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Dell inc.

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# **AI-based Transportation System (SALAMTAK)**

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# Abstract

In recent years, with the rapid development of the economy, road construction has entered a phase of coexistence between construction and maintenance. Even road maintenance has become a major aspect of road construction. The government invests a lot of money in road maintenance every year. Therefore, it is very important to detect road problems, including cracks and potholes, in order to reduce maintenance costs. This study aims to address the issues of poor real-time performance and low accuracy in traditional road problem detection. By leveraging the advantages of deep learning networks in target detection, a method based on YOLOv8 and YOLOv5 has been designed for road problem detection. The method utilizes annotated images from a training set consisting of approximately 15,000 images. Finally, the YOLOv8 model has demonstrated exceptional performance, achieving an impressive 74.8 mAP, surpassing the results obtained by YOLOv5, which achieved a still commendable 71.9 mAP. Additionally, the speed of road problem detection has been improved compared to traditional identification methods.

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# List of Abbreviations

AI:	Artificial Intelligence
ML:	Machine Learning
DL:	Deep Learning
ANN:	Artificial Neural Network
CNN:	Convolutional Neural Network
SVM:	Support Vector Machines
PCA:	Principal Component Analysis
MDPs:	Markov Decision Processes
DQN:	Deep Q-Networks
ReLU:	Rectified Linear Unit
tanh:	hyperbolic tangent
D:	Dimension
PCC:	Portland Cement Concrete
AC:	Asphalt Concrete
YOLO:	You Only Live Once
v:	version
UAV:	Unmanned Aerial Vehicle
ResNet:	Residual Convolutional Neural Network
fps:	frame per second
SCSE:	Spatial and Channel Squeeze and Excitation
mAP:	mean average precision

TP:	True Positive
FP:	False Positive
OpenCV:	Open Source Computer Vision
Colab:	Colaboratory
GPU:	Graphical Processing Unit
TPU:	Tensor Processing Unit
VS Code:	Visual Studio Code
TML:	Traditional Machine Learning
SSD:	Solid-State Drive
CPU:	Central Processing Unit
GPU:	Graphics Processing Unit
RAM:	Random Access Memory
GTX:	Giga Texel Shader eXtreme
RTX:	Ray Tracing Texel eXtreme
CUDA:	Compute Unified Device Architecture
AMD:	Advanced Micro Devices



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# **Chapter 1**

## **Introduction**

### **1.1 Problem Definition**

Road problems including cracks, potholes on the road, cause the vehicle to change its lane, which leads to loss of driving control and many accidents that lead to many people being injured or even losing their lives. These defects not only reduce the quality of the driving experience but also pose a safety hazard to drivers. However, detecting and repairing cracks and potholes can be a time-consuming and costly process, particularly for large road networks.

## **1.2 Motivation**

Road accidents continue to pose a significant threat to public safety worldwide. According to statistical reports, a significant percentage of accidents are attributed to the deteriorating condition of road infrastructure, particularly the presence of cracks and potholes. These road defects not only contribute to discomfort and inconvenience for motorists but also increase the risk of accidents, vehicle damage, and personal injuries. Therefore, addressing this issue is crucial to enhance road safety and save lives.

## **1.3 Objective**

The objective is to develop a robust and efficient system for the automated detection of cracks and potholes on roads. The system aims to accurately identify and categorize road defects in real-time using computer vision and machine learning techniques. By implementing this system, the goal is to provide authorities with a reliable tool to identify areas in need of repair and prioritize maintenance efforts effectively. The system will contribute to reducing the risk of accidents caused by road conditions by enabling timely interventions and facilitating targeted repair initiatives.

## **1.4 Methodology**

In the development of the crack and pothole detection system, we have chosen to adopt an Agile methodology as our software development model. Agile is a flexible and iterative approach that allows us to continuously adapt and respond to the evolving needs and challenges of the project. This section provides an overview of how we have incorporated Agile principles and practices into our software development process.

### **Iterative Development:**

Agile emphasizes iterative development, breaking down the development process into smaller increments called sprints. Each sprint typically lasts for a fixed duration, such as two weeks, during which a specific set of features or tasks is planned, developed, tested, and reviewed. This iterative approach enables us to gather feedback early and incorporate changes and improvements throughout the development lifecycle.

### **Continuous Integration and Testing:**

Agile methodologies emphasize continuous integration and testing practices. Throughout the development process, we employ automated testing techniques to ensure the stability and quality of the codebase. Continuous integration helps us identify and resolve issues promptly, reducing the risk of introducing bugs or regressions. Regular testing cycles allow for early bug detection and facilitate faster feedback loops.

## **Adaptability and Flexibility:**

Agile methodologies value adaptability and flexibility in response to changing requirements or project constraints. As we encounter new insights or potential modifications, we embrace a flexible mindset to accommodate adjustments in priorities, features, or implementation details. Agile enables us to adapt to emerging needs, seize opportunities, and deliver a more refined and effective crack and pothole detection solution.

By adopting the Agile methodology in our software development model, we aim to enhance collaboration, maintain a rapid development pace, and deliver a high-quality crack and pothole detection system that aligns closely with user requirements. The iterative nature of Agile ensures that we can respond promptly to challenges, incorporate feedback, and continuously improve our solution throughout the development lifecycle.

## 1.5 Time plan

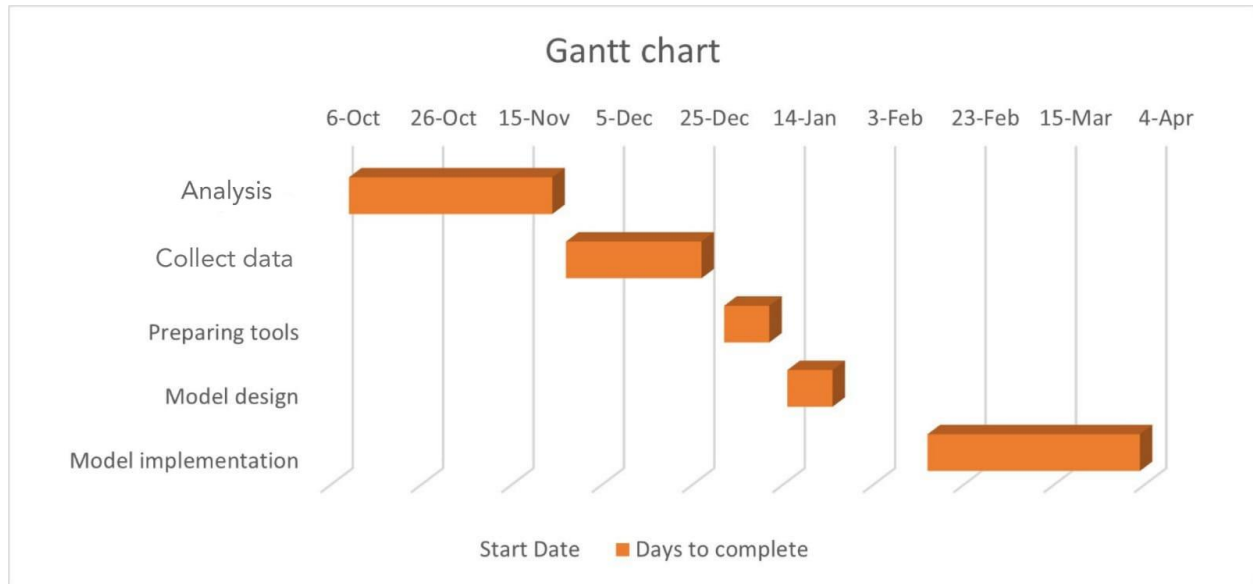


Figure 1.2: time plan

## **1.6 Thesis outline**

### **Chapter 2 (Literature Review)**

Provide a theoretical background on the concepts and principles related to crack and pothole detection in the context of computer vision and image processing.

Discuss relevant theories, algorithms, and techniques used in object detection and road defect analysis.

Review the existing literature and studies related to crack and pothole detection, highlighting different approaches, methodologies, and their limitations.

### **Chapter 3 (System Architecture and Methods)**

This chapter includes the following:

- System Architecture showing main components of the systems and the relations between these components.
- Description of methods and procedures used.

### **Chapter 4 (System Implementation and Results)**

We will discuss system architecture and steps done to detect road anomalies such as cracks and potholes on the roads. Explain dataset used. Explain algorithms and techniques used. Define software tools that we used. Show results of project. Compare results obtained in this project with the results of other researchers.



## **Chapter 5 (Run the Application)**

In this chapter we will talk about how the user will use the system.

## **Chapter 6 (Conclusion and Future Work)**

In this chapter we state the conclusion and results that we got from our work and the work we plan to do in the future.

## **Chapter 2**

### **Literature Review**

#### **2.1 Introduction**

Developing a robust crack and pothole detection system for roads is of paramount importance due to the risks they pose to safety and the economic implications involved [1]. By proactively identifying these hazards, accidents can be minimized, lives can be saved, and maintenance costs can be reduced. Implementing advanced technologies such as computer vision and sensors automates the detection process, streamlining infrastructure maintenance [2]. The aggregated data obtained can inform transportation planning, optimizing resource allocation and enhancing overall connectivity [2]. Investing in this project will revolutionize road maintenance, ensuring safer and more efficient transportation networks for all.

