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Automatic Detection of Sewage Defects, Traffic Lights Malfunctioning, and Deformed Traffic Signs Using Deep Learning

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Abstract: Effective urban management relies on timely detection and resolution of infrastructural anomalies such as sewage defects, malfunctioning traffic lights, and deformed traffic signs. Traditional methods of inspection often prove inefficient and time-consuming. In this paper, an automatic detection of the urban infrastructural issues, it presents a multi-task convolutional neural network architecture capable of simultaneously identifying sewage defects, malfunctioning traffic lights, and deformed traffic signs from street-level imagery. The model is trained on a diverse dataset comprising annotated images of urban scenes captured under various environmental conditions. We demonstrate the effectiveness of our approach through extensive experimentation and evaluation on real-world datasets. Results indicate that the model achieves high accuracy and robustness in detecting the specified anomalies, outperforming existing methods. Furthermore, we discuss the potential implications of our research for urban management, including improved efficiency in maintenance operations, enhanced safety for commuters, and cost savings for municipal authorities. About 2438 images were collected of 6 categories and were augmented twice. The first augmentation increased by (X9) for by generating data from Keras. The second augmentation was carried out on training data only by (X3) using the Roboflow tool, where we defined the angles of the shape and gave it a class name. An overall accuracy of 86% based on F1-Measure value for all classes while individual classes shows different F1-value based on the available training samples. Overall, this research contributes to the advancement of automated infrastructure inspection systems, facilitating smarter and more sustainable urban environments.

Keywords: Convolutional Neural Network (CNN), Deep Learning, Sewage Defects, Traffic Lights Malfunctioning, Manhole Damage, YOLO v5.

INTRODUCTION

Urban infrastructure maintenance is crucial for ensuring the functionality and safety of cities. However, detecting and addressing issues such as sewage defects, malfunctioning traffic lights, and deformed traffic signs in a timely manner is challenging due to the sheer scale and complexity of urban environments. Traditional manual inspection methods are often inefficient and labor-intensive, necessitating the exploration of automated solutions to streamline these processes.

Because traditional manual inspection techniques are frequently labor-intensive and inefficient, it is necessary to look at automated ways to improve these procedures. Deep learning techniques have become increasingly potent tools in recent years for picture recognition tasks, with the potential to automate the identification of anomalies in urban infrastructure. You Only Look Once (YOLO), a well-liked object identification algorithm renowned for its quickness and accuracy in real-time applications, is one of these methods. Neural networks are a special type of computer algorithms that power YOLO. Their name stems from the fact that they are pattern-recognition machines, just like human brains. YOLO is a type of convolutional neural network, which is particularly good at seeing patterns in images, and hence, in objects and similar items.

Using YOLO, we want to create a system that can automatically recognize from street-level imagery flaws in the sewage system, broken traffic lights, and distorted traffic signs.

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In order to work, the YOLO algorithm divides an image into a grid and concurrently predicts bounding boxes and class probabilities for every grid cell. This method is ideal for real-time applications since it allows for effective object detection with just one neural network run. We can teach YOLO to reliably identify and locate these things by using a dataset of annotated photos showing anomalies in urban infrastructure.

In this study, we report our implementation and evaluation of YOLO 5, a YOLO algorithm variation, for autonomous identification of deformed traffic signs, malfunctioning traffic lights, and sewage issues. We outline YOLO 5's architecture and discuss how well suited it is for our detection task, emphasizing its benefits in terms of deployment ease, speed, and accuracy. We tested our approach on a variety of dataset that included annotated street-level photos taken in a range of environmental settings in order to verify its functionality. Using this dataset, we optimized and refined the YOLO 5 model and conducted extensive testing to assess its detection performance. Our findings show how well YOLO 5 performs in real-world circumstances when it comes to precisely identifying and localizing anomalies in urban infrastructure.

We also go over the possible uses and consequences of our findings for public safety and urban management. Our solution can decrease reaction times to infrastructure problems, improve the general efficiency and safety of urban environments, and enable preventative maintenance plans by automating the identification of sewage flaws, faulty traffic lights, and deformed traffic signs.

In the subsequent sections of this paper, we provide detailed insights into the methodology, experimental setup, results, and discussions regarding our approach to automatic detection using YOLO 5.

