase, the model is provided with labelled images of potholes and non-pothole road conditions so that it can learn to recognize them accurately.

Once the model is trained, it can classify new road images and determine whether a pothole is present or not. The system can also highlight the detected pothole region in the image, making it easier for authorities to identify the damaged area. The use of deep learning improves the accuracy and reliability of pothole detection compared to traditional image processing methods. This project can be applied in smart transportation systems, where vehicles or monitoring devices continuously capture road images and send them for analysis. The detected pothole information can then be used by road maintenance departments to schedule repairs quickly. Overall, the system provides an efficient, automated, and intelligent solution for monitoring road conditions and improving road safety.

2.LITERATURE REVIEW

1. **Youngtae Jo, et.all** These authors proposed a pothole detection method based on image processing techniques that analyze intensity and motion characteristics of road images. The system collects road surface images using a camera mounted on a moving vehicle. It examines variations in pixel intensity and detects irregular surface patterns that indicate potholes or damaged road areas. Motion information from sequential frames helps distinguish potholes from normal road textures. The algorithm focuses on identifying abnormal regions on the road surface and classifies them as potholes. The system improves the reliability of road condition monitoring by reducing dependence on manual inspection. Experimental evaluation showed that the method provides better accuracy than traditional visual inspection methods. The approach demonstrates the effectiveness of computer vision techniques in detecting road surface defects

2. **MadhuraKatageri, et.all** The researchers proposed an automated pothole detection and management system using image processing methods such as edge detection and morphological operations. Road images are captured and processed to identify the boundaries and shapes of potholes. The system uses segmentation techniques to isolate pothole regions from the surrounding road surface. After detection, the algorithm calculates parameters such as pothole area, width, and approximate depth. This information can be used to estimate repair requirements and maintenance costs. The proposed system aims to assist road authorities in prioritizing damaged areas that require immediate attention. The method reduces the time and effort required for manual road inspection. The results demonstrated that image processing techniques can provide reliable pothole detection for road monitoring systems.

3. **K. Punithavathyet.all** In this study, the authors developed a computer vision-based pothole detection system that uses blob detection techniques. The method treats potholes as dark and irregular blobs that appear on the road surface. Images captured from a camera are processed using segmentation and feature extraction algorithms to highlight damaged areas. The system analyzes the texture and intensity patterns to differentiate potholes from normal road surfaces. A Raspberry Pi camera module was used to capture road images and process them in real time. The proposed solution is cost-effective and suitable for embedded systems. It also enables continuous road monitoring during vehicle movement. Experimental results showed that the approach successfully identifies potholes with good accuracy and efficiency.

4. **Gandhi J. et.all** This research presented a review of various pothole detection techniques including vision-based systems, sensor-based methods, and vibration-based approaches. The authors analyzed different computer vision techniques such as thresholding, edge detection, and image segmentation for detecting road surface defects. Vision-based methods were found to provide more detailed information about pothole shape, size, and location. The study compared the advantages and limitations of different detection methods used in road monitoring systems. It also highlighted the importance of automated systems in improving road maintenance efficiency. The researchers emphasized that image processing can play a key role in smart transportation infrastructure. Their work provided valuable insights for developing improved pothole detection algorithms. The study also suggested future improvements using advanced vision techniques.

5. **Sachin Rathod, et.all** The authors proposed an IoT-based pothole detection system that integrates image processing techniques with sensor data. The system captures road surface images using cameras mounted on vehicles and analyzes them using computer vision algorithms. Image processing techniques are applied to detect potholes and speed breakers by identifying irregular surface patterns. Once a pothole is detected, the information is transmitted to a monitoring system through IoT communication. The system can notify authorities about the exact location of damaged roads.

This helps road maintenance departments take timely corrective actions. The approach improves road safety and reduces the risk of accidents caused by potholes. Experimental results showed that the system effectively detects potholes in real-time conditions.

6. F. Nex and F. Remondino These researchers explored the use of UAV-based imaging and photogrammetry for monitoring road surface conditions. High-resolution images captured from aerial platforms are processed using computer vision and image processing techniques. The method enables detection of road damages such as cracks, potholes, and surface deformation. Aerial imaging provides a wider coverage area compared to traditional ground inspection methods. The captured images are analyzed to identify irregular patterns and damaged regions on road surfaces. This approach improves the efficiency of road infrastructure inspection. It also reduces the time and cost involved in manual inspection processes. The study demonstrated that UAV-based image processing systems can effectively support large-scale road monitoring.