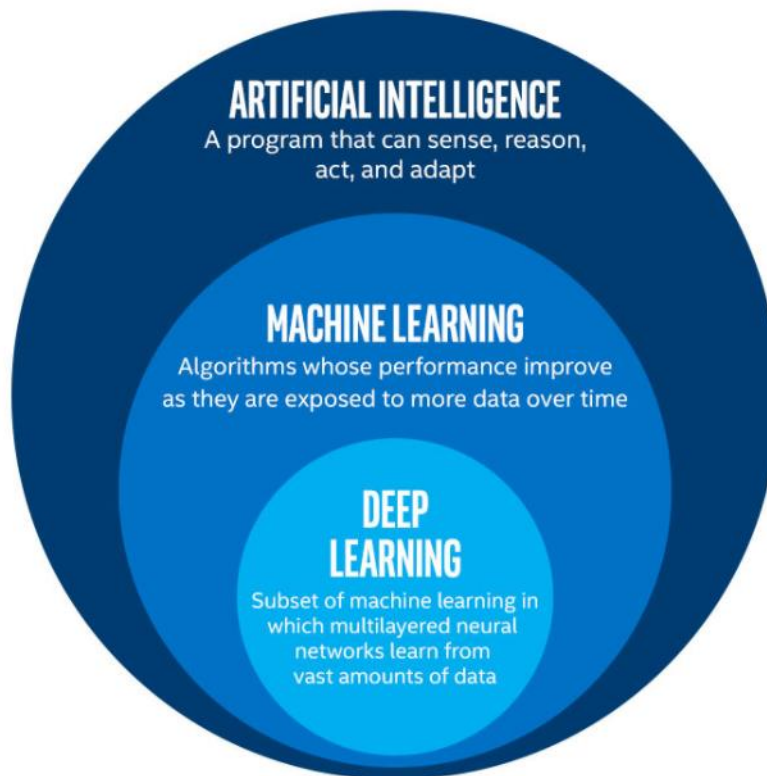
#### **2.2 Theoretical Background**

We will talk about the following:

1. Artificial Intelligence (AI)
2. Machine Learning (ML)
3. Deep Learning (DL)
4. Artificial Neural Network (ANN)
5. Convolutional Neural Network (CNN)

### 2.2.1 Artificial Intelligence

Artificial Intelligence (AI) is a field of computer science that focuses on developing intelligent systems capable of performing tasks that typically require human intelligence. It encompasses various subfields, such as machine learning, natural language processing (NLP), computer vision, and robotics.



**Figure 2.1 : AI**

Machine learning algorithms form the backbone of AI systems, enabling them to learn from large datasets and make predictions or decisions without explicit programming. Supervised learning uses labeled data to train models, while unsupervised learning discovers patterns and structures in unlabeled data.

Reinforcement learning employs an agent interacting with an environment to learn optimal actions through rewards and penalties.

NLP enables machines to understand and generate human language. Techniques like text classification, named entity recognition, and sentiment analysis are employed. Chatbots and virtual assistants utilize NLP to process user queries and provide relevant responses.

Computer vision deals with enabling machines to interpret and understand visual data. Techniques such as object detection, image recognition, and image segmentation allow machines to recognize objects, faces, and scenes. Convolutional neural networks (CNNs) are commonly used in computer vision tasks.

Overall, AI is a multidisciplinary field that combines mathematics, statistics, computer science, and domain expertise to create intelligent systems capable of understanding, reasoning, and learning, with vast potential for transformative impact.

### **2.2.2 Machine Learning**

Machine Learning (ML) is a subset of Artificial Intelligence (AI) that focuses on the development of algorithms and models that enable computers to learn and make predictions or decisions without being explicitly programmed. ML leverages statistical techniques and large datasets to train models, allowing them to generalize and perform tasks with accuracy.

## Types of Machine Learning



Figure 2.2 : types of ML

Supervised learning is a common ML approach where models are trained using labeled data, with input-output pairs, to learn patterns and make predictions. Classification tasks assign data points to predefined categories, while regression tasks estimate continuous values. Decision trees, support vector machines (SVM), and random forests are popular supervised learning algorithms.

Unsupervised learning aims to discover patterns and structures in unlabeled data without specific output labels. Clustering algorithms group similar data points together, while dimensionality reduction techniques reduce the complexity of the data by extracting relevant features. K-means clustering and principal component analysis (PCA) are commonly used in unsupervised learning.

Reinforcement learning involves an agent interacting with an environment, learning optimal actions through trial and error and receiving rewards or penalties. This learning paradigm is useful in training autonomous systems, such as self-driving cars or game-playing agents. Markov Decision Processes (MDPs) and deep

reinforcement learning methods, like Deep Q-Networks (DQN), have gained significant attention.

### 2.2.3 Deep Learning

Deep Learning is a subset of Machine Learning (ML) that focuses on training artificial neural networks with multiple layers to learn and extract hierarchical representations from complex data. It enables the development of models capable of processing vast amounts of data and extracting high-level features for accurate predictions and decision-making.

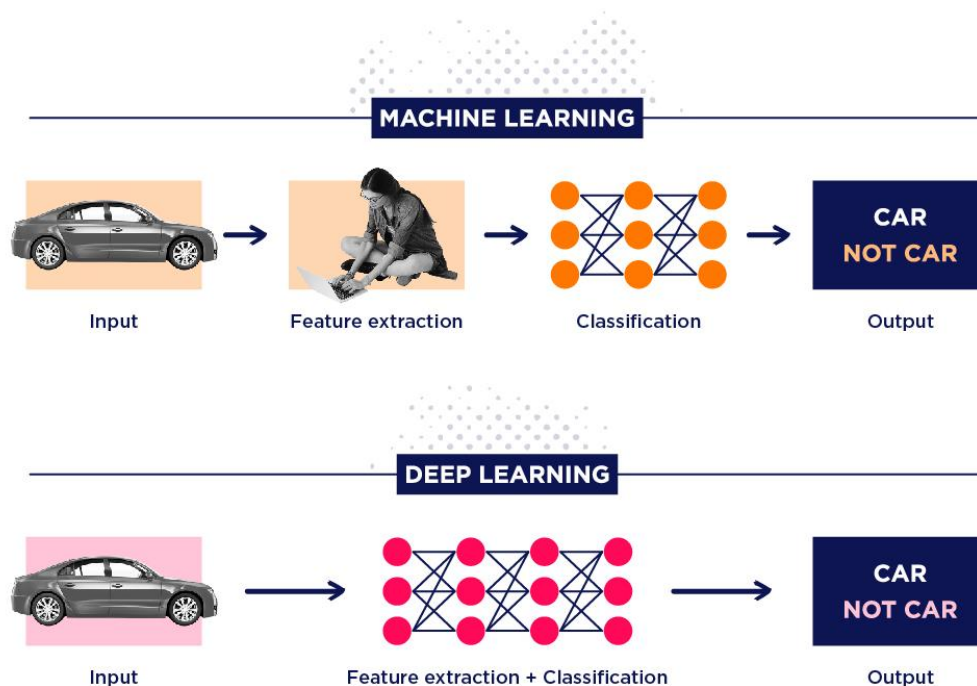


Figure 2.3 : feature extraction on DL & ML

Neural networks, inspired by the structure of the human brain, consist of interconnected nodes called neurons. Deep Learning architectures, such as

Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer models, have revolutionized various domains.

CNNs excel in computer vision tasks, leveraging hierarchical feature extraction through convolutional layers. They can detect patterns and objects within images, classify them into different categories, and perform tasks like image segmentation. CNNs have played a significant role in advancements such as object detection, facial recognition, and autonomous driving.

RNNs are designed to handle sequential data, making them ideal for natural language processing, speech recognition, and time series analysis. They have a feedback mechanism that allows them to capture dependencies and long-term context. Applications include language translation, sentiment analysis, and speech synthesis.

Training deep neural networks requires large labeled datasets and substantial computational resources. Graphics processing units (GPUs) and specialized hardware accelerators have accelerated the training process, enabling the training of deep learning models on massive datasets in reasonable timeframes.

