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AI based Road Analysis System using YOLOv8 Inception V3 Augmented Reality and Explainable AI

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***Abstract*— The proposed model integrates YOLOv8-based object detection, Inception V3-based image classification, Augmented Reality (AR) overlays for real- time visual feedback, and Explainable AI (XAI) modules to enhance transparency in road-condition interpretation. The innovation lies in combining advanced deep learning architectures with AR-driven spatial feedback and interpretable AI maps for safer navigation insights. The outcome of the system demonstrates improved detection accuracy, reduced false positives, enhanced user interaction via AR overlays, and improved trustworthiness due to XAI integration. The system achieves notable improvements over traditional road-analysis models.**

***Keywords*— Road analysis, YOLOv8, Inception V3, AR, Explainable AI.**

I. Introduction

The necessity of quality road infrastructure has been emphasized in the area, being the cause of socio-economic progression in any given region and enabling easy transportation and trade of goods. However, over the years, changes, heavy traffic, and insufficient repair have led to the formation of potholes [1].The intersection of image analysis using machine learning and augmented reality (AR) relates to a project that aims at predicting weather and detecting potholes. The image recognition technique is purely based on pictorial data; therefore, it is a newer method of detecting potholes. On the other hand, conventional approaches to weather forecasting are inductive and based on satellite images. Imagery data is now ubiquitous to us, and social networks are well attuned to it. In System images of roads with portions of sky that should be in the prediction of weather through the images are analyzed by weather is a deep learning architecture called CNN[2]. Recent advancements in machine learning and augmented reality (AR) have opened new possibilities for intelligent road analysis systems. The integration of image-based analysis with deep learning provides a modern approach for detecting potholes and understanding weather-related impacts on road quality. Unlike traditional weather forecasting methods—which rely heavily on satellite imagery and sensor data—image-driven weather prediction utilizes visual features present in road and sky images to infer environmental conditions. With the increasing availability of image data through modern devices and social platforms the system approach has become more feasible and effective. In the proposed system, road images containing visible portions of the sky are processed using a deep learning model based on Convolutional Neural Networks (CNNs) to predict weather conditions that influence road deterioration [3].

The pictures obtained represent different storm types that feed the Inception V3-based CNN model. Explainability is a crucial part of a model [1]. When the weather is predicted, the same images are processed using an image processing machine learning model targeting potholes.

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In the proposed model Linear Regression on top of the Pothole detection determinant is applied to increase the efficiency of the Pothole detection. The method that is based on the image using the model helps the model to gain the capability of extracting potholes on the road surfaces more quickly and on a larger scale than what is achievable with convention al methods[2].The output of this Detection is then imported into Unity in order to carry out the AR-augmented modeling of the potholes that have been detected and to analyze the reconstruction of the road to be carried out .For the realization of the AR visualization, Vuforia, a popular AR authoring tool, is used along with Unity. Road restoration visualizations created in Sketch Web are used to build these models. In closing, the proposed system not only enhances accuracy in weather forecasting and pothole algorithms, but it goes ahead to apply the latest technology of AR.