7. Jiahe Fan, Mohammudet.all The researchers proposed a road defect detection method based on analyzing multi-scale visual features of road images. The system processes images captured from vehicles and applies segmentation techniques to identify damaged pavement areas. Feature extraction algorithms are used to analyze texture patterns and surface irregularities. By studying multiple scales of visual information, the system can detect potholes even in complex road environments. The method improves detection accuracy compared with single-scale analysis techniques. It also helps differentiate potholes from shadows and other road artifacts. The proposed approach demonstrates the effectiveness of computer vision techniques in road condition monitoring. Experimental evaluations showed improved performance in detecting road surface defects.

8. HabeebSalaudeen and ErbuğÇelebi The authors studied challenges in pothole detection under real-world conditions such as poor lighting, shadows, and image noise. They proposed improved pre-processing techniques to enhance road images before analysis. Image enhancement methods were applied to highlight pothole boundaries and improve visibility of damaged areas. The system uses segmentation and pattern recognition techniques to identify pothole regions. By improving image quality, the detection algorithm becomes more reliable and accurate. The study highlights the importance of pre-processing in computer vision-based pothole detection systems. The proposed method reduces errors caused by environmental conditions. Experimental results confirmed that enhanced image processing techniques significantly improve pothole detection performance.

9. GuruprasadParasnis, et.all This research focused on developing a road inspection system capable of automatically detecting potholes using computer vision techniques. Road images are captured from vehicles and processed using texture analysis methods. The algorithm examines structural patterns and irregularities on the road surface to identify pothole regions. Feature extraction techniques are used to differentiate potholes from normal road conditions. The system can monitor roads continuously during vehicle movement. This reduces the need for manual inspection and improves efficiency in road maintenance planning. The research demonstrates that automated vision systems can enhance transportation safety. The experimental results show that the method effectively identifies potholes in different road environments.

10. N. Bhavana, et.all This study discussed recent developments in automated pothole detection systems used in smart transportation infrastructure. The authors reviewed different image processing techniques used for identifying road surface defects. These methods include segmentation, edge detection, and feature extraction algorithms. The research highlighted the importance of automated road monitoring systems for maintaining transportation safety. The study also emphasized the limitations of manual road inspection methods. Image processing techniques were shown to provide faster and more reliable road condition analysis. The authors suggested integrating these systems with smart city infrastructure for better road maintenance planning. Their work demonstrates the growing importance of computer vision in intelligent transportation systems.

3.EXISTING SYSTEM

The **existing system for pothole detection using image processing** mainly relies on cameras mounted on vehicles or roadside units to capture images of road surfaces. These images are processed using computer vision techniques such as edge detection, texture analysis, and intensity variation to identify irregularities on the road. Algorithms analyse the captured images to detect dark spots, cracks, or uneven regions that indicate potholes. In this approach, road images or sensor data are first collected from cameras mounted on vehicles or mobile devices. The captured images are pre-processed to remove noise and enhance important features such as edges, texture, and intensity variations. K-Means clustering is then applied to segment the road surface into different regions based on pixel similarity, helping to separate possible pothole areas from the normal road surface. After segmentation, relevant features such as shape, depth variation, and texture are extracted from the candidate regions. These extracted features are then given to the SVM classifier, which is trained using labelled datasets containing pothole and non-pothole images. The SVM model learns to distinguish between damaged and undamaged road surfaces by finding the optimal boundary between the classes. When a new road image is captured, the trained SVM model classifies the segmented regions and identifies whether a pothole is present. This hybrid approach improves detection accuracy by combining clustering for region segmentation and supervised learning for classification. The system can be integrated with vehicle-mounted cameras or smartphones for real-time road monitoring. It helps in early identification of potholes and assists authorities in maintaining safer roads and reducing accidents.

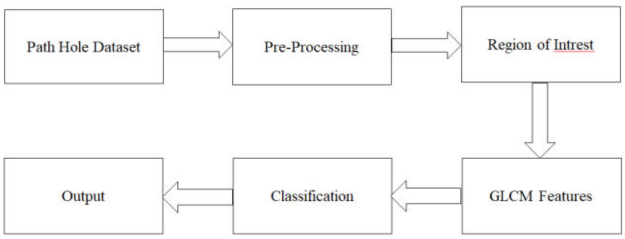

Figure 1: Existing system

The diagram shows the **working process of pothole detection using image processing**. Here's a brief explanation of each step:

- The system first collects road images from a dataset or camera. These images contain different road surface conditions including normal roads and potholes.
- The collected images are enhanced to improve quality. Operations such as noise removal, resizing, grayscale conversion, and contrast adjustment are performed so that the important features of the road surface become clearer.
- In this step, the system selects the specific part of the image that mainly contains the road surface. This reduces unnecessary background information and focuses only on the area where potholes may appear.
- The **Gray Level Co-occurrence Matrix (GLCM)** technique is used to extract texture features such as contrast, energy, homogeneity, and correlation from the selected region. These features help distinguish potholes from normal road surfaces.
- The extracted features are given to a classification algorithm (such as SVM, Random Forest, or other machine learning methods) to determine whether the detected region is a pothole or a normal road surface.