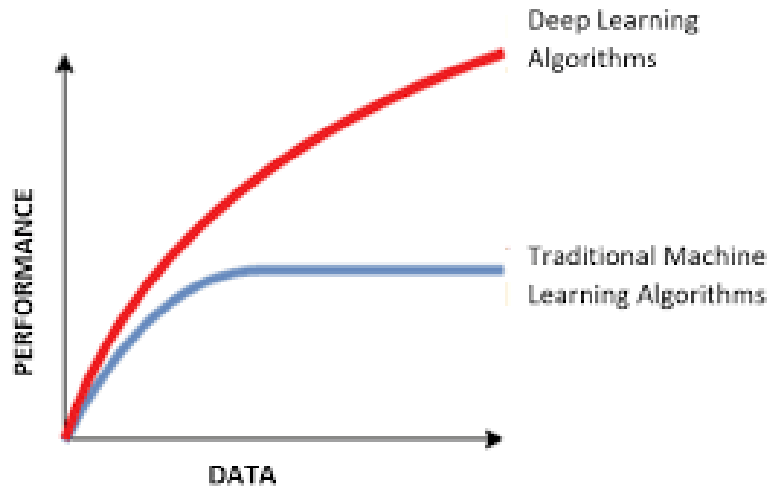


Figure 2.4 : DL vs TML

### 2.2.4 Artificial Neural Network

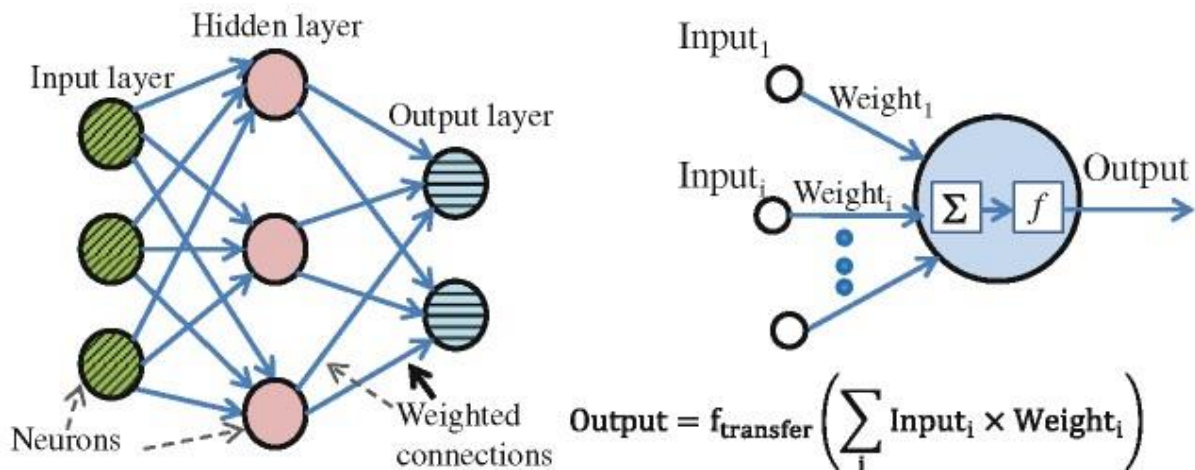
Artificial Neural Networks (ANNs) are a type of computational model inspired by the structure and functionality of the human brain. They are widely used in the field of artificial intelligence and machine learning to solve complex problems and make predictions based on data.

An ANN consists of interconnected artificial neurons, also known as nodes or units, organized into layers. The three main types of layers in an ANN are the input layer, hidden layer(s), and output layer. Information flows through the network from the input layer, which receives the initial data, through the hidden layers, where computations and transformations occur, and finally to the output layer, which provides the network's predictions or decisions.

Each connection between neurons in an ANN is associated with a weight, which determines the strength and impact of the signal transmitted between the connected



neurons. During the training phase of an ANN, the weights are adjusted based on a process called backpropagation. Backpropagation involves propagating the error or difference between the network's predicted output and the desired output backward through the network to update the weights and improve the network's performance.



**Figure 2.5 : ANN**

The activation function plays a crucial role in determining the output of a neuron based on the weighted sum of its inputs. Common activation functions include sigmoid, tanh, and rectified linear unit (ReLU), each with its own characteristics and areas of application.

ANNs can be classified into different architectures based on their connectivity patterns. Feedforward neural networks are the simplest type, where information flows in one direction from input to output without loops. Recurrent neural networks (RNNs) allow feedback connections, enabling them to process sequential or time-dependent data. Convolutional neural networks (CNNs) are designed for processing grid-like data, such as images, by exploiting the spatial structure through convolutions.

The success of ANNs relies heavily on data availability and quality. Large datasets are used to train ANNs, and their performance often improves with more data. However, overfitting, where the network becomes too specialized to the training data and performs poorly on new data, is a common challenge. Techniques such as regularization, dropout, and early stopping are employed to address this issue.

ANNs have demonstrated remarkable performance in various domains, including image and speech recognition, natural language processing, recommendation systems, and predictive analytics. They continue to advance through ongoing research and development, with new architectures, optimization algorithms, and training techniques being explored to enhance their capabilities and overcome limitations.

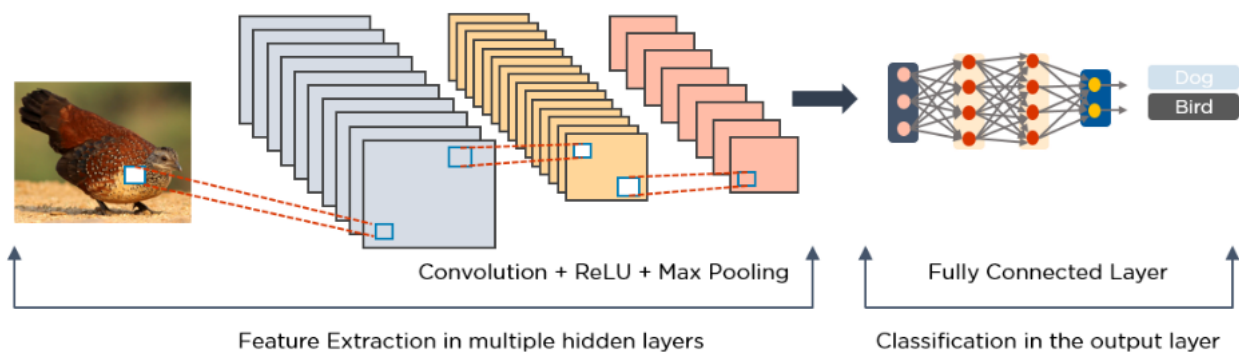
### **2.2.5 Convolutional Neural Network**

Convolutional Neural Networks (CNNs) are a specialized type of artificial neural network designed for processing grid-like data, such as images or sequential data with spatial relationships. They have revolutionized the field of computer vision and achieved state-of-the-art results in various tasks like image classification, object detection, and image segmentation.

The key feature of CNNs is their ability to automatically learn hierarchical representations of the input data through the use of convolutional layers. A convolutional layer applies a set of learnable filters, also known as kernels or feature detectors, to the input data. Each filter convolves across the input, performing a dot

product operation at each position. This operation captures local patterns or features in the input, effectively detecting edges, corners, and other visual attributes.

CNNs typically consist of multiple layers stacked together. In addition to convolutional layers, they include pooling layers and fully connected layers. Pooling layers reduce the spatial dimensions of the data, which helps in creating more abstract representations and making the network more robust to variations in the input. Common pooling operations include max pooling and average pooling.



**Figure 2.6 : CNN layers**

The fully connected layers are responsible for making predictions based on the learned features. They take the high-level representations from the previous layers and perform classification or regression tasks. These layers are like those found in traditional artificial neural networks.

## 2.3 The previous studies and works

Safaei et al. [3] develop an automatic crack assessment method to detect and classify cracks from 2-D and 3-D pavement images. A tile-based image processing method was proposed to apply a localized thresholding technique on each tile and detect the cracked ones (tiles containing cracks) based on crack pixels' spatial distribution. For longitudinal and transverse cracking, a curve is then fitted on the cracked tiles to connect them. Next, cracks are classified, and their lengths are measured based on the orientation axes and length of the crack curves. This method is not limited to the pavement texture type, and it is cost-efficient as it takes less than 20 s per image for a commodity computer to generate results. The method was tested on 130 images of Portland Cement Concrete (PCC) and Asphalt Concrete (AC) surfaces; test results were found to be promising (Precision = 0.89, Recall = 0.83, F1 score = 0.86, and Crack length measurement accuracy = 80%).

Mingxin Nie, Cheng Wang. [4] Aiming at the problems of poor real-time performance and low accuracy of traditional pavement crack detection, and using the advantages of deep learning network in target detection, a method based on YOLOv3 for pavement crack detection is designed. The collected pictures are manually marked, and the network model is obtained through YOLOv3 network training. Finally, the cracks are detected and verified by the obtained model. The accuracy of crack detection in this work reached 88%, and the crack detection speed was also improved compared with the traditional identification method.

Sung-Sik Park, Van-Than Tran, et al.[5] The goal of this study is to apply different YOLO models for pothole detection. Three state-of-the-art object detection frameworks (i.e., YOLOv4, YOLOv4-tiny, and YOLOv5s) are

experimented to measure their performance involved in real-time responsiveness and detection accuracy using the image set. The image set is identified by running the deep convolutional neural network (CNN) on several deep learning pothole detectors. After collecting a set of 665 images in  $720 \times 720$  pixels resolution that captures various types of potholes on different road surface conditions, the set is divided into training, testing, and validation subsets. A mean average precision at 50% Intersection-over-Union threshold (mAP<sub>0.5</sub>) is used to measure the performance of models. The study result shows that the mAP<sub>0.5</sub> of YOLOv4, YOLOv4-tiny, and YOLOv5s are 77.7%, 78.7%, and 74.8%, respectively. It confirms that the YOLOv4-tiny is the best fit model for pothole detection.

