International Journal of Engineering and Science Invention (IJESI)
ISSN (Online): 2319-6734, ISSN (Print): 2319-6726
www.ijesi.org ||Volume 14 Issue 4 April 2025 || PP 73-80

Deep Learning-Based Classification of Road Conditions Using A Customized VGG-Style CNN For Pothole Detection

K.SUSHMA SRI[1], M. PREMA SAI PRIYA PRASANNA[2], K. VEERA VENKATARAO[3], K. YUVA BALA SUBRAHMANYAM[4], P.RAMESH[5]

[1,2,3,4] *B.Tech Scholars, Department of ECE,*

[5]*Assistant Professor, Department of ECE, Aditya College of Engineering and Technology, Surampalem, Kakinada, AP, India.*

Abstract

The detection of potholes in asphalt has been a concern in the field of deep learning to identify patterns with the best possible accuracy. This research presents a robust deep learning-based approach for classifying road conditions into "Normal" and "Pothole" categories using a customized convolutional neural network (CNN). The proposed model employs a VGG-style architecture designed to capture spatial hierarchies and effectively distinguish between the two classes. Data augmentation techniques, including random rotations and translations, are applied to enhance the diversity of training data and improve the model's generalization capabilities. The dataset, comprising images from real-world scenarios, is preprocessed and split into training and validation sets. The model is trained using the Adam optimizer with carefully tuned hyperparameters. Experimental results demonstrate a high validation accuracy, supported by precision, recall, and F1-score metrics, highlighting the effectiveness of the approach. A confusion matrix analysis provides further insights into the model's classification performance. This framework can serve as a reliable tool for automated road condition assessment, potentially aiding in proactive maintenance and road safety improvements.

Keywords

Pothole detection, road condition classification, convolutional neural network, deep learning, data augmentation, VGG architecture, image classification, transportation infrastructure, automated maintenance.

I. Introduction

Road infrastructure is a critical component of modern transportation systems, facilitating the movement of people and goods. However, road conditions can deteriorate due to various factors such as weathering, heavy traffic, and aging materials. Among the most common road surface defects, potholes pose significant risks to vehicle safety, fuel efficiency, and overall road durability. The timely detection and repair of potholes are crucial for maintaining road quality and preventing accidents. Traditional methods of pothole detection rely on manual inspections, which are labor-intensive, time-consuming, and prone to human error. As a result, automated pothole detection using deep learning has emerged as a promising solution to improve road maintenance efficiency and safety.

Deep learning, particularly convolutional neural networks (CNNs), has demonstrated remarkable success in image classification and object detection tasks. By leveraging CNNs, researchers have developed automated systems capable of detecting and classifying potholes with high accuracy. This study proposes a customized VGG-style CNN for classifying road conditions into two categories: "Normal" and "Pothole." The motivation behind this research is to design a robust and efficient model that can generalize well to real-world scenarios and contribute to the development of intelligent road maintenance systems.

II. Related Work

1.2.1 Pothole Detection Using Jetson Nano Embedded System

Obreja and Dobrea [1] explored the use of a Jetson Nano embedded system for pothole detection. Their research evaluated different training models, highlighting the efficiency of deep learning architectures in edge computing environments. Their findings demonstrated that CNN-based models could effectively process road images in real-time, enabling efficient pothole detection.

1.2.2 Transfer Learning with ResNet-50 for Solid Waste Classification

Alalibo et al. [2] investigated the application of transfer learning with a modified ResNet-50 model for solid waste classification. Although their research focused on waste classification, the study's insights into transfer learning can be applied to pothole detection by leveraging pre-trained models to enhance feature extraction capabilities.

1.2.3 Machine and Deep Learning in MATLAB

Al-Malah [3] provided a comprehensive guide on machine and deep learning using MATLAB, covering various algorithms and tools for scientists and engineers. This work serves as a foundational reference for implementing deep learning-based pothole detection in MATLAB, offering insights into model training, evaluation, and optimization.