Finally, the system produces the result by identifying and marking the pothole in the image or providing a detection alert.

4. PROPOSED SYSTEM

The proposed system for pothole detection using a Convolutional Neural Network (CNN) is designed to automatically identify damaged road surfaces from captured images. In this system, road images are collected using vehicle-mounted cameras or mobile devices and stored as a dataset for training and testing. Initially, the images undergo pre-processing, where operations such as resizing, noise removal, and image enhancement are applied to improve image quality and reduce computational complexity. The processed images are then fed into the Convolutional Neural Network, which is a deep learning model specially designed for analysing visual data. The CNN automatically extracts important features from the road images through multiple layers such as convolution layers, pooling layers, and fully connected layers. The convolution layers detect patterns like edges, cracks, and irregular textures that are commonly associated with potholes. Pooling layers reduce the dimensionality of the feature maps while preserving the important information, which helps improve processing speed and reduces over fitting. As the image passes through deeper layers of the network, the model learns more complex features that help differentiate between normal road surfaces and pothole regions.

After feature extraction, the fully connected layers perform the classification process by analysing the learned features and predicting whether the input image contains a pothole or not. The model is trained using labelled images of potholes and normal roads so that it can learn the differences between them. During testing, the trained CNN model analyses new road images and accurately detects pothole areas. The final output highlights or marks the detected pothole region in the image. This proposed CNN-based system improves detection accuracy, reduces manual inspection, and enables automatic road damage monitoring for safer transportation systems

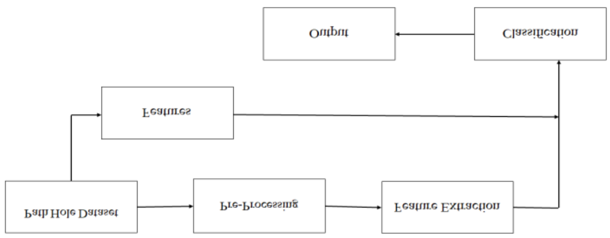

Figure 2: Proposed system

- The pothole dataset is collected, which contains images of roads with and without potholes. These images are given to the
- pre-processing stage, where operations such as resizing, noise removal, normalization, and contrast enhancement are performed to improve image quality and make the data suitable for analysis.
- Next, the system selects the Region of Interest (ROI) from the image. This step focuses only on the important part of the road surface where potholes are likely to appear, reducing unnecessary background information.
- These extracted features are then passed to the CNN classifier, which learns patterns from the dataset and classifies the image as pothole or non-pothole.
- Finally, the output stage displays the detection result, indicating whether a pothole is present in the road image.

Dataset

The **pothole dataset** consists of a collection of road surface images used to train and test the pothole detection system. These images are usually captured using vehicle-mounted cameras, mobile phones, or public road datasets under different lighting and weather conditions. The dataset includes both **pothole and non-pothole road images**, allowing the system to learn the differences between damaged and normal road surfaces. Each image may be labeled to indicate the presence or absence of potholes. This dataset is essential for training the image processing and machine learning model to accurately identify potholes on roads.

Pre-processing

Pre-processing is an important step in pothole detection using image processing. It prepares the input images so that the system can analyse them more accurately.

Step-1: Image Compression

The captured road images are resized to a fixed resolution. This reduces the image size, decreases memory usage, and speeds up the processing without losing important road surface details.

Step-2: Image Enhancement:

In this step, the quality of the image is improved by reducing noise and adjusting brightness and contrast. Techniques such as filtering and smoothing help to make pothole regions clearer and easier to detect.

Step-3: Colour Image Processing:

The original colour images are processed to highlight important features. Sometimes the RGB image is converted into gray scale or other color formats to simplify analysis and improve the detection of texture variations on the road surface.