Qiuwen Qiu, Denvind Lau. [6] the goal of this study is to integrate of YOLO into an unmanned aerial vehicle (UAV) is proposed to achieve real-time crack detection in tiled sidewalks. Different network architectures of YOLOv2 tiny, Darknet19-based YOLOv2, ResNet50-based YOLOv2, YOLOv3, and YOLOv4 tiny are reframed and compared to get better accuracy and speed of detection. The results show that ResNet50-based YOLOv2 and YOLOv4 tiny offer excellent accuracy (94.54% and 91.74%, respectively), fast speed (71.71 fps and 108.93 fps, respectively), and remarkable ability in detecting small cracks. Besides, they demonstrate excellent adaptability to environmental conditions such as shadows, rain, and motion-induced blurriness. From the assessment, the appropriate altitude and scanning area for the YOLO-UAV-based platform are suggested to achieve remote, reliable, and rapid crack detection.

Jingwei Liu, et al. [7] the goal of this study is using A two-step pavement crack detection and segmentation method based on convolutional neural network. An automated pavement crack detection algorithm was developed using the modified YOLO 3rd version in the first step. The proposed crack segmentation method in the second step was based on the modified U-Net, whose encoder was replaced with a pre-trained ResNet-34 and the up-sample part was added with spatial and channel squeeze and excitation (SCSE) modules. Proposed method combines pavement crack detection and segmentation together, so that the detected cracks from the first step are segmented in the second step to improve the accuracy. A dataset of pavement crack images in different circumstances were also built for the study. The F1 score of proposed crack detection and segmentation methods are 90.58% and 95.75%, respectively, which are higher than other state-of-the-art methods. Compared with existing one-step pavement crack detection or segmentation methods, proposed two-step method showed advantages of accuracy.

Muhammad Haroon Asad et al. [8] this work is intended to explore the potential of deep learning models and deploy three superlative deep learning models on edge devices for pothole detection. The Artificial Intelligence Toolkit (OAK-D) was exploited on a single board computer (Raspberry Pi) as an edge platform for hole detection. Detailed real-time performance comparison of state-of-the-art deep learning models and object detection frameworks (YOLOv1, YOLOv2, YOLOv3, YOLOv4, Tiny YOLOv4, YOLOv5, and SSD-mobilenetv2) for pothole detection is presented. The experimentation is performed on an image dataset with pothole in diverse road conditions and illumination variations as well as on real-time video captured through a moving vehicle. The Tiny YOLOv4, YOLOv4, and YOLOv5 evince the highest mean average precision (mAP) of

80.04%, 85.48%, and 95%, respectively, on the image set, thus proving the strength of the proposed approach for pothole detection and deployed on OAK-D for real time detection. The study corroborated Tiny-YOLOv4 as the befitted model for real time pothole detection with 90% detection accuracy and 31.76 FPS.

Bhavan Kumar S B et al.[9] The goal of this study is to apply YOLO V5 and evaluate the performance of YOLO V5 on a dataset of images, including potholes in varying road conditions and illumination fluctuations, as well as on real-time video acquired from a moving car And it had a detection accuracy of about 91%.

Bhanu Prakash K Y, Sankhya N Nayak . [10]The goal of this study is to apply YOLO v2,this system is works faster when compared to conventional detection system. The system took an average of 23 seconds to process an image irrespective of its size, quality or color. This works fine with negative testing too. During validation observed that the system is working pretty well with 89.41% of accuracy, Precision of 95.55%, 91.42% of Recall and F1-score of 93.43%.

Duo Ma, Hongyuan Fang, et al. [11] The goal of this study is to crack detection method based on a convolutional neural network (CNN) with multiple feature layers. The model extracts multi-scale features to increase the accuracy of pavement crack recognition. After hyper parameters tuning, the model accuracy reached 98.217%, and the detection rate reached 96.6 frame per second (FPS). These results showed that the model could be feasibly used for real-time crack detection. Using multiple aspect ratio anchor boxes and multi-scale feature maps, the accuracy can be improved by 1.809% and 5.016%, respectively. Compared with the traditional detection algorithm, our model was optimal in terms of F1

score and Precision-recall curve, and it was less affected by shadows and road markings and detected the crack boundaries more accurately. An on-site crack detection experiment was carried out to quantify the effectiveness of the model in crack detection.

Vishal Mandal, Lan Uong, Yaw Adu-Gyamfi. [12] The goal of this study is to apply YOLO v2 deep learning framework. The system is trained using 7,240 images acquired from mobile cameras and tested on 1,813 road images. The detection and classification accuracy of the proposed distress analyzer is measured using the average F1 score obtained from the precision and recall values.

Mohd Oma et al. [13] The goal of this study is to apply YOLOv4 algorithm and a dataset of about 200 images is trained for detection of potholes and the average IoU of 38.38% is achieved , Precision is 0.58, Recall is 0.37, TP is 58, FP is 42.

P. S. Ezekiel, O. E. Taylor et al. [14] The aim of this study is to apply transfer learning and annotated dataset using yolov3. Then set the batch size to be equal to 4, with tensorflow Gpu of version == 1.13.1, number of trials = 200, and train\_from\_pre\_trained\_model = pretrained-yolov3 (the weight file we downloaded). After training, the application is evaluated and savedTrainer model. Training accuracy is about 97%. using a real implementation Time hole detection on a live video stream using the opencv library, where we are detection of multiple pit images.



## **Chapter 3**

### **System Architecture and Methods**

#### **3.1 System Architecture**

##### **3.1.1 Introduction about YOLO:**

YOLO is a popular object detection algorithm introduced in 2016 by Joseph Redmon, Ali Farhadi, and others at the University of Washington. It's a real-time object detection system that can detect objects in images and videos with high accuracy and speed.

The YOLO algorithm works by dividing the input image into a grid and predicting bounding boxes and class probabilities for each grid cell. The bounding boxes are predicted using regression, and the class probabilities are calculated using a softmax function. The final output is a set of bounding boxes, each with a corresponding class probability.

One of the major advantages of YOLO is its speed. Unlike other object detection algorithms that use a sliding window approach, YOLO processes the entire image in a single forward pass of a neural network. This makes it possible to detect objects in real-time, even on low-powered devices such as smartphones and embedded systems.

YOLO has been used in a variety of applications, including autonomous vehicles, surveillance systems, and robotics. It's also been used in research and development in computer vision and machine learning.

### 3.1.2 Advantages of YOLO:

1. **Real-Time Performance:** YOLO's key advantage is its ability to perform object detection in real-time. By processing images and making predictions in a single pass, YOLO achieves impressive speed, enabling applications that require immediate and on-the-fly detection, such as autonomous vehicles, video surveillance systems, and real-time robotics.
2. **High Accuracy:** Despite its real-time performance, YOLO maintains remarkable accuracy in object detection. Through the use of deep neural networks and sophisticated network architectures, YOLO achieves competitive results, effectively detecting and localizing objects with high precision.
3. **Multiple Object Detection:** YOLO is capable of detecting multiple objects within a single image simultaneously. This feature is crucial in scenarios where there are multiple objects of interest present, allowing for a comprehensive understanding of complex scenes. It provides valuable information for tasks like tracking, counting, and scene analysis.
4. **Availability of Pretrained Models:** YOLO has gained significant popularity in the computer vision community, resulting in the availability of pretrained models. These pretrained models serve as a starting point for developers and researchers, accelerating the implementation of object detection systems and reducing the need for extensive training from scratch.

5. Continued Development: YOLO has seen multiple iterations and improvements over time, such as YOLOv2, YOLOv3, and YOLOv4. These advancements have introduced new features, improved performance, and enhanced accuracy. The ongoing development of YOLO ensures that it remains at the forefront of object detection research and technology.

### **3.1.3 YOLO Algorithm:**

The algorithm works based on the following four approaches [29]:

- Residual blocks
- Bounding box regression
- Intersection Over Unions or IOU for short
- Non-Maximum Suppression

### Residual blocks:

This first step starts by dividing the original image (A) into  $N \times N$  grid cells of equal shape, where  $N$  in our case is 4 shown on the image on the right. Each cell in the grid is responsible for localizing and predicting the class of the object that it covers, along with the probability/confidence value.