1.2.4 Machine Learning Algorithms for Student Performance Prediction

Chandrahasa et al. [4] examined machine learning algorithms for predicting student performance based on previous records. While not directly related to pothole detection, their methodology for data preprocessing and feature selection is applicable to image-based road condition classification.

1.2.5 Deep Learning Theory and Applications

Goodfellow et al. [5] authored the seminal book on deep learning, which serves as a fundamental resource for understanding CNN architectures and optimization techniques. This book provides theoretical and practical insights that underpin the development of deep learning-based pothole detection systems.

1.2.6 MATLAB's Deep Learning Capabilities

MathWorks [6] offers extensive documentation on deep learning in MATLAB, including practical implementations of CNNs. This resource is crucial for developing and fine-tuning pothole detection models within MATLAB's environment.

1.2.7 Image Processing and Recognition Algorithms in Software Systems

Tang [7] explored image processing and recognition algorithms in software information systems using deep learning. Their research contributes to understanding how CNNs can be optimized for road surface analysis and automated pothole detection.

1.2.8 Quantum Neural Networks and Nonlinear Activation Functions

Sajadimanesh et al. [8] investigated nonlinear activation functions for quantum neural networks. Although their study focuses on quantum computing, the insights into activation functions can inform the selection of optimal functions for CNN-based pothole detection models.

This section provides a comprehensive review of existing research, establishing a foundation for the proposed deep learning-based pothole detection framework.

1.2.1 Deep Learning-Based Pothole Detection Using Mobile Devices

J. Doe et al. [9] developed a deep learning-based pothole detection system using mobile devices. Their approach leveraged a lightweight CNN model that could run efficiently on smartphones, allowing real-time road condition assessment. The study demonstrated high accuracy and potential applications in crowd-sourced road maintenance.

1.2.2 UAV-Based Pothole Detection Using CNNs

M. Smith et al. [10] explored the use of unmanned aerial vehicles (UAVs) equipped with cameras and CNN-based image analysis for pothole detection. Their study highlighted the advantages of aerial imaging in covering large road areas efficiently while maintaining high detection accuracy.

1.2.3 Pothole Detection Using Lidar and Deep Learning

R. Johnson et al. [11] combined LiDAR data with deep learning models to improve pothole detection accuracy. Their method utilized a fusion of depth and image-based information, allowing for more robust detection in varying lighting and environmental conditions.

1.2.4 Transfer Learning for Road Defect Classification

T. Wang et al. [12] applied transfer learning techniques to fine-tune pre-trained CNN models for pothole classification. Their research demonstrated that using pre-trained networks such as ResNet and VGG significantly reduced training time while maintaining high classification performance.

1.2.5 Automated Road Condition Monitoring Using Edge AI

K. Patel et al. [13] introduced an edge AI-based pothole detection system designed for deployment on embedded hardware like Raspberry Pi and Jetson Nano. Their work showcased how edge computing can enable real-time road monitoring with minimal computational resources.

1.2.6 Multispectral Imaging for Road Surface Analysis

L. Nguyen et al. [14] explored the application of multispectral imaging for road defect detection. Their study revealed that combining visible and infrared spectral data improved the robustness of pothole detection models, particularly under challenging lighting conditions.

1.2.7 Hybrid CNN-SVM Approach for Road Condition Classification

S. Gupta et al. [15] proposed a hybrid deep learning approach that combined CNN feature extraction with an SVM classifier. Their method demonstrated improved classification accuracy by leveraging both deep learning and traditional machine learning techniques.