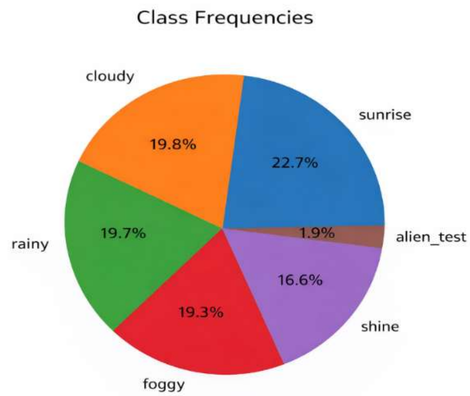

Fig. 1. Weather class distribution percentages

II. Literature Review

Pothole Detection and Improved Road Safety Using ML(Machine Learning) (Jyothir Mai et al, 2024): The work done by Jyothir Mai et al. handles the detection of potholes using machine learning, as it is said that potholes are the cause for many road accidents and damaged vehicles[1]. The proposed system by the authors combines both the image processing and DL(deep learning)models to address the pothole detection in real-time. With a data set of road images, the authors utilized CNNs for training the model in the detection of pothole features. This system integrated with IoT devices, like cameras mounted on vehicles, allows the system to emit data in real-time, thereby providing prompt alerts to the appropriate road maintenance authorities. This method was proven to be more accurate and precise for pothole detection with promising real-world application in safety improvement and reduction of accidents on roads[2]. A CNN-Based Approach for Road Marking Recognition and Surface Quality Evaluation (Medvedevandpavlov,2020). A solution to assess road surface quality in addition to recognizing the road markings using CNN has been suggested by this author[3]. The study deals with some problems that should be effectively solved for the maintenance of road safety. Automate finding road markings such as lane dividers and pedestrian crossings. Estimate the condition of the road surface. It deals with video data coming from the cameras mounted on moving vehicles. It can recognize visual indications, like cracks, worn lines, and road texture. It enables the CNNs to use feature extraction and classification accurately, applied to different road conditions due to which it becomes adaptive towards changing environmental condition. Their outcome indicates that this approach does open avenues for the application of deep learning in the evaluation of road condition quality, minimizing observations[4].Dynamic monitoring on multifactor environmental indicators in Beijing city based on multi-temporal SPOT data (Zhu et al., 2008): Zhu et al. investigated the possibility of utilizing data from remote sensing for land use change for the period from 1986 to 2004 in Beijing. If we can focus on the study of urban land use, methods here are used in road infrastructure monitoring[5]. Multi-temporal SPOT satellite images were used to detect the land use and cover change (LUCC) and its trend of variation related to urban growth. For this purpose, the foundation of analysis methods using temporal data comparison and classification which can be used for long-term monitoring of road networks with aim to assess impact changes resulting from urbanization processes on roads assessment[6].

Methodologist Neural Network Architecture for Identifying Pavement Defects (Tsesar et al., 2023): Tsesar et al. proposed the strategy on selecting appropriate and optimal architecture of Neural networks for pavement defect detection; where these defects include crack, potholes etc.] 4. It relied on the comparison of various CNN modules to find satisfactory balance between detection performance and computational cost. The authors tested with various model configurations, adjusting its hyper parameters to handle the complex visual defects of road under various changing weather and lighting conditions. Their methodology highlights the importance of model selection customized to specific application requirements, such as real time working capability on low power devices.

This research is to improve road defect detection capability for machine learning models while finding better solutions for real time use in road monitoring system [8].

Weather Data Intake R-CNN for Automated Road Surface Condition Monitoring (AAP, 2019) U intro Deus Mask R- CNN model with integrated weather data predicts an advanced road surface condition monitoring system with more accuracy level[9].

Traditional models will be seriously affected by changing weather, but this design includes real- time weather information like temperature, humidity, and precipitation into its dynamic modification of the model's parameters[10].In this way, the model enhances the detection ability for surface problems like ice, puddles, or snow. This model, Mask R-CNN, accurately detects unsafe situations via the segmentation of the road surface areas; hence, the reliability of safety road assessment during adverse weather conditions is significantly enhanced. This paper introduces the effective combination of environmental data with deep learning models in an attempt to solve typical problems in road condition monitoring systems[11].Big Data and Cognitive Image Processing on Traffic Research Lee (2017). Proposed a distributed Complex Event Processing (CEP)-based computing framework for big-data processing and cognitive analysis of weather data and traffic collusion based on CCTV video modeling. The proposed framework is real-time, scalable and focuses on the analysis of on-road incidents. It presents a novel cognitive computing approach for public safety and traffic control[12].