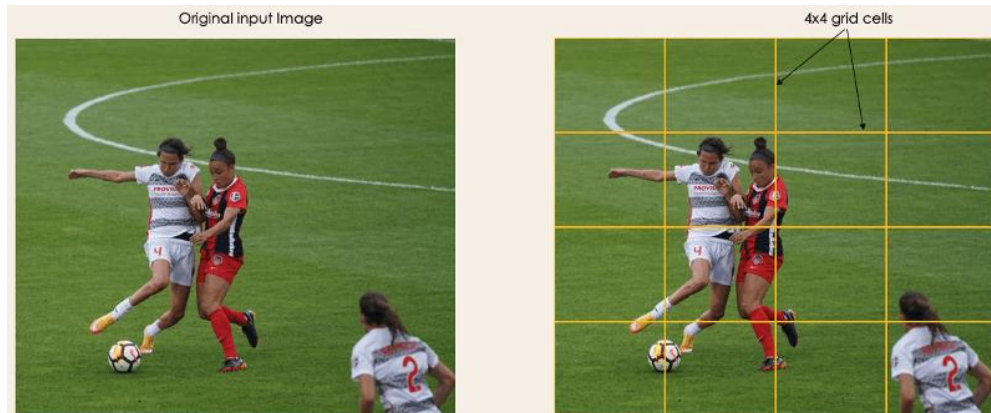


Figure 3.1 : Residual blocks

### Bounding box regression:

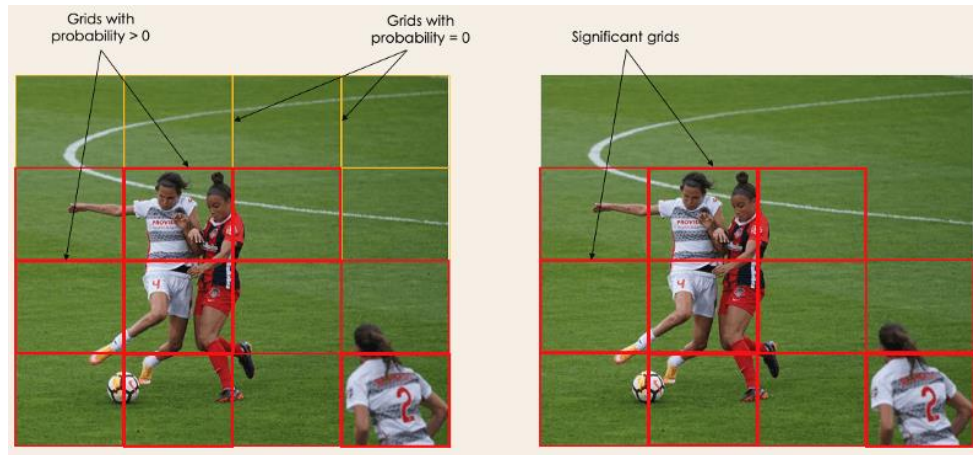
The next step is to determine the bounding boxes which correspond to rectangles highlighting all the objects in the image. We can have as many bounding boxes as there are objects within a given image.

YOLO determines the attributes of these bounding boxes using a single regression module in the following format, where  $Y$  is the final vector representation for each bounding box.

$$Y = [pc, bx, by, bh, bw, c1, c2]$$

This is especially important during the training phase of the model.

- pc corresponds to the probability score of the grid containing an object. For instance, all the grids in red will have a probability score higher than zero. The image on the right is the simplified version since the probability of each yellow cell is zero (insignificant).



**Figure 3.2 : Bounding box**

- bx, by are the x and y coordinates of the center of the bounding box with respect to the enveloping grid cell.
- bh, bw correspond to the height and the width of the bounding box with respect to the enveloping grid cell.
- c1 and c2 correspond to the two classes Player and Ball. We can have as many classes as your use case requires.

To understand, let's pay closer attention to the player on the bottom right.

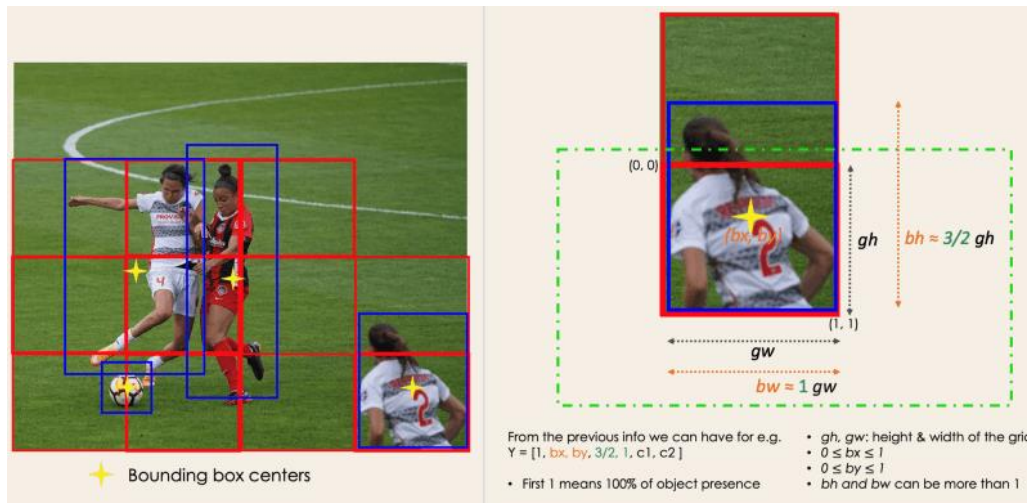


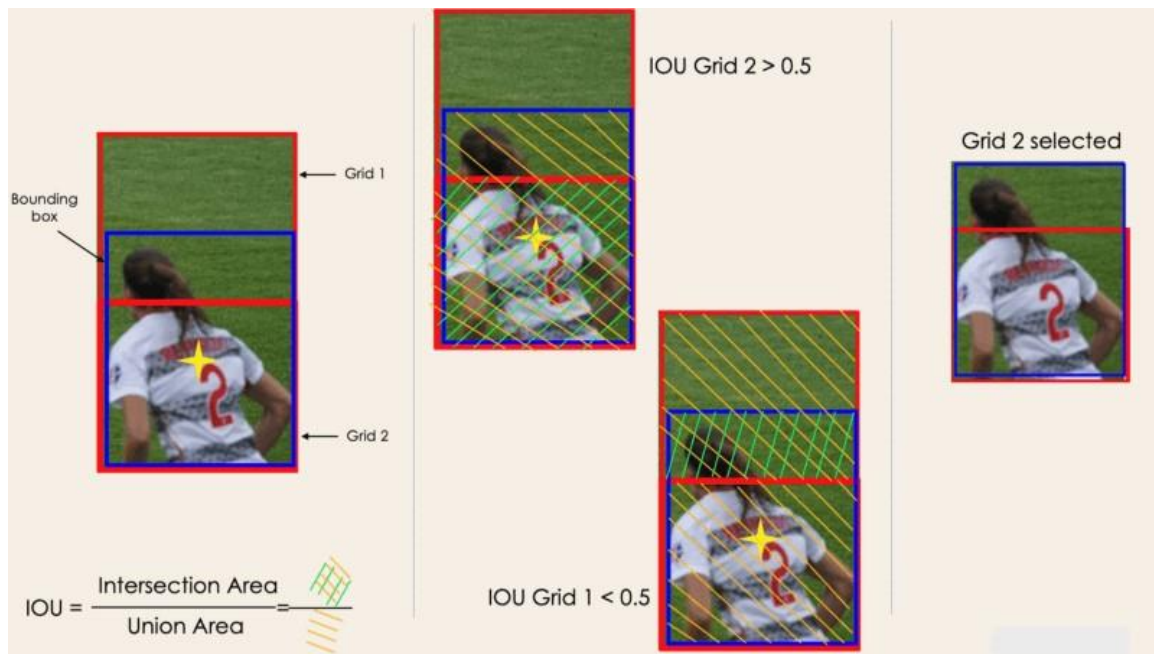
Figure 3.3 : attention to the player

### Intersection Over Unions or IOU:

Most of the time, a single object in an image can have multiple grid box candidates for prediction, even though not all of them are relevant. The goal of the IOU (a value between 0 and 1) is to discard such grid boxes to only keep those that are relevant. Here is the logic behind it:

- The user defines its IOU selection threshold, which can be, for instance, 0.5.
- Then YOLO computes the IOU of each grid cell which is the Intersection area divided by the Union Area.
- Finally, it ignores the prediction of the grid cells having an  $IOU \leq \text{threshold}$  and considers those with an  $IOU > \text{threshold}$ .

Below is an illustration of applying the grid selection process to the bottom left object. We can observe that the object originally had two grid candidates, then only “Grid 2” was selected at the end.