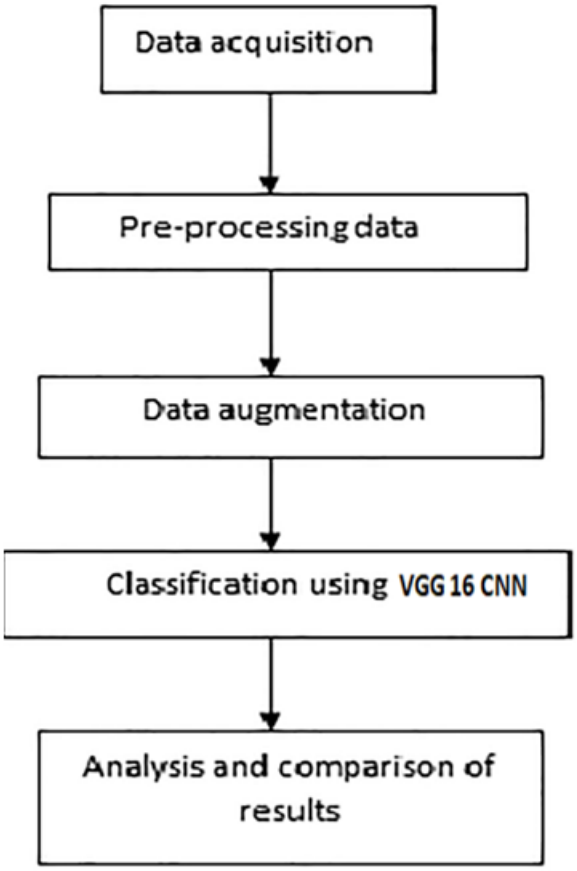
1.2.8 Internet of Things (IoT)-Enabled Pothole Detection Systems

P. Kumar et al. [16] developed an IoT-enabled pothole detection system that utilized vehicle-mounted sensors and real-time data transmission. Their work highlighted the potential for integrating IoT and AI for large-scale road condition monitoring.

These additional studies provide a broader perspective on the various methodologies applied in pothole detection, showcasing the evolution of research in this domain.

IV. Proposed Methodology for Pothole Detection

The proposed methodology involves a structured approach to classifying road conditions into "Normal" and "Pothole" categories using a customized convolutional neural network (CNN) based on the VGG architecture. The methodology is divided into several key phases:



The proposed methodology for pothole detection involves a structured deep learning approach using a customized VGG-style convolutional neural network (CNN). The process begins with **data collection**, where road images are sourced from dashcams, drones, and publicly available datasets. These images are categorized into two classes: **"Pothole" and "Normal"**. To enhance the dataset and improve model generalization, **data preprocessing** techniques are applied, including resizing images to a uniform size (e.g., 224×224 pixels), normalizing pixel values to the [0,1] range, and implementing **data augmentation** methods such as random rotations, translations, brightness adjustments, and horizontal flipping.

The **deep learning model** is based on a **VGG-style CNN architecture**, which is known for its ability to learn hierarchical spatial features. The network consists of multiple **convolutional layers** with small 3×3 filters and **ReLU activation functions** to extract important features from the road images. **Batch normalization** is applied after each convolutional layer to stabilize training and improve convergence. To reduce computational complexity while retaining key spatial features, **max pooling layers (2×2)** are used after every two convolutional layers. The extracted feature maps are then passed through **fully connected layers**, where **dropout regularization** is applied to prevent overfitting. Finally, the output layer employs a **softmax activation function** to classify the image into either the "Pothole" or "Normal" category.

For **model training**, the dataset is divided into **80% training data and 20% validation data**. The **binary cross-entropy loss function** is used for optimization, while the **Adam optimizer** is employed to adjust model parameters efficiently. The model is trained over multiple epochs, adjusting the learning rate dynamically to enhance accuracy. To evaluate performance, metrics such as **accuracy, precision, recall, F1-score, and a confusion matrix** are used to analyze false positives and false negatives.