Pothole detection using the Convolutional Neural Network (CNN) process is a deep learning–based method where road images are automatically analyzed to identify potholes. First, the captured road images are pre-processed by resizing, noise removal, and normalization to improve image quality and make them suitable for training the model. These processed images are then provided to the CNN model, which consists of multiple layers such as convolution layers, pooling layers, and fully connected layers. The convolution layers automatically extract important features like edges, textures, and shapes from the road surface, while pooling layers reduce the image size and computational complexity. During the training phase, the CNN learns patterns from labeled images of roads with and without potholes. After learning these patterns, the trained model can analyze new road images and classify them as pothole or non-pothole regions. Finally, the system produces an output indicating the presence and location of potholes on the road surface, improving the accuracy and efficiency of road damage detection compared to traditional image processing methods.

Pothole detection using Convolutional Neural Networks (CNN) begins with collecting and pre-processing road surface images captured from cameras mounted on vehicles or roadside systems. The images are first resized to a fixed resolution (such as 224×224 or 256×256 pixels) to maintain uniformity and reduce computational complexity. Noise removal techniques such as Gaussian filtering or median filtering are applied to remove unwanted disturbances like shadows, dust, or lighting variations. Image normalization and contrast enhancement are also performed to highlight road surface irregularities so that pothole regions become more visible. The pre-processed images are then fed into the CNN model, where multiple convolutional layers automatically extract important spatial features such as edges, texture variations, cracks, and irregular patterns on the road surface. Pooling layers reduce the dimensionality of the feature maps while preserving important information, which improves computational efficiency and helps prevent overfitting. As the data passes through deeper layers of the network, the CNN learns complex patterns that distinguish pothole regions from normal road surfaces.

The fully connected layers perform the final classification by mapping the extracted features into categories such as pothole and non-pothole. A Softmax activation function is used in the final layer to generate probability scores for each class. During training, the CNN learns from labelled road images and adjusts its internal weights using optimization algorithms to minimize classification errors and improve detection accuracy. Once the model is trained, it can analyze new road images and automatically detect pothole regions with high accuracy. The proposed CNN-based system eliminates the need for manual feature extraction and provides a more efficient solution compared to traditional image processing methods. It supports real-time road condition monitoring, faster road damage detection, and improved road maintenance planning, helping authorities identify damaged road sections and reduce accidents caused by potholes.

In the proposed system, feature extraction and classification of road images are performed automatically using a Convolutional Neural Network (CNN) for pothole detection. After preprocessing, the resized and normalized road surface images are given as input to the CNN model. The convolutional layers scan the images using small filters to identify important visual patterns such as edges, cracks, texture variations, shadows, and irregular road surface structures that may indicate potholes. In the initial layers, the network learns basic features like edges, intensity gradients, and simple texture patterns of the road surface. As the data passes through deeper layers, the CNN learns more complex patterns such as pothole shapes, depth variations, and irregular surface regions that distinguish potholes from normal road areas. Each convolution operation is followed by a ReLU activation function to introduce non-linearity and a pooling layer to reduce the size of the feature maps while preserving the most important information. This hierarchical learning process allows the CNN to automatically extract meaningful features from road images without manual feature engineering. The extracted feature maps are then flattened and passed to fully connected layers, where the network learns the relationship between the extracted features and the output classes. Finally, the model classifies the road image as pothole or non-pothole, enabling accurate and efficient detection of road surface damages.

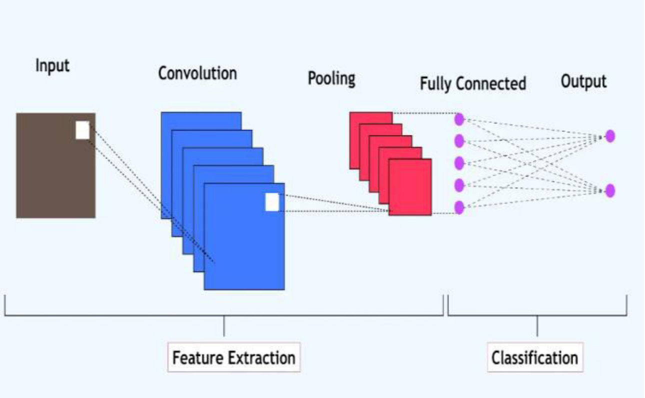

Figure 3: CNN Architecture

Convolutional Layers: We used three sets of convolutional layers with increasing filter sizes - 16, 32, and 64. Each set consists of two layers, with the first layer having a ReLU activation function and the second layer not having any activation function.

Max Pooling Layers: After each set of convolutional layers, we added a max pooling layer to reduce the spatial dimensions of the output.

Dense Layers: After flattening the output from the convolutional layers, we added two dense layers with ReLU activation functions, followed by a dropout layer with a rate of 0.2 to prevent over fitting. Finally, we added a dense layer with a soft max activation function to produce the output probabilities.