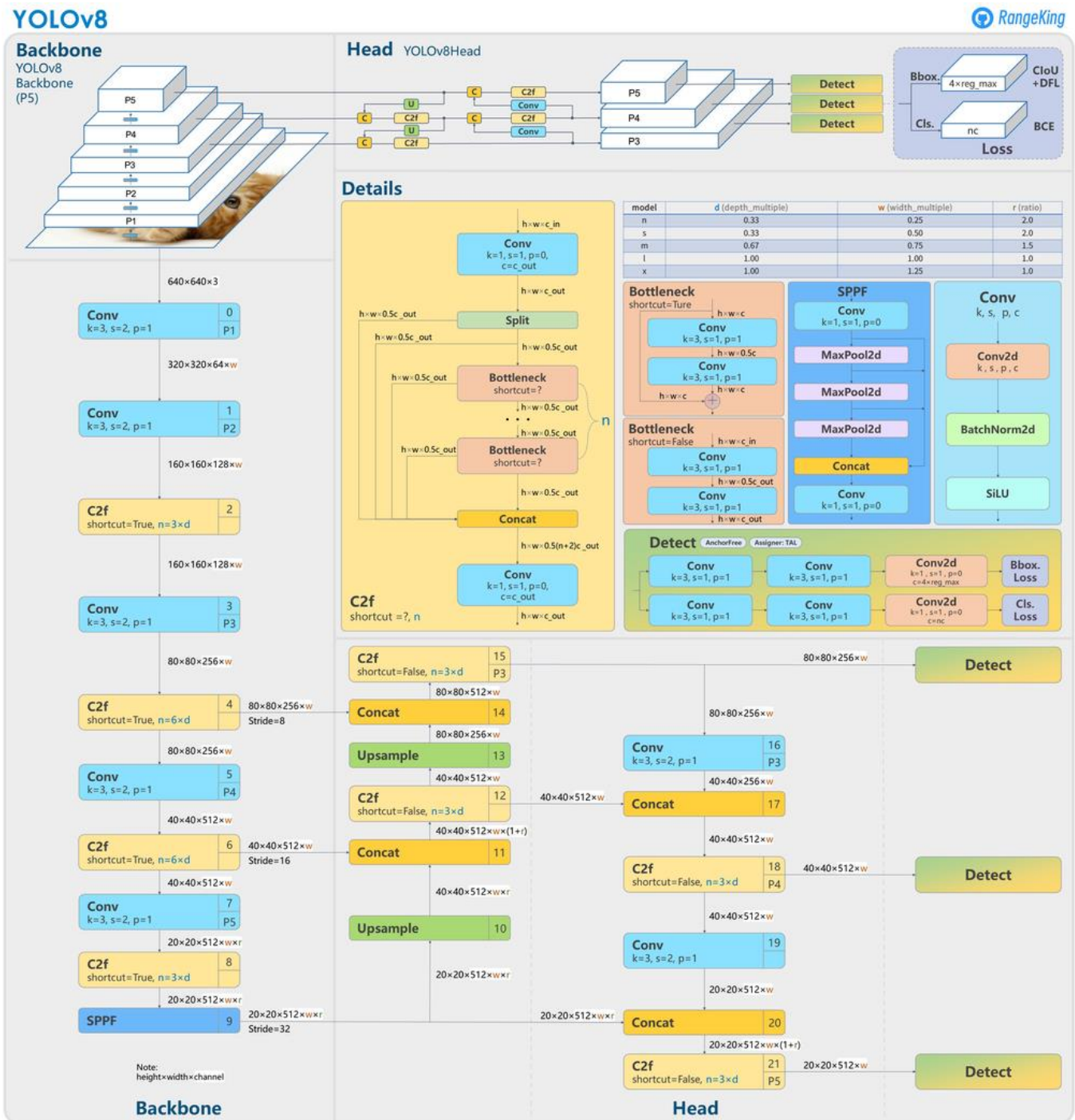
**Figure 3.4 : IOU**

### **Non-Max Suppression or NMS:**

Setting a threshold for the IOU is not always enough because an object can have multiple boxes with IOU beyond the threshold, and leaving all those boxes might include noise. Here is where we can use NMS to keep only the boxes with the highest probability score of detection.



### 3.1.4 YOLO V8 Architecture:





**The YOLO network consists of three main pieces:**

- **Backbone:**

The backbone typically consists of convolutional layers, pooling layers, and sometimes other architectural components like residual blocks or skip connections. It is designed to learn and encode meaningful features from the raw pixel values of the input image. By processing the image through multiple layers, the backbone extracts features at different scales and levels of abstraction.

The extracted features from the backbone are then passed on to subsequent layers in the YOLO network for further processing. These features contain rich information about the objects present in the image, including their shapes, textures, and contextual cues. The subsequent layers in YOLO utilize these features to predict bounding boxes, class probabilities, and other object detection attributes.

- **Head:**

The head module typically consists of fully connected layers, convolutional layers, and activation functions to process the features and produce the final predictions. Its design and architecture are crucial in determining the accuracy and quality of the object detection results.

The specific characteristics of the head module depend on the specific YOLO variant or other object detection architecture being used. However, there are some common components and techniques often employed in the head module, including:

**Convolutional Layers:** The head module often includes additional convolutional layers to further refine the feature representations. These layers can have different kernel sizes, strides, and padding, allowing for more detailed feature extraction.

**Spatial Pooling:** Spatial pooling operations, such as global average pooling or max pooling, are sometimes used in the head module to summarize the spatial information within the feature maps. These pooling operations reduce the spatial dimensions of the features while retaining important information.

**Fully Connected Layers:** Fully connected layers are commonly used in the head module to map the features to the desired output dimensions. These layers perform computations to generate the final predictions, including bounding box coordinates, class probabilities, and potentially other object detection attributes like object masks or key points.

**Activation Functions:** Activation functions, such as the Rectified Linear Unit (ReLU), are applied to introduce non-linearity and add expressive power to the head module. These functions help in capturing complex relationships and patterns within the features.

**Output Layers:** The head module ends with output layers that produce the final predictions. These layers usually have specific dimensions corresponding to the number of classes to be detected and the desired bounding box attributes (e.g., coordinates, confidence scores).

### 3.1.5 YOLO v8 vs YOLO v5 (in general) [30]:

#### Similarities:

**Backbone:** Both YOLOv5 and YOLOv8 use the CSPDarknet53 backbone architecture.

**Anchor Boxes:** Both algorithms use anchor boxes to improve object detection accuracy.

**Non-Maximum Suppression (NMS):** Both algorithms use NMS to suppress multiple detections of the same object.

**Post-processing:** Both algorithms use post-processing techniques to improve the accuracy of object detection.

**Optimizer:** Both YOLOv5 and YOLOv8 use the Adam optimizer for training the model.

**Activation Function:** Both algorithms use the Mish activation function in their architecture.

**Accuracy Comparison:** YOLOv5 is known for its accuracy in object detection. It has achieved state-of-the-art performance in terms of accuracy, with an average precision of 50.5% on the COCO dataset. YOLOv5 has also performed exceptionally well in detecting small objects, which was a significant challenge in previous versions

of YOLO. YOLOv5 has also demonstrated superior performance in real-world applications, such as detecting pedestrians in a video stream.

YOLOv8 has outperformed YOLOv5 in terms of accuracy. The YOLOv8s model has achieved an average precision of 51.4% on the COCO dataset, while the YOLOv8m model has achieved an average precision of 54.2% on the same dataset. YOLOv8 has also shown superior performance in detecting small objects and has addressed some of the limitations of YOLOv5.

### 3.1.6 YOLO v8 **vs** YOLO v5 (in our domain):

We have conducted a comparison between YOLOv8 and YOLOv5 on our dataset, specifically evaluating their mean Average Precision (mAP) results. By assessing the differences in mAP scores, we can gain insights into the varying performance of the two models when applied to our dataset. Higher mAP values indicate superior object detection accuracy and precision.

Model Version	YOLO v8	YOLO v5
mAP	74.8%	71.9%

**Table 3.1: comparison between YOLOv8 and YOLOv5 mAP**

The outputs obtained from YOLOv8 and YOLOv5 exhibit noticeable differences:





YOLO v8	YOLO v5
	
	

Table 3.1: comparison between YOLOv8 and YOLOv5 output

## **3.2 Description of methods and procedures used.**

The proposed methodology consists of several key steps to detect cracks and potholes on roads using YOLO v8 algorithm. The process involves:

### **1. Data Preprocessing:**

- Convert the road images to annotated images by manually labeling the cracks and potholes with bounding boxes.
- Resize the annotated images to a standardized resolution to ensure consistency.
- Apply data augmentation techniques, such as flipping the images, adding noise to simulate different conditions, and rotating the bounding boxes to introduce variations in orientation.

### **2. Training Data Preparation:**

- Split the preprocessed dataset into training, validation, and testing sets.
- Assign appropriate labels to the annotated images to indicate the presence and location of cracks and potholes.

### **3. Model Training:**

- Train the YOLO v8 model using the annotated images from the training set, consisting of approximately 15,000 images.
- Configure the model with appropriate hyperparameters and loss functions.
- Perform iterations of training to optimize the model's performance.

### **4. Model Evaluation:**

- Evaluate the trained model using the annotated images from the validation set, which contains 332 images.

- Measure the accuracy, precision, recall, and other relevant metrics to assess the model's performance.
- Test the trained model on the testing set, which contains 178 images, to further evaluate its performance.

## **5. Model Deployment:**

- Deploy the model on a desktop application.

## Chapter 4

### System Implementation and Results

#### 4.1 Dataset

##### 4.1.1 Details

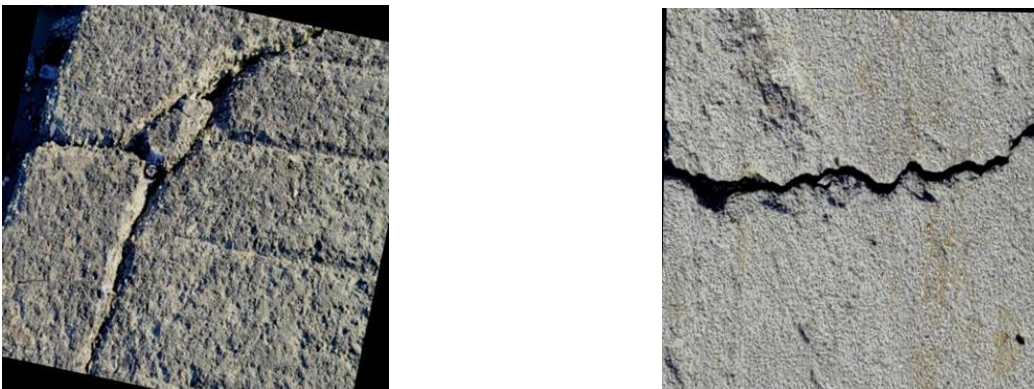
We utilized two distinct datasets for our project: one focusing on cracks, while the other centered around potholes. Presented here is a concise summary of these datasets.