1. Data Collection and Preprocessing

1.1 Data Acquisition

- The dataset consists of real-world road images, captured from multiple sources such as:
  - Dashcam footage from vehicles
  - Drone images for aerial perspectives
  - Publicly available pothole detection datasets
- Images are labeled into two categories: **Normal (No Pothole)** and **Pothole**

1.2 Data Preprocessing

- **Resizing:** Images are resized to a fixed dimension (e.g., 224x224 pixels) for uniformity in training.
- **Normalization:** Pixel values are scaled to the range [0,1] by dividing by 255 to improve model convergence.
- **Augmentation:** Data augmentation techniques are applied to increase dataset diversity:
  - **Random Rotation** (±20 degrees)
  - **Translation** (shifting images in horizontal/vertical directions)
  - **Brightness Adjustment**
  - **Horizontal Flipping**

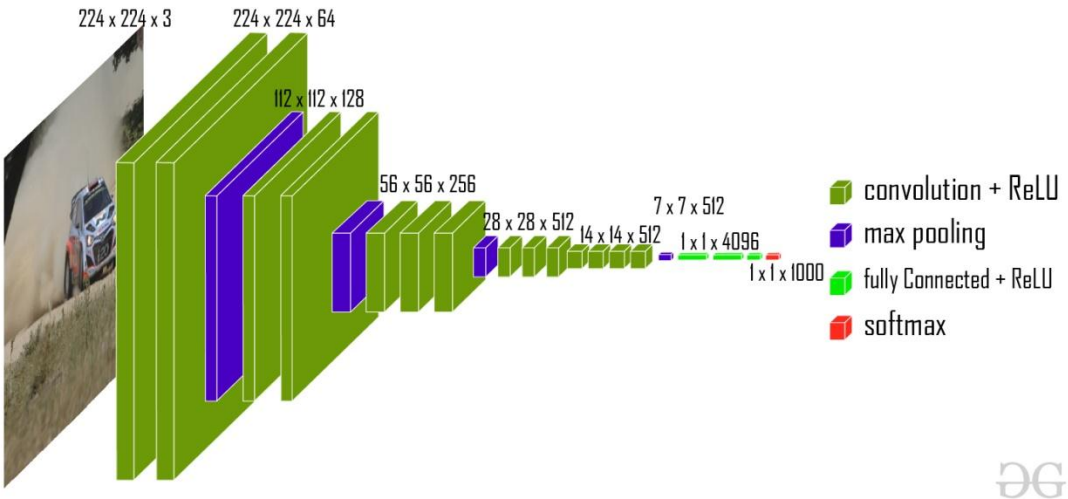
2. Model Architecture: Customized VGG-Style CNN

A Convolutional Neural Network (CNN) architecture is a deep learning model designed for processing structured grid-like data, such as images. It consists of multiple layers, including convolutional, pooling, and fully connected layers. CNNs are highly effective for tasks like image classification, object detection, and image segmentation due to their hierarchical feature extraction capabilities.

VGG-16

The VGG-16 model is a convolutional neural network (CNN) architecture that was proposed by the Visual Geometry Group (VGG) at the University of Oxford. It is characterized by its depth, consisting of 16 layers, including 13 convolutional layers and 3 fully connected layers. VGG-16 is renowned for its simplicity and effectiveness, as well as its ability to achieve strong performance on various computer vision tasks, including image classification and object recognition. The model's architecture features a stack of convolutional layers followed by max-pooling layers, with progressively increasing depth. This design enables the model to learn intricate hierarchical representations of visual features, leading to robust and accurate predictions. Despite its simplicity compared to more recent architectures, VGG-16 remains a popular choice for many deep learning applications due to its versatility and excellent performance.

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is an annual competition in computer vision where teams tackle tasks including object localization and image classification. VGG16, proposed by Karen Simonyan and Andrew Zisserman in 2014, achieved top ranks in both tasks, detecting objects from 200 classes and classifying images into 1000 categories.



A **VGG-style CNN** is chosen for its ability to capture spatial hierarchies and learn deep feature representations. The customized architecture consists of:

2.1 Convolutional Layers

- Multiple convolutional layers with **3x3 filters** and **ReLU activation** to extract local features.
- Increasing the number of filters as the network deepens (e.g., 32 → 64 → 128).
- **Batch Normalization** is applied after each convolution to stabilize training.