Traffic lights are light machines located at the cross of a road traffic flow and guarantee accident free on the road cross. Traffic lights are one of the most popular tools that maintains the safety of vehicles flow on highways or internal roads. Traffic lights gained popularity all over the world due to the ease of use as they have three well-known colors (Green, Yellow, and Red) which safely tells the driver to either pass, standby, or stop respectively. Moreover, traffic lights play a significant role in protecting pedestrians on the road. The traffic light changes the lights every few minutes, as it at a certain time allows a certain direction to pass through the intersection, and it is mostly located at the main intersections that are crowded with cars, and it is linked to a computerized system which works when receiving electronic indicators from the sensors that are placed in the street which is also known as the smart traffic light [1][2]. Traffic lights have a wide range of styles, and there is a big difference in how they are mounted and placed. The majority of current systems only prioritize "circle" type or "arrow" type detection [3]. For safe driving, it's crucial to understand traffic signals. A motorist will have important information to comprehend the road environment if it is feasible to identify and recognize a traffic signal [4]. The number of lives saved by light signals and prevented from accidents and injuries is estimated to be equivalent to 11,000 per year, which shows that their presence and continuous operation is the invention that preserves human safety the most and that they are very faithful to their intended purpose [5]. Sewage manholes: A separate underground conveyance system intended for transporting waste water from homes and commercial buildings for treatment or disposal. Other sewers serving industrial areas also carry industrial wastewater. The sewage system is called the sewer network system, and the sewage is part of the water distribution network. This network means the discharge of liquid waste from buildings and factories to the treatment plant or disposal sites [6].

A. Historical overview of the YOLO

The Yolo algorithm is applied to the input data. The output of the algorithm is a class and a bounding box around the object. Yolo1 is identified by the speed of recognizing objects, but with less accuracy than Fast_RCNN. As a result, scientists have developed YOLO2. Although YOLOv3 has made significant strides in both detection accuracy and speed, its ability in detecting tiny objects is still far from ideal. In April 2020, scientists developed a new version of YOLO(YOLOV4), they Noticed a big difference between YOLOV3 and YOLOV4 when applied on the same dataset[2]. Five alternative model versions are included in the YOLOv5 release: YOLOv5s (the smallest), YOLOv5m, YOLOv5l, and YOLOv5x (the largest). Figure 1 show the development of YOLOv5 models. GPU latency(ms) is shown in (x-axis) and COCO AP val is shown in (y-axis) and then they were compared as shown in the graph.

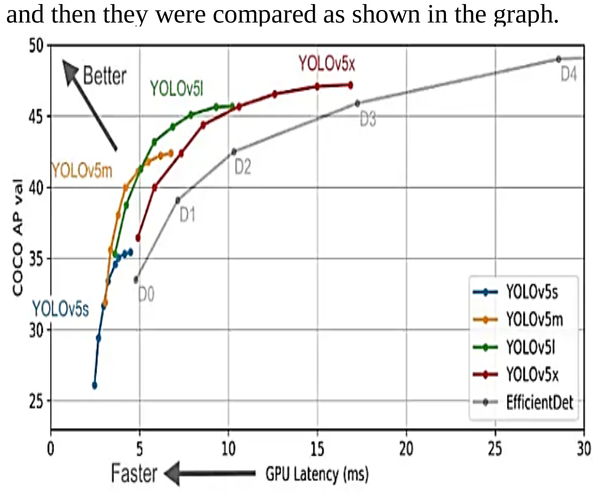

Figure 1: The evaluation of YOLOv5 model [7]

B. Comparison between Yolo versions

the authors wrote about helping Anki Vector detect another Vector in its camera feed using multi-version of YOLO (YOLOv5 vs YOLOv6 vs YOLOv7) and presents an evaluation between them, the performance depends on the use case and the KPIs targeted. the authors used dataset comprised of 590 images of training, 61 for validation, and 30 for test. the authors trained each model to 50 iteration and used the accuracy metrics. The Table 1 compares the Yolo versions based on: Accuracy, Time to Train and Time to run inference[8].

Table 1 Comparison of Yolo versions (V5,V6,V7)

50 iterations	YOLOV5	YOLOV6	YOLOV7
Precision	0.982	0.951	1
Recall	0.98	0.805	0.982
mAP@0.5	0.974	0.9514	0.985
mAP@0.5:0.95	0.854	0.768	0.916
Time of train	7m,48s	14m,2s	16m,40s
Parameters	20.87m	17.2m	37.2m
Inference time	19ms	22ms	19ms

from the Table 1 above , others evaluate three YOLO version (v5,v6,v7),we conclude There is no simple approach to choose the optimal machine learning model, its dependent on our problem case .so, we will use yolo v5,because it has the least training time compared to the rest of the versions, and it has the same inference time as the Yolo v7 it was 19ms.

In the upcoming parts the paper presents the related work, the proposed model, the model evaluation metrics used, the experimental results, and lastly in the last part the conclusion.