Type	Number of images
Cracks	4029
Potholes	1593
Total	5622
Total with augmentation	15846

**Table 3.1: Dataset Details**

##### 4.1.2 Random Samples

Presented here is a sample from the comprehensive Cracks dataset, encompassing various types of cracks observed under different conditions.



**Figure 4.1 : Random Samples for crack**



Moreover, we have compiled an additional dataset known as the Potholes dataset, which consists of a sample showcasing various instances of potholes.



**Figure 4.2 : Random Samples for pothole**

## **4.2 Description of programs used**

- **Google Colaboratory**

Google Colab is a cloud-based platform provided by Google for running and collaborating on Python code. It offers a Jupyter notebook environment, allowing users to write and execute code in a browser. With Colab, there's no need to set up local development environments or worry about hardware limitations since it leverages Google's powerful infrastructure. It provides access to popular libraries and frameworks, along with GPU and TPU support for accelerated computations. Colab also enables seamless sharing and collaboration by allowing multiple users to work on the same notebook simultaneously.

- **Kaggle**

Kaggle is an online platform that hosts data science and machine learning competitions. It provides a community-driven environment where data scientists and machine learning enthusiasts can collaborate, learn, and showcase their skills. Kaggle offers a vast repository of public datasets that can be used for analysis and modeling. Participants can join competitions, work on real-world data challenges, and submit their solutions to compete for prizes and rankings. The platform also serves as a hub for sharing and discovering data science projects, tutorials, and code notebooks. Kaggle offers a range of tools and resources, including Jupyter notebooks, cloud-based computational resources, and access to popular machine learning libraries. Overall, Kaggle provides a platform for data scientists to gain experience, learn from others, and engage in friendly competition to solve complex data problems.

- **Roboflow**

Roboflow is a comprehensive platform designed to streamline and simplify the process of training computer vision models. Here are some of its notable advantages:

1. **Data Labeling and Augmentation:** Roboflow provides powerful tools for annotating and labeling images, enabling users to efficiently annotate datasets for training computer vision models. Additionally, it offers various data augmentation techniques to enhance the diversity and quality of the training data, which leads to improved model performance.
2. **Dataset Management:** With Roboflow, managing large-scale datasets becomes more organized and convenient. It offers features for dataset versioning, collaboration, and sharing, making it easier for teams to work together on building and iterating models.

3. Integration with Popular Frameworks: Roboflow seamlessly integrates with popular deep learning frameworks such as TensorFlow, PyTorch, and Keras. It provides export capabilities in the required formats, simplifying the integration of trained models into existing workflows and deployment pipelines.

- **VS Code**

VS Code is a lightweight and highly customizable source code editor developed by Microsoft. It provides a user-friendly interface with features like syntax highlighting, code completion, and customizable themes. It supports a wide range of programming languages and frameworks, making it suitable for various development tasks. VS Code offers integrated Git integration for version control and collaboration. It has a vast ecosystem of extensions that enhance functionality and cater to specific development needs. The editor includes a powerful integrated terminal and debugging capabilities for efficient code execution and troubleshooting. With its cross-platform compatibility and popularity among developers, Visual Studio Code is a versatile and widely used code editor.

- **Pytorch**

PyTorch is an open-source machine learning library that is primarily used for developing deep learning models. It was developed by Facebook's AI Research team and is known for its flexibility, ease of use, and dynamic computational graph.

### 4.3 Stepup Configuration (hardware)

The minimum hardware specifications for running YOLOv8 on a desktop application would typically include:

**CPU:** An Intel Core i5 or equivalent processor. However, a more powerful CPU, such as an Intel Core i7 or AMD Ryzen 7, is recommended for better performance.

**GPU:** A dedicated GPU with CUDA support is highly recommended for accelerated processing. NVIDIA GPUs, such as the GeForce GTX 10 series or higher, are commonly used. YOLOv8 benefits greatly from GPU acceleration, so a powerful GPU, such as an NVIDIA RTX 20 series or higher, would provide the best performance.

**RAM:** A minimum of 8 GB RAM is usually sufficient, but 16 GB or more is recommended for better multitasking and smoother performance, especially when dealing with larger models and datasets.

**Storage:** A solid-state drive (SSD) is recommended to ensure faster data access, which can significantly speed up the loading and inference times of YOLOv8 models.

**Operating System:** YOLOv8 is compatible with various operating systems, including Windows, Linux, and macOS. Ensure that you have a supported operating system and the necessary dependencies installed for GPU acceleration.

## 4.4 Experimental and Results

Our YOLO v8 model has demonstrated exceptional performance, achieving a remarkable 74.8 mAP, surpassing the results obtained by YOLO v5, which achieved a still commendable 71.9 mAP. These results were observed specifically in the detection of images containing a single crack or pothole. This signifies the superior accuracy and precision of our YOLO v8 model in identifying and localizing these specific anomalies.

Input



Figure 4.3 : Experimental input 1

Output



Figure 4.4 : output result 1



Figure 4.5 : Experimental input 2



Figure 4.6 : output result 2



Here are additional samples showcasing the detection capabilities of our model on images containing multiple cracks and potholes. These examples highlight the robustness and effectiveness of our YOLO v8 model in accurately identifying and localizing multiple instances of these anomalies within a single image.

Input



Figure 4.7 : Experimental input 3

Output

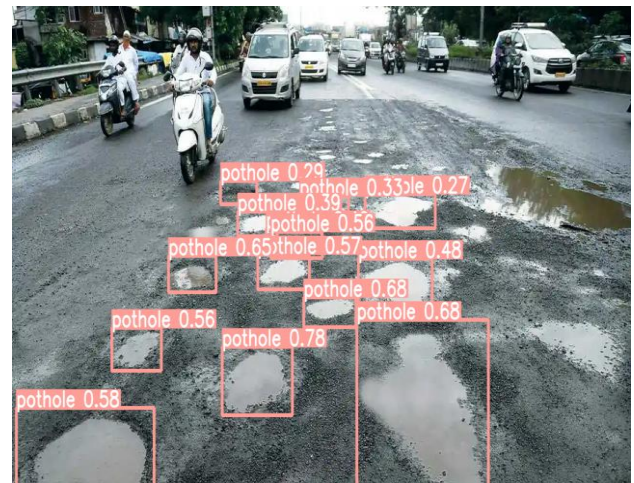


Figure 4.8 : output result 3



Figure 4.9 : Experimental input 4



Figure 4.10 : output result 4

Presented here is a sample image demonstrating the presence of both cracks and potholes within the same scene. Our YOLO v8 model effectively detects and distinguishes between these two types of anomalies, showcasing its ability to identify and localize multiple instances of cracks and potholes within a single image. This capability enhances the model's utility in comprehensive infrastructure assessment and maintenance applications.