Model Training: With the model compiled, we trained it on the training data for 10 epochs with a batch size of 256. We also used two callbacks Model Check point - to reduce the learning rate and save the best model during training.

Model Evaluation: Once the model was trained, we evaluated it on the test data and computed the accuracy and confusion matrix to measure its performance.

An automated procedure for detecting potholes from road images follows a systematic pipeline consisting of image acquisition, pre-processing, feature extraction, and classification. The process begins with capturing road surface images using cameras mounted on vehicles or mobile devices. These images may contain noise, shadows, lighting variations, and background objects due to different environmental conditions. Therefore, the collected road images are first pre-processed using techniques such as resizing, intensity normalization, noise removal, and contrast enhancement to improve image quality and highlight road surface irregularities. These pre-processing steps help enhance the visibility of potholes and prepare the images for accurate analysis. After pre-processing, the system performs automatic feature extraction using a deep learning model. A Convolutional Neural Network (CNN) is designed to learn important spatial patterns such as edges, cracks, texture variations, and irregular shapes that are commonly associated with potholes on road surfaces. The architecture of the proposed system consists of multiple convolutional and pooling layers followed by fully connected layers for classification. The input to the model is a resized road image (for example, 150 × 150 × 3 for RGB images). The initial convolutional layers use small filters (such as 3 × 3) with ReLU activation to extract low-level features like edges and intensity changes, while deeper layers learn high-level patterns such as pothole boundaries, depth variations, and damaged road textures. Pooling layers reduce the feature map size and help prevent overfitting while improving computational efficiency.

Finally, the extracted features are passed to fully connected dense layers that perform classification using a Softmax output layer. The system categorizes the road images into pothole and non-pothole classes based on the learned visual patterns. This automated deep learning–based architecture improves detection accuracy, reduces the need for manual inspection, and enables faster road condition monitoring, helping authorities identify damaged road sections and improve road maintenance and safety. The third and fourth layers are also convolutional layers with 32 filters of size 3 x 3 and a ReLU activation function. These layers also have the same padding and ensure that the size of the input image remains the same. The fifth and sixth layers are again convolutional layers with 64 filters of size 3 x 3 and a ReLU activation function. These layers have the same padding and are followed by a max-pooling layer of size 2 x 2. The max-pooling layer reduces the size of the image by a factor of 2 in both the width and height dimensions. The overall architecture of the CNN can be represented by the following formulas: First convolutional layer:

$$h_1 = \max(0, x * w_1 + b_1)$$

where x is the input image, w_1 are the weights of the first convolutional layer, b_1 is the bias term, and h_1 is the output of the first convolutional layer.

Second convolutional layer:

$$h_2 = \max(0, h_1 * w_2 + b_2)$$

where w_2 are the weights of the second convolutional layer, b_2 is the bias term, and h_2 is the output of the second convolutional layer.

Third convolutional layer:

$$h_3 = \max(0, h_2 * w_3 + b_3)$$

The first convolutional layer has 16 filters with a filter size of 3x3, followed by a ReLU activation function and padding to maintain the size of the input image. The second convolutional layer has the same settings as the first layer.

After the third convolutional layer, another 3x3 convolutional layer is added with 32 filters and ReLU activation. The output shape of this layer is also 32x150x150. The number of parameters in this layer can be calculated. Next, a fourth convolutional layer is added with 64 filters and a receptive field of 3x3 pixels. The output shape of this layer is 64x150x150. The number of parameters in this layer can be calculated Another 3x3 convolutional layer is added after the fourth convolutional layer with 64 filters and ReLU activation. The output shape of this layer is also 64x150x150. The number of parameters in this layer can be calculated using the same formula as before, which gives:

num_params = (3 * 3 * 64 + 1) * 64 = 36,928

Dropout is a regularization technique used to prevent over fitting in neural networks by randomly dropping out (setting to zero) a certain percentage of the neurons during each training epoch. This prevents the model from becoming too dependent on any one neuron and promotes the learning of more robust features.

To reduce the dimensionality of the feature maps and capture the most important features, a max pooling layer with a pool size of 2x2 is added after the fifth convolutional layer. The output of the max-pooling layer is flattened and passed through a fully connected layer with 64 neurons and a ReLU activation function. This layer is followed by a dropout layer with a dropout rate of 0.2, which helps prevent over fitting.

In our implementation, we added a Dropout layer with a rate of 0.2 after the first fully connected layer. This means that during each training epoch, 20% of the neurons in the layer will be randomly set to zero. Early Stopping is another regularization technique used to prevent over fitting. It works by monitoring the model's performance on a validation set during training and stopping the training process early if the model's performance on the validation set has not improved for a certain number of epochs.