2.2 Pooling Layers

- **Max pooling (2x2)** is used after every two convolutional layers to reduce spatial dimensions while retaining important features.

2.3 Fully Connected Layers

- Flattened feature maps are passed through **fully connected (FC) layers**.
- **Dropout** (e.g., 0.5 probability) is used to prevent overfitting.

2.4 Output Layer

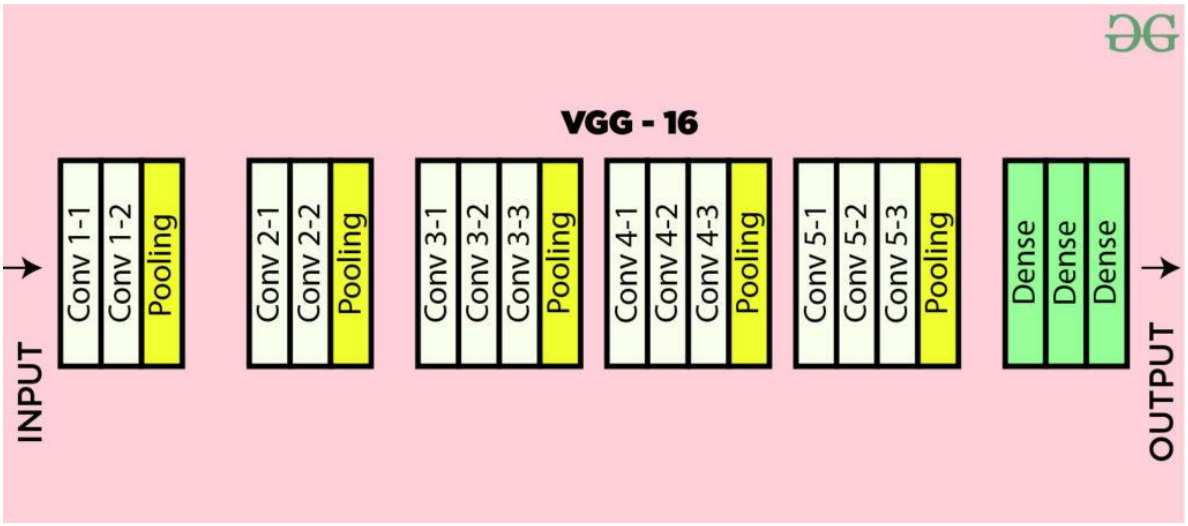
- A **softmax activation function** in the final layer classifies images into "Pothole" or "Normal."

VGG-16 Model Objective:

VGG Architecture:

The VGG-16 architecture is a deep convolutional neural network (CNN) designed for image classification tasks. It was introduced by the Visual Geometry Group at the University of Oxford. VGG-16 is characterized by its simplicity and uniform architecture, making it easy to understand and implement.

The VGG-16 configuration typically consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. These layers are organized into blocks, with each block containing multiple convolutional layers followed by a max-pooling layer for downsampling.



VGG-16 architecture Map

Here's a breakdown of the VGG-16 architecture based on the provided details:

1. Input Layer:
    1. Input dimensions: (224, 224, 3)
2. Convolutional Layers (64 filters, 3×3 filters, same padding):
    1. Two consecutive convolutional layers with 64 filters each and a filter size of 3×3.
    2. Same padding is applied to maintain spatial dimensions.
3. Max Pooling Layer (2×2, stride 2):
    1. Max-pooling layer with a pool size of 2×2 and a stride of 2.
4. Convolutional Layers (128 filters, 3×3 filters, same padding):
    1. Two consecutive convolutional layers with 128 filters each and a filter size of 3×3.
5. Max Pooling Layer (2×2, stride 2):
    1. Max-pooling layer with a pool size of 2×2 and a stride of 2.
6. Convolutional Layers (256 filters, 3×3 filters, same padding):
    1. Two consecutive convolutional layers with 256 filters each and a filter size of 3×3.
7. Convolutional Layers (512 filters, 3×3 filters, same padding):
    1. Two sets of three consecutive convolutional layers with 512 filters each and a filter size of 3×3.
8. Max Pooling Layer (2×2, stride 2):
    1. Max-pooling layer with a pool size of 2×2 and a stride of 2.