Input



Figure 4.11 : Experimental input 5

Output

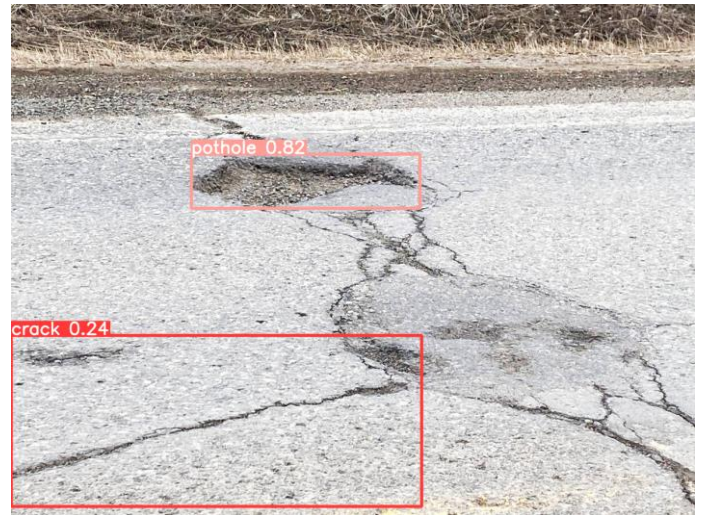


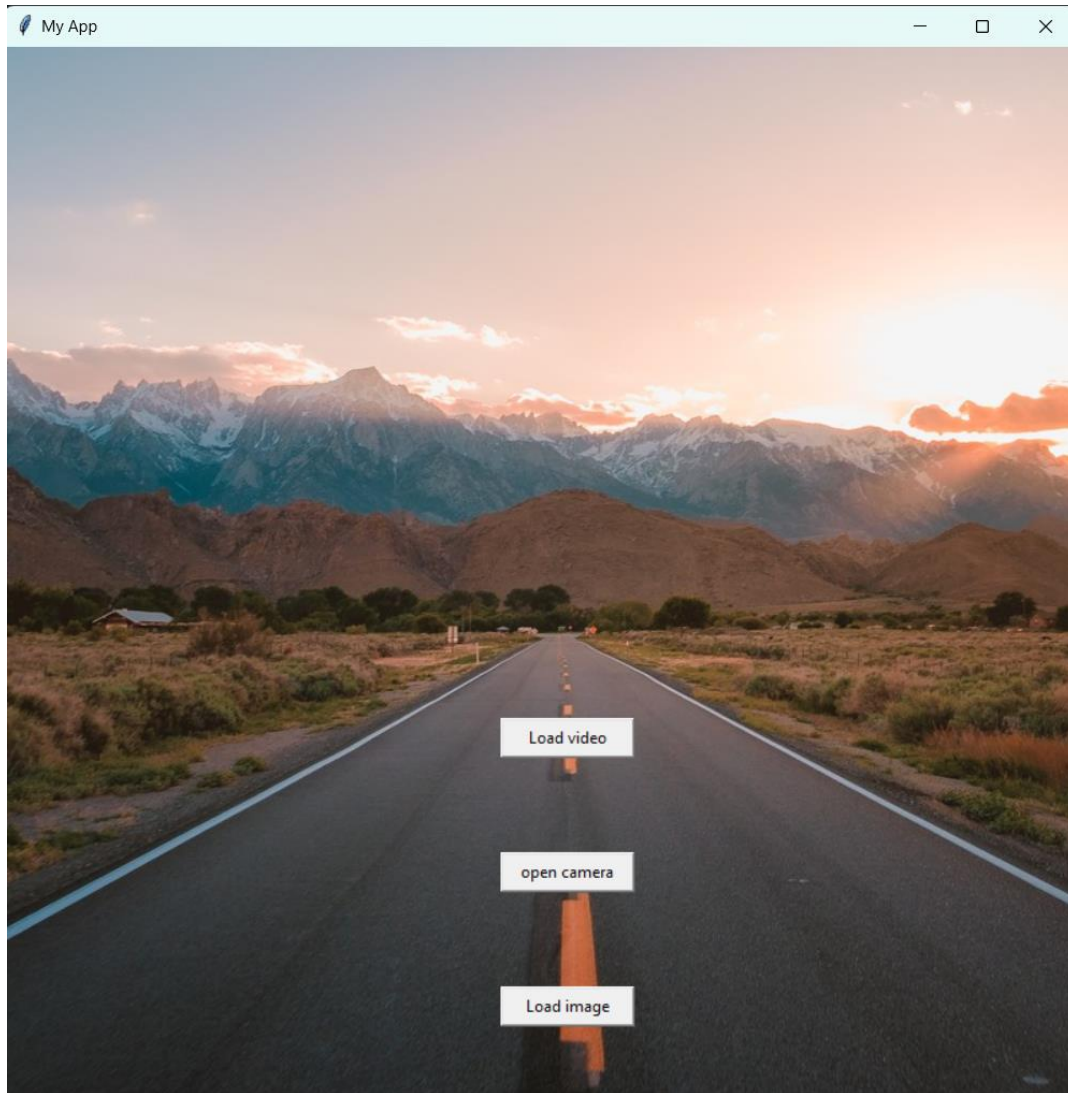
Figure 4.12 : output result 5



## Chapter 5

### Run the Application

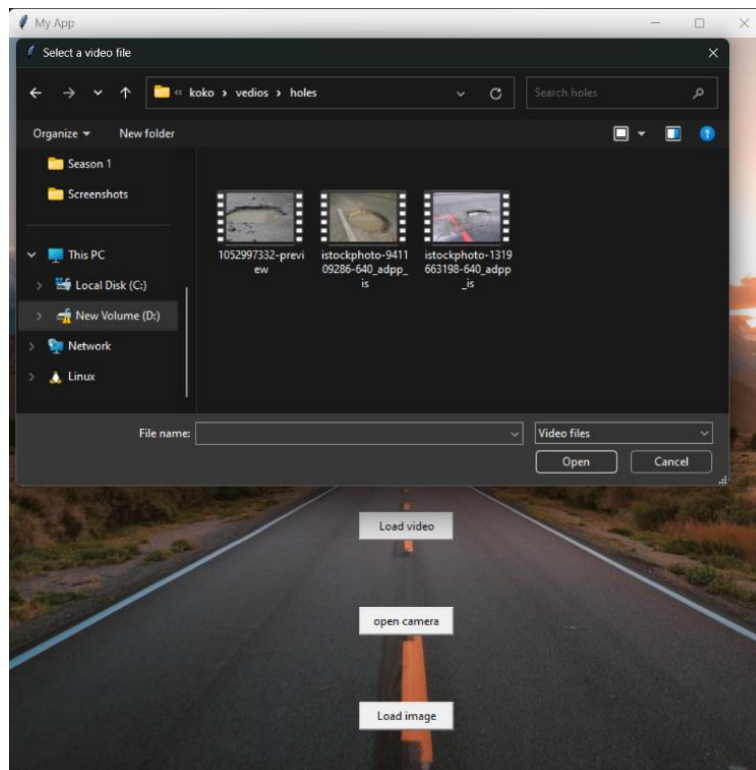
**GUI home page:**



**Figure 5.1 : GUI home page**



**Load video:**

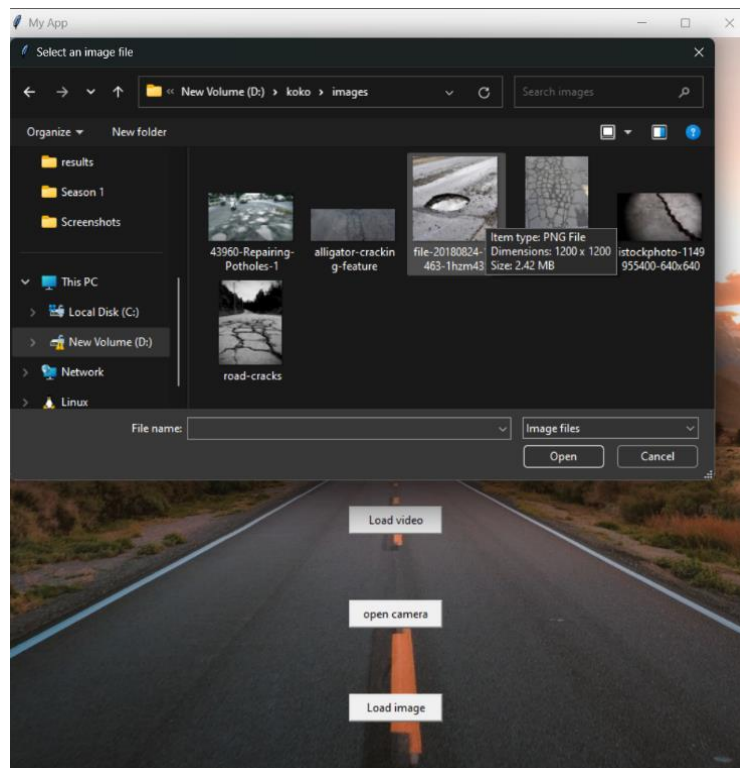


**Figure 5.2 : choose video**



**Figure 5.3 : Load video**

**Load image:**



**Figure 5.4 : choose image**



**Figure 5.5 : Load image**

## Chapter 6

### Conclusion and Future Work

#### 6.1 Conclusion

Upon evaluating the performance of YOLO v8 and YOLO v5 on our dataset, it was observed that YOLO v8 achieved a higher mAP of 74.8 compared to YOLO v5's mAP of 71.9. This demonstrates the superiority of YOLO v8 in terms of overall detection accuracy. Notably, YOLO v8 exhibited an improved ability to detect cracks and potholes compared to YOLO v5, capturing certain instances that were missed by the latter.

Our dataset, consisting of 5,622 images, was collected from two distinct sources - one focused on cracks and the other on potholes. To enhance the dataset and diversify the training samples, we performed augmentation techniques resulting in a total of 15,846 images. The augmentation process, carried out using the Roboflow platform, successfully merged and preprocessed the two datasets, creating a comprehensive and varied training set.

Utilizing the Tkinter library, we developed a desktop application equipped with essential functionalities, including real-time detection and the capability to analyze both saved photos and videos.

## 6.2 Future Work

For future work, the following possibilities can be explored:

1. Fine-tuning and optimization: Further investigate techniques to fine-tune and optimize the YOLO v8 model. This can involve adjusting hyperparameters, exploring different network architectures, or employing advanced optimization algorithms to further enhance the model's performance and accuracy in crack and pothole detection.
2. Data collection: Consider expanding the existing dataset by collecting additional images from diverse sources. Increasing the size and diversity of the dataset can help improve the model's generalization capabilities, enabling it to perform better in real-world scenarios with a wider range of crack and pothole variations.
3. Road anomaly detection: Extend the model's capabilities to detect various road anomalies, including bumps, ruts, and uneven surfaces, by expanding the dataset and training the model accordingly. This expanded detection capability enables a comprehensive assessment of road conditions, facilitating effective road maintenance and safety measures.
4. Installed camera on car deployment: Deploy the crack and pothole detection model on car-mounted cameras to detect road anomalies in real-time and provide drivers with immediate alerts for enhanced safety.

5. On-road camera deployment: Integrate the crack and pothole detection model with roadside cameras for real-time monitoring of road conditions, enabling immediate detection and alerts for cracks and potholes. This proactive approach ensures timely maintenance and contributes to safer roads, while collected data supports further research and analysis of road anomalies.

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