The formula for Early Stopping is as follows:

$$f(x) = \begin{cases} x & \text{if } x \leq t \\ t & \text{otherwise} \end{cases}$$

Where x is the validation loss and t is the minimum validation loss observed so far. In our implementation, we used This means that if the validation loss does not improve for 2 epochs, the training process will be stopped early. In the proposed CNN-based pothole detection system, the final output layer is a fully connected layer with neurons corresponding to the number of road condition classes and uses a Soft max activation function. The Soft max function converts the network output into a probability distribution over different classes such as pothole and normal road surface. The class with the highest probability is selected as the final prediction. This probabilistic output helps road monitoring authorities understand the confidence level of the model and supports accurate identification of damaged road sections.

The performance of the proposed system is evaluated using standard metrics such as accuracy, precision, recall, specificity, and F1-score to measure the reliability and robustness of the model. The evaluation is carried out using a separate test dataset of road images to ensure that the trained CNN can generalize well to unseen road conditions. A confusion matrix is used to analyze classification performance and understand how effectively the model distinguishes between pothole and non-pothole images. High recall is particularly important in this application to ensure that pothole regions are not missed, as early detection helps reduce road accidents and improves maintenance planning.

The system can also that allows road maintenance authorities to upload road surface images or video frames and obtain automated pothole detection results within a short time. The interface displays detection results along with probability scores and highlighted pothole regions, making the output easy to interpret for monitoring and maintenance purposes. The platform is designed to be simple and efficient so that operators can use it without requiring advanced technical knowledge. To ensure reliable operation, the system can incorporate secure data storage, system monitoring, and regular model updates to improve detection accuracy over time. Continuous testing and maintenance help maintain stability and performance when analyzing large volumes of road images. Overall, the proposed system supports automatic road condition monitoring, faster pothole detection, and improved road maintenance planning, helping authorities identify damaged roads quickly and enhance transportation safety.

5. RESULTS& DISCUSSION

The proposed CNN-based pothole detection system was tested using a dataset of road surface images containing both pothole and non-pothole samples. After training the Convolutional Neural Network with the pre-processed images, the model was able to successfully learn the visual patterns associated with potholes such as irregular shapes, cracks, dark regions, and uneven textures on the road surface. The trained model was then evaluated using a separate test dataset to measure its performance and ability to correctly identify potholes in unseen images. The experimental results showed that the CNN model achieved high accuracy in distinguishing pothole and non-pothole road images. Performance metrics such as accuracy, precision, recall, and F1-score were used to evaluate the reliability of the system. The confusion matrix analysis indicated that the model correctly classified most of the road images, with only a small number of misclassifications caused by shadows, water-filled potholes, or lighting variations. The results demonstrate that deep learning techniques are more effective than traditional image processing methods for detecting road surface damages. The discussion of the results indicates that the CNN-based approach provides improved detection accuracy and automation, reducing the need for manual road inspection. The system can analyze road images quickly and identify damaged areas in real time, which helps road maintenance authorities take faster corrective actions. However, performance may vary depending on image quality, environmental conditions, and the diversity of the training dataset. Increasing the dataset size and using advanced deep learning models can further improve the robustness and accuracy of the system. Overall, the proposed system provides an efficient and reliable solution for automatic pothole detection and road condition monitoring.

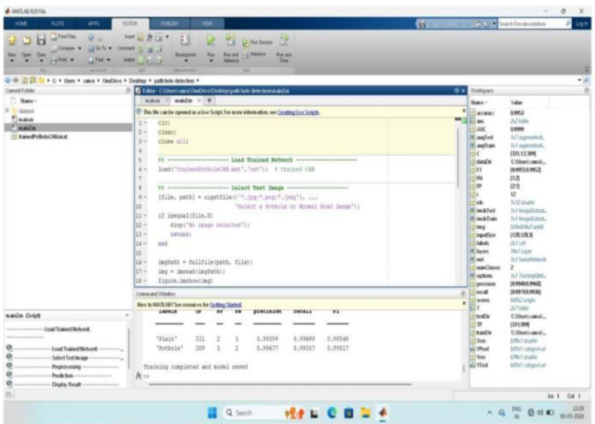

Figure 4: MATLAB Pothole Detection Interface

The dataset consists of road surface images categorized into two classes: pothole and normal road conditions. It includes images captured under different lighting conditions, angles, and environments to ensure variability and robustness, enabling accurate classification and detection performance in real-world scenarios.