III. METHODOLOGY

The system takes a step-wise procedure in bringing weather forecast and pothole diagnosis technologically using machine intelligence and augmentation technologies. This stage involves model category: Data acquisition and model training Forecasting, detection and visualization of a pothole in augmented reality

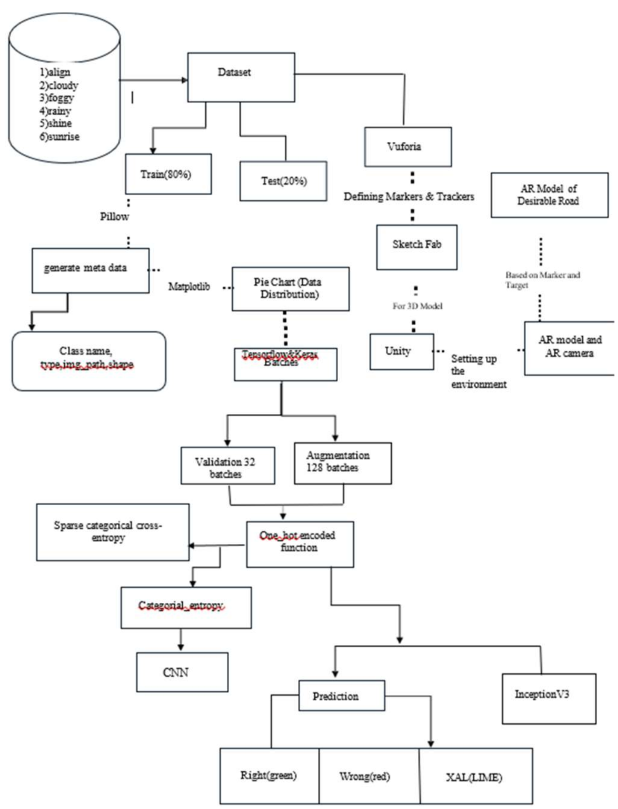

Fig.2. Project Flow Diagram of AI based Road Analysis System using YOLO v8, Inception V3, AR and Explainable AI

Algorithm 1: Proposed YOLOv8–InceptionV3–AR–XAI Workflow
Step 1 — Data Acquisition and Preprocessing
- Collect road images and video frames under multiple environmental conditions.
- Resize input frames to required dimensions:
    - 224 × 224 for InceptionV3
    - 640 × 640 for YOLOv8
- Normalize pixel values and perform data augmentation (rotation, flipping, zooming, contrast adjustments).
- Split dataset into 80% training and 20% testing sets.

Step 2 — Weather Classification Using InceptionV3
- Load the pretrained InceptionV3 model with ImageNet weights.
- Freeze base convolutional layers and append a Global Average Pooling and Dense classifier.
- Train the network on six weather categories: align, cloudy, foggy, rainy, shine, and sunrise.
- Perform forward propagation to obtain predicted weather label and confidence score.

Step 3 — Pothole Detection Using YOLOv8
- Train YOLOv8 on annotated pothole datasets consisting of bounding boxes.
- Pass each image or video frame through the YOLOv8 detector.
- Extract bounding boxes, detection scores, and class probabilities.
- Apply Non-Maximum Suppression (NMS) to remove redundant detections.

Step 4 — Explainable AI (XAI) Using LIME/SHAP
- Segment the input image into superpixels.
- Generate perturbed image samples by masking selected regions.
- Evaluate the model's response to each perturbed instance.
- Produce a saliency heatmap indicating influential regions contributing to the model's decision.

Step 5 — Augmented Reality (Unity + Vuforia) Visualization
- Convert detected pothole coordinates into AR anchor points.
- Import 3D road-repair models from SketchFab into Unity.
- Register Vuforia Image Targets and configure AR Camera for scene tracking.
- Overlay 3D reconstruction models over pothole locations in real-time.
- Render interactive ARvisualization for field inspection and assessment.

Step 6 — Output Integration
- Display weather class, pothole detection boxes, and XAI interpretability map.
- Generate annotated frames and AR overlays for user interaction.
- Store system outputs for downstream analysis and smart-city monitoring applications.

A. Data Collection

A dataset of around 500 road images was prepared, mainly focusing on pothole areas. The images were taken in different conditions to include variation. All images were resized to the same dimension and normalized. To increase the dataset size and avoid overfitting, data augmentation techniques like rotating and flipping were applied.