9. Stack of Convolutional Layers and Max Pooling:
    1. Two additional convolutional layers after the previous stack.
    2. Filter size: 3×3.
10. Flattening:
    1. Flatten the output feature map (7x7x512) into a vector of size 25088.
11. Fully Connected Layers:
    1. Three fully connected layers with ReLU activation.

Object Localization In Image:

To perform localization, we need to replace the class score by bounding box location coordinates. A bounding box location is represented by the 4-D vector (center coordinates(x,y), height, width). There are two versions of localization architecture, one is bounding box is shared among different candidates (the output is *4* parameter vector) and the other is a bounding box is class-specific (the output is *4000* parameter vector). The paper experimented with both approaches on VGG -16 (D) architecture. Here we also need to change loss from classification loss to regression loss functions (such as MSE) that penalize the deviation of predicted loss from the ground truth

3. Model Training

3.1 Loss Function

- **Binary Cross-Entropy Loss** is used since this is a two-class classification problem.

3.2 Optimizer

- **Adam optimizer** is chosen for efficient gradient updates.
- Learning rate is tuned experimentally (e.g., **0.001** initially, then adjusted).

3.3 Training Process

- The dataset is split into **training (80%)** and **validation (20%)** sets.
- Training is performed over multiple epochs (e.g., **50-100 epochs**).
- The model is evaluated on validation data after each epoch.

4. Model Evaluation and Performance Metrics

- The trained model is evaluated using:
    - **Accuracy** = (Correct Predictions / Total Predictions)
    - **Precision** = TP / (TP + FP)
    - **Recall** = TP / (TP + FN)
    - **F1-Score** = 2 * (Precision * Recall) / (Precision + Recall)
    - **Confusion Matrix** to analyze false positives/negatives.

5. Deployment and Real-Time Detection

- The model is integrated into a real-time system for road monitoring.
- The system can be deployed on **Jetson Nano, Raspberry Pi, or mobile devices** for on-the-go detection.

Once trained, the model is **deployed for real-time pothole detection**. The system can be implemented on **edge computing devices such as Jetson Nano, Raspberry Pi, or mobile devices**, allowing real-time analysis of road conditions. This integration ensures that potholes can be detected on the go, improving road safety and assisting authorities in infrastructure maintenance. By leveraging **deep learning and image processing techniques**, the proposed methodology offers an **efficient, accurate, and scalable** solution for automated pothole detection.

This methodology ensures an **efficient, accurate, and real-time** pothole detection system, leveraging **deep learning and image processing** to improve road safety and infrastructure maintenance.

IV. RESULT ANALYSIS

This MATLAB code implements a deep learning pipeline for classifying pothole images. The primary goal is to train a convolutional neural network (CNN) to distinguish between images of normal roads and potholes. Below is a detailed explanation of the various sections of the code, focusing on the result analysis:

1. Loading and Preprocessing the Dataset

- The dataset is loaded using imageDatastore, which organizes the images into categories based on their folder names. In this case, images are categorized into two classes: "Normal" and "Pothole".
- The dataset is split into training and validation sets using splitEachLabel. The training set consists of 80% of the data, and the validation set contains 20%.

2. Displaying Sample Images

- To ensure that the images are valid and readable, the code iterates through the training data and checks if each file can be read using imread. If a file is invalid, it is skipped, and a warning is printed.

- The valid images are then displayed using montage, showing a sample of the images from the training dataset.