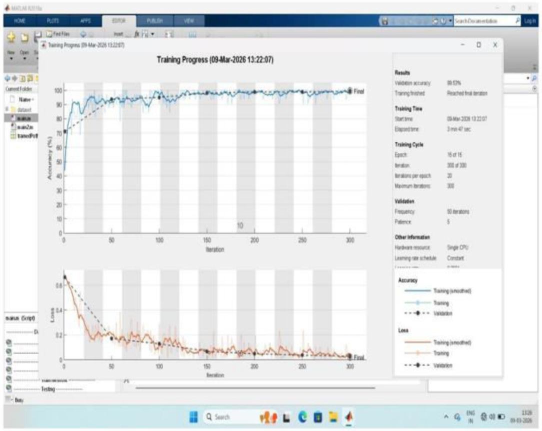

Figure 5: CNN Training Progress and Performance Model

This figure illustrates the training progress of a Convolutional Neural Network, showing accuracy and loss curves over iterations. It indicates that the model achieves high validation accuracy while the loss decreases steadily, demonstrating effective learning and convergence.

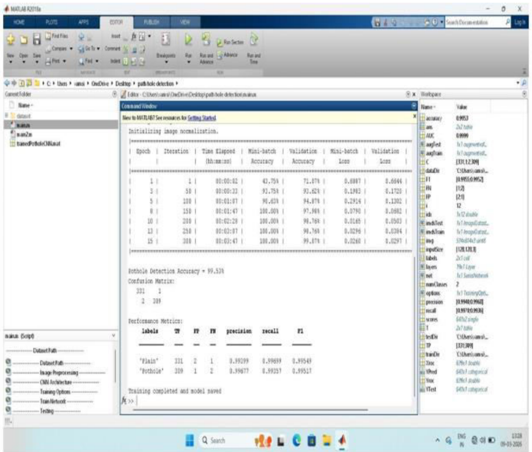

Figure 7: CNN-Based Pothole Detection Performance Metrics

This fig illustrates the MATLAB environment where a trained Convolutional Neural Network (CNN) model is implemented to classify road images as pothole or normal. The workspace and command window display key evaluation metrics such as accuracy, precision, and recall, demonstrating the effectiveness of the model.

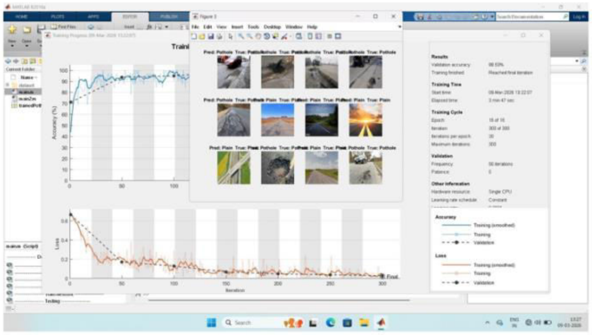

Figure 8: Training Progress and Classification Results for Pothole Detection Model

This figure shows the model's training performance, including accuracy improving and loss decreasing over iterations. It also displays sample predictions comparing detected classes (pothole/plain) with true labels to evaluate model effectiveness.

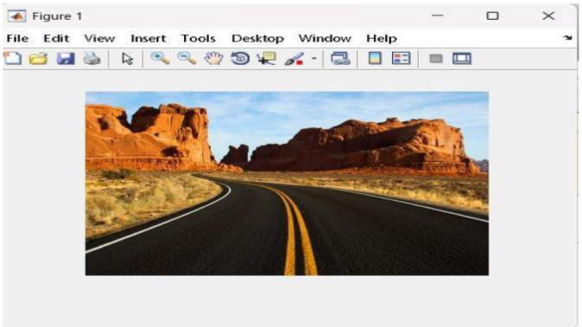

Figure 9: Input Image

This figure shows the original input image before any preprocessing or analysis. It serves as the raw data provided to the system for further processing such as feature extraction or classification.

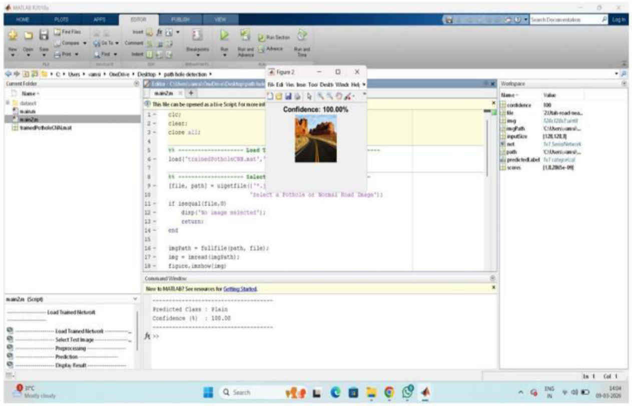

Figure 10: Model Prediction Output Interface

This figure displays the classified input image along with its predicted label (plain road) and corresponding confidence score, indicating the model's certainty. It represents the final stage of the system where the trained model processes the image and outputs the prediction result.