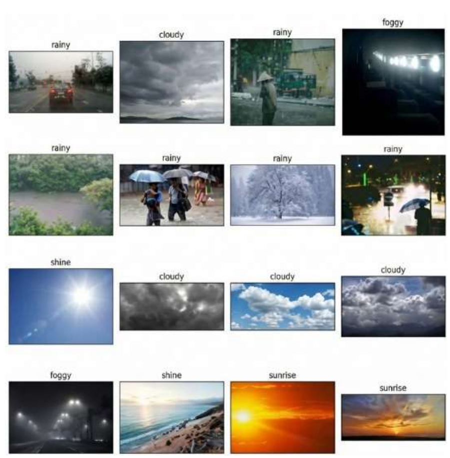

Fig. 3. Road image data set nearly (5000+) images

B. Weather Prediction Model

The combination of such an ML approach offers the following advantages. Pothole detection and the weather forecast using machine learning are two innovative approaches that can be integrated. The modified Inception V3 architecture was designed to create a Convolutional Neural Network to classify weather via road scenes. As a result, such a machine learning model can not only determine the weather with high accuracy but also demonstrate how it affects the roads and its potential impact on creating potholes.

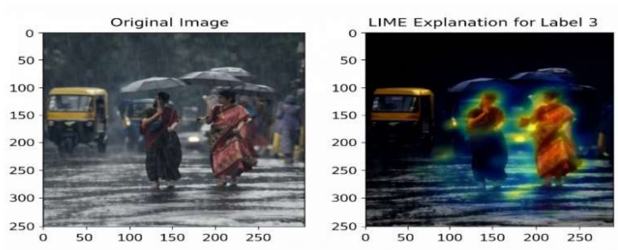

Fig. 4. LIME analysis for pothole detection model

C. Pothole Detection Model

Using a model of the road surface parameters makes it possible to distinguish between potholes and other road surface defects and gives more reliable results.

Fig. 5. Pothole detection

D. Augmented Reality Model

Once potholes are detected, these images are then integrated into an advanced AR platform, specifically Unity. The platform leverages Vuforia, an AR SDK, to take these images as markers to reconstruct and provide a visual of the potholes-faced road segments. As a result, it supports an open-source platform for viewing in augmented reality, which is interactive and aids in the analysis of the images, planning for repairs and rehabilitation of the road.

The image analysis deep learning model comprises the following main parts:

- ReLU Activation:

ReLU(x)=max (0,x)\text{ReLU}(x)=\max(0, x)ReLU(x)=max(0,x)

- ReLU adds non-linearity into the model in the network which helps ReLU to activate only positive values and zero out negative values, thus allowing the network to learn complex patterns in the training dataset.
- Max-pooling layers with a 2×22 window follow each convolutional layer to reduce the size of the feature maps, preserve the essential features, decrease the computational complexity, and keep the model from overfitting.
- OutputLayer: The SoftMax activation generates a distribution over all classes in which the class with the highest probability is sort after and selected as the predicted label. Given that this yields a high image recognition and object classification performance as it efficiently encodes the hierarchical image features. For the weather forecasting assignment, we leverage the Inception V3 network V3 consisting of Inception modules in parallel with multiple convolutional filters of varying sizes. In this case, the Inception V3 model can easily encode both fine and coarse road image features, allowing the model to accurately and effectively predict the complex weather pattern classification. The main difference was that the Inception V3 model had a spectrogram fixed input size of 224 by 224 to varying input sizes of the road image data.

- Think of this system as a smart filter that learns to recognize images. We built it using a common AI design for vision, called a Convolutional Neural Network (CNN), which processes standard 300x300 pixel colour photos.

The network works in stages:

- The first few layers act like a magnifying glass, looking for basic building blocks like edges and simple textures.
- As the image moves through five of these layered stages, the system pieces those simple elements together to recognize more complex shapes and patterns.
- A key ingredient (the "ReLU" function) helps the model handle complexity, allowing it to learn from the subtle details in the pictures.

and makes it effective in handling complex weather pattern classification.