RELATED WORK

This section presents the related work to the identification of damaged traffic signs, traffic lights and manholes as it is divided into two subparts:

A. Object recognition using YOLO

in this paper [9], the authors show the identification and recognition of damaged roads. because deep learning takes a long-time to complete computation calculations, the authors used YOLO-LRDD which balances detection accuracy and speed. the authors in the paper used the RDX 2020 dataset which consists of 6800 image training, 860 image validation, and 900 images for testing, consisting of 4 classes longitudinal, lateral cracks, alligators, and potholes. And using a new backbone network called ShuffleECA-Net, which increases the speed of detection, the authors used employed BiFPN rather than PANet to improve detection accuracy. In this paper [10], the authors use yolo to detect illegal immigrants by a thermal camera, the model retrain on thermal images extracted from video in Protected border areas, authors used seven datasets (ASL ETH FLIR, LITIV2012 Dataset, KAIST, OSU Thermal Pedestrian Database from OTCBVS Benchmark Dataset Collection, Terravic Motion IR Database, CVC-09: FIR Sequence Pedestrian Dataset, VOT-TIR2015 Dataset) and they compared between them, authors achieve 97.93% AP score. in this paper [11], the author shows a vision system to determine what stationery items could obstruct a moving robot's route by Microsoft Kinect sensor using YOLO, the accuracy ratio was 96.36%.

B. Traffic Sign Recognition

The author of this [12], used CNN, a deep learning algorithm, to identify traffic signs and extract the main features of the images, and connect the output of all convolutional layers to the Multilayer Perceptron (MLP), the author used the GTSB dataset which has 43 classes, the data is divided into 34799 images for training, 4410 images for validation and 12630 images for testing, and the author got the accuracy ratio 97.1%. The author of this paper [13], used Yolo based on an active learning approach and real-time object detection to identify traffic signs, YOLOv2 gives the highest accuracy and reduces the size of the labeling dataset, and the algorithm got an accuracy ratio was 97%in real-time object detection. In this paper [1], the authors detect traffic signs using yolov3 as well as CNN, autonomous driving system required real-time detection, and the authors use pre-trained YOLO for the detection and used 5 objects for classification which are (cars, trucks, pedestrians, traffic signs, and traffic lights), used CNN for classifying traffic sign into 75 classes, authors got accuracy ration 99.2% and used German traffic sign recognition benchmark dataset which consists of 120000 images and 75 categories. in this paper [14] the authors suggest a method in which detection and classification the traffic sign by image analysis, in detection, the color and shapes were chosen as features, in classification, the authors used the input pattern for a neural network.

In [15] the author creates a new benchmark for detecting and classifying traffic signs, author collected 10000 images under different conditions, with more resolution than other datasets. The author trained two networks: one, detected all traffic signs as one category, other networks detect and classify traffic signs as multiple categories.

In [16], the author suggests two algorithms for classification and detection, in detection, the author extract traffic sign proposal by using the color probability model and MSER region detector. the author used SVM and novel color HOG feature to filter out the false positives and classify the remaining proposal. the author detects and classifies the traffic sign at 6 fps on 1360*800 and suggests using GPU to accelerate detection and classification.

In [17] , the author used YOLOV2 and end-to-end learning to achieve fast detection of Chinese traffic signs in real time. authors have solved the small size of the traffic sign by a fine grid to divide the images, authors used the CTSD dataset which contains 1100 images with sizes 1024*768 and 1280*720 .

Table 2. Summary of Related Work

Ref	Objective	Dataset	Approach	Accuracy
[9]	Identification and recognition of damaged roads	RDDC data set	YOLO_LRDD	Precision 58.9%
[10]	detect illegal immigrants people by a thermal camera	The 6 databases mentioned above	Faster R-CNN, SSD, Cascade R-CNN, and YOLOv3	97.93% AP score
[1]	detect traffic signs using yolov3 extended CNN	(GTSRB)	YOLOV3 and CNN for classification	99.2%
[11]	Object recognition Items can obstruct the path of a moving robot	A special data set was collected of where the robot is walking	YOLOV2	96.36%
[12]	identify traffic signs(CNN)	(GTSRB)	LeNet-5 network	97.1%.
[13]	real-time object detection traffic sign(YOLOV2)	(GTSRB)	YOLOV2	97%
[17]	detection of Chinese traffic signs in real-time	CTSD	YOLOV2	91.58% Recall
[15]	detecting and classifying traffic signs	collected 10000 images	FAST CNN	84% accuracy
[16]	classification and detection of traffic sign	(CTSD and GTSDB)	CNN	98.4% recall

From Table 2 and after reading the previous research, some researchers used YOLO (v2, v3, v5), CNN, YOLO_LRDD [9][13][15] and the maximum accuracy was 97.1% using LetNet-5 but targeting only traffic signs. Meanwhile, this paper target traffic sign, traffic light and manholes damage using YOLOv5 for detection and recognition.

RESEARCH METHODOLOGY

In this paper, we tackled the problem of identifying, Traffic lights, traffic signs, and sewage manholes using Yolo 5, which will be identified in real-time object detection from video streaming. The proposed methodology consists of the following steps:

1. Data Collection.
2. Data Augmentation.
3. Data Annotation.
4. Training, Validation, and Testing.
5. Results and Evaluation

Figure 2 is the pictorial view of the proposed methodology.