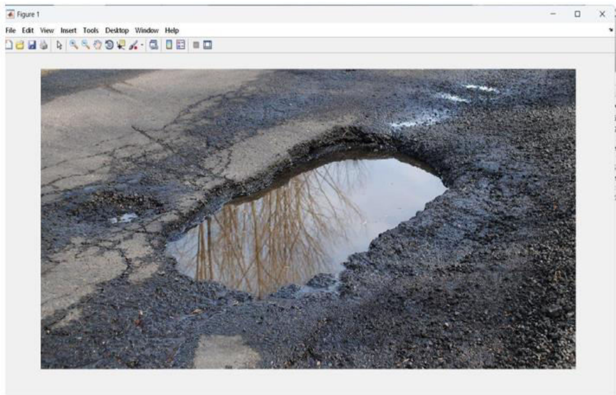

Figure 11: Another Input Image

This figure shows the original input image before any pre-processing or analysis. It serves as the raw data provided to the system for further processing such as feature extraction or classification.

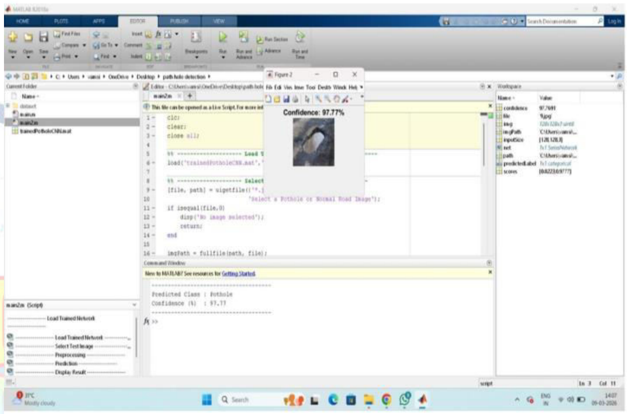

Figure 12: Model Prediction Output Interface

This figure displays the classified input image along with its predicted label (path hole) and corresponding confidence score, indicating the model's certainty. It represents the final stage of the system where the trained model processes the image and outputs the prediction result.

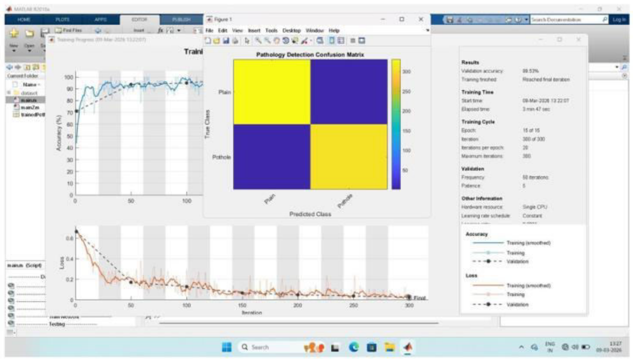

Figure 13: Confusion Matrix for Pothole Detection Model

This figure presents the confusion matrix showing the classification performance of the model for plain and pothole classes. It highlights correct and incorrect predictions, helping evaluate the accuracy and reliability of the trained model.

5. CONCLUSIONS

The proposed **CNN-based pothole detection system** provides an effective and automated solution for identifying road surface damages using image processing and deep learning techniques. By using a Convolutional Neural Network, the system can automatically extract important features such as edges, cracks, and irregular textures from road images without the need for manual feature engineering. The experimental results show that the model can accurately classify road images into **pothole and non-pothole categories,** improving the efficiency of road condition monitoring. This approach reduces the time, cost, and human effort involved in manual road inspection. Overall, the system helps road maintenance authorities detect damaged road sections quickly, which can contribute to improved road safety and better infrastructure management.

Future scope

In the future, the pothole detection system can be improved by using Vision Transformer (ViT)–based transfer learning models, which have shown strong performance in image recognition tasks. Pre-trained vision models can be fine-tuned with road surface datasets to improve detection accuracy even with limited training data. These models can capture global image features more effectively than traditional CNNs, helping to detect complex pothole patterns under different lighting and weather conditions. Integrating Vision Transformer models with real-time camera systems and smart transportation networks can further enable faster, scalable, and more reliable road damage monitoring.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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