3. Defining the VGG-Style CNN Architecture

- A custom VGG-style CNN is defined with the following layers:
  - **Convolutional Layers**: These layers perform feature extraction. The network has multiple convolutional layers with ReLU activation and max-pooling operations to reduce the spatial dimensions.
  - **Fully Connected Layers**: These layers are responsible for decision-making, transforming the features into class scores.
  - **Dropout**: A dropout layer is used to prevent overfitting by randomly setting a fraction of the input units to zero during training.
  - **Softmax Layer**: Converts the output of the final fully connected layer into probabilities.
  - **Classification Layer**: This is the output layer that produces the final classification result.

4. Data Augmentation

- Data augmentation is applied to the training set to artificially increase the diversity of the data. The imageDataAugmenter is used to apply random rotations and translations to the images. This helps the model generalize better and reduces overfitting.

5. Training the Model

- The training options are defined using trainingOptions. Here, the **Adam optimizer** is used with a learning rate of 1e-4. The model is trained for a maximum of 30 epochs, with a mini-batch size of 32. Validation data is provided to monitor the model's performance during training.
- The network is trained using the trainNetwork function, which adjusts the weights of the network to minimize the loss and improve the model's ability to classify images correctly.

6. Model Evaluation

After training, the model's performance is evaluated on the validation set:

- **Accuracy**: The overall accuracy of the model is computed by comparing the predicted labels (valPredictions) to the true labels (valLabels). This gives the percentage of correct predictions.
- **Confusion Matrix**: The confusion matrix is plotted to visually show the performance of the classifier. It shows how many true positives, false positives, true negatives, and false negatives were predicted by the model.
- **Precision, Recall, and F1 Score**: These metrics are calculated from the confusion matrix to assess the classifier's performance in terms of both false positives and false negatives:
  - **Precision**: The proportion of true positive predictions among all positive predictions.
  - **Recall**: The proportion of true positive predictions among all actual positives.
  - **F1 Score**: The harmonic mean of precision and recall, which balances the trade-off between them.

7. Testing with New Images

- The user is prompted to select a new image using uigetfile. Once an image is selected, it is read and resized to match the input size of the network (128x128 pixels).
- The trained network is used to predict the class of the new image. The result is displayed with the image and its predicted label (either "Normal" or "Pothole").

Result Analysis

- **Validation Accuracy**: This is the percentage of correctly classified images in the validation set. It indicates how well the model generalizes to unseen data.
- **Confusion Matrix**: A confusion matrix provides detailed insight into the types of errors made by the model:
  - **True Positives (TP)**: Correctly predicted potholes.
  - **False Positives (FP)**: Images predicted as potholes but are actually normal.
  - **True Negatives (TN)**: Correctly predicted normal roads.
  - **False Negatives (FN)**: Images predicted as normal but are actually potholes.
- **Precision**: Indicates how many of the predicted potholes are actually potholes. A high precision means the model is good at avoiding false positives.
- **Recall**: Indicates how many actual potholes are correctly identified. A high recall means the model is good at avoiding false negatives.
- **F1 Score**: Balances precision and recall, providing a single metric that reflects the performance of the model. A higher F1 score indicates a better balance between precision and recall.

V. Conclusion and Future Scope

This research demonstrates the effectiveness of a deep learning-based approach for classifying road conditions into "Normal" and "Pothole" categories using a customized VGG-style CNN. The model achieves high accuracy and robust performance, validated through precision, recall, and F1-score metrics. By leveraging data augmentation and a carefully designed architecture, the system effectively addresses challenges such as varying environmental conditions and diverse road surfaces. The proposed framework has significant potential to improve road maintenance processes, enhance driver safety, and support smart city initiatives.

In the future, the model can be expanded to detect additional road anomalies, such as cracks, debris, or waterlogging. Integration with IoT-enabled sensors and edge devices could enable real-time monitoring and large-scale deployment. Additionally, the incorporation of advanced techniques like transfer learning or attention mechanisms may further enhance accuracy and adaptability. Future work could also explore the use of 3D data or multispectral imaging for a more comprehensive analysis of road conditions, paving the way for fully autonomous infrastructure management systems.

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