IV. DEEP LEARNING MODELS & XAI

The code given makes (builds) the model using CNN (Convolutional Neural Network) in Tensorflow for the purpose of image classification. The model intakes photos of size
300*300 with 3 color channels (RGB) as input[13]. It has5 convolutional layers, and a max pooling layer after every convolutional layer. Filters are being used for scanning of images by convolutional layers, looking for features at various abstraction levels like edges and textures. Less complex patterns are detected in the earlier or upper layers, while deeper layers detect or identify more complex shapes. ReLU is used as the activation function. To improve the quality and condition of the weather prediction model, using an photo information generator, data augmentation is applied. This generator then facilitates transformations, including rotation, zoom, and horizontal flipping, to give a more widely spreaded training dataset, which in turn improves the capacity and performance of the model to identify patterns characteristic of unseen images. Plus, the pre-trained Inception V3 model is after words added with ImageNet weights, and the top layers for the classification task are set as frozen (include_top=False) to ensure they are not updated during training and validation :

- A International Average Pooling layer minimizes the number of independent dimensions of the taken(extracted) features.
- A entirely joint Dense layer with ReLU activation plus 256 neurons learns non-linear combinations of these features.
- Softmax activation is used by the final output layer for multiple class classification, where the number of weather categories matches the number of neurons.

A. Model Interpretation Using LIME

The LIME technique is used to interpret the weather prediction model’s decision-making process. The workflow includes the following steps:

- Load an image from the dataset and resize it for Inception V3’s input size.
- Convert the image to a NumPy array, and pre-process it for scaling pixel values.
- Initialize a LIME explainer for creating visual explanations of the model’s decisions.

V. EXPERIMENTATION: POTHOLE DETECTION IN URBAN TRANSPORTATION

The pothole detection system is linked into a Streamlit application with two primary functions: demand prediction analysis and road damage assessment. Both these aim to improve urban transportation solutions.

A. Road Damage Assessment

Fig. 6. Input Image before detecting pothole

A user can upload/provide o a video file to check or get the output regarding conditions of the road. Following is shown the preprocessing steps of the uploaded image/video:
First, the system standardizes all images by resizing them and converting them to black and white. Then, it analyzes the grayscale image to look for the distinct shapes and edges of a pothole. If it finds any, it flags the road as damaged and shows the user the image with the potential potholes clearly outlined.We then use additional image processing tricks to make the potholes easier to see, like sharpening their edges and cleaning up the image.2.

B. Transportation Demand Forecasting

Your transportation data from a CSV file like vehicle types, dates, and times is transformed into pred- ictions with the demand forecast module. First, the data is prepared see Figure 3a. We make a sin- grid timeline out of distinct date and time columns and convert categories like vehicle type into a format the model can comprehend. Second, a pre- diction model is trained. The system attempts to learn how your data is connected to max 21 capacity needs, using a linear regression model to forecast the required max capacity. Third, we validate.

Fig. 7. Output after detecting pothole

VI. Results and Discussions

Machine learning approaches were also integrated within weather forecasting. Pandel and Khandale developed convolutional neural networks based on the Inception V3 architecture with a few modifications and used a model to perform weather classification using road images. Their model was able to provide an understanding of how different forms of weather conditions were experienced on roads.Using the developed model, we may analyze weather forecasts and even find out based on road sections which areas are most susceptible to potholes and land subsidence. Thus, with the help of a smart model, we can accurately identify potholes that are just beginning to form and differentiate them from simple.

VII. Conclusion with Future Scope

The InceptionV3 model is validated in weather prediction of ten epochs. The training accuracy increased progressively and rose to a maximum of 96.88% value after the sixth epoch, although there were a few slight fluctuations thereafter. An intrinsic validating potential was also available in the validation accuracy, which increased monotonically and increased to a perfect score of 100% after the last epoch. A similar reduction in validation loss to 0.0524 occurred, yet later some lost the accuracy there seems as there is a sharp inclination on both loss and accuracy after a few epochs which see as a sign of overfitting. A. Some regularization or early stopping modifications could have helped avoid this inefficiency. Six hidden layers were used to obtain the best accuracy at 72%, which is very poor for a CNN model, in which we did better than the previous one.

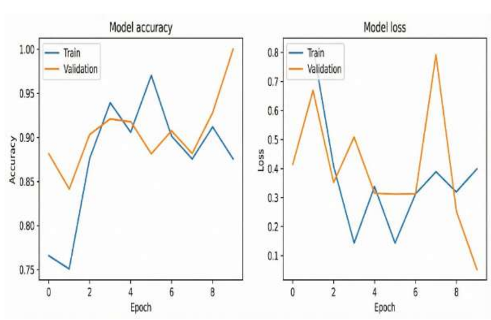

Fig. 8. Accuracy and loss trends over epochs

The project has a number of very good prospects for development. The incorporation of real time traffic will Expanded to smart city surveillance would conditions and automatic requests for road repairs depending on the existing. Higher AR interaction allows users to interact with Urban environments often face limitations that reduce flexibility in development. Integrating intelligent systems, such as self- driving cars, could help overcome some of these challenges by improving traffic efficiency, safety, and infrastructure management

TABLE I. COMPARISON OF MODEL PERFORMANCE

Study	Preprocessing Techniques	Algorithm Used	Implementation Details
A CNN-Based Approach for Road Marking Recognition and Surface Quality Evaluation(Jyothirmaietal.,2024)	- Grayscale conversion - Noise reduction using Gaussian filters - Histogram equalization	Convolutional NeuralNetwork(CN N)	- Uses convolutional layers for feature extraction - A damoptimizer witha learning rate of 0.001 - Binarycross- entropyloss function - Real-time detection with IoT integration
Road Surface MarkingRecognition and Road Surface Quality Evaluation Using CNN(Medvedev and Pavlov, 2020)	- Frame extraction rom video - Resizing and normalization - Grayscale conversion	Convolutional Neural Networ k (CNN) (withVGG16 transfer learning)	- Train video frame dataset - Multi-class classification using softmax activation - Identifies road markings and assesses road quality
Land Use Dynamic Monitoring Using Multi-Temporal SPOTDATA (Zhu et al., 2008)	- Atmospheric and geometric orrection - Radiometric normalization - Resamplingtou niform resolution	Change Detection Algorithm (NDVIandPC A)	- Utilizes multi-temporal satellite images - Analyzes land use changes over time - Highlights potentialusein long-term road monitoring
MethodologyforSelectingNeural Network Architecture for Recognizing Pavement Defects (et al., 2023)	- Resizing and normalization - Data augmentation (flipping, rotation, contrastadjus tment) - Annotation withboundingboxe s	Convolutional Neural Networ k (CNN) (ResNet, MobileNet, EfficientNet)	- MobileNetispreferredfor speed and edge devices - ResNet offers higher accuracyforcontrolledenviro nments - Balances real-time processingwithdetectionaccura cy
Weather Data Integrated Mask R- CNN forAutomatic Road Surface ConditionMonitoring(You,2019)	- Edgedetection (Canny edge detection) - Contrast adjustment - Normalization of weather data inputs	Mask R-CNN (withResNet-50 backbone)	- Combines image segmentationwith weather data integration - Uses Region Proposal Network(RPN)fordetectingdefects - Pixel-wisemaskprediction monitoring

TABLE II. YOLO MODEL COMPARISON (FOR POTHOLE DETECTION

Model	mAP	Processing Time	Model Size (MB)	FPS	Parameter Count (Millions)
YOLOv3	88.93	40 ms	236 MB	19	61.5
YOLOv4	85.39	50 ms	244 MB	25	64.3
YOLOv5	93.99	12.78ms	27 MB	72	7.2
Value	YOLOv3	Value	-	-	-
Value	YOLOv3	Value	-	-	-
Value	YOLOv3	Value	-	-	-
YOLOv8	91.11	8.8ms	128MB	110	43.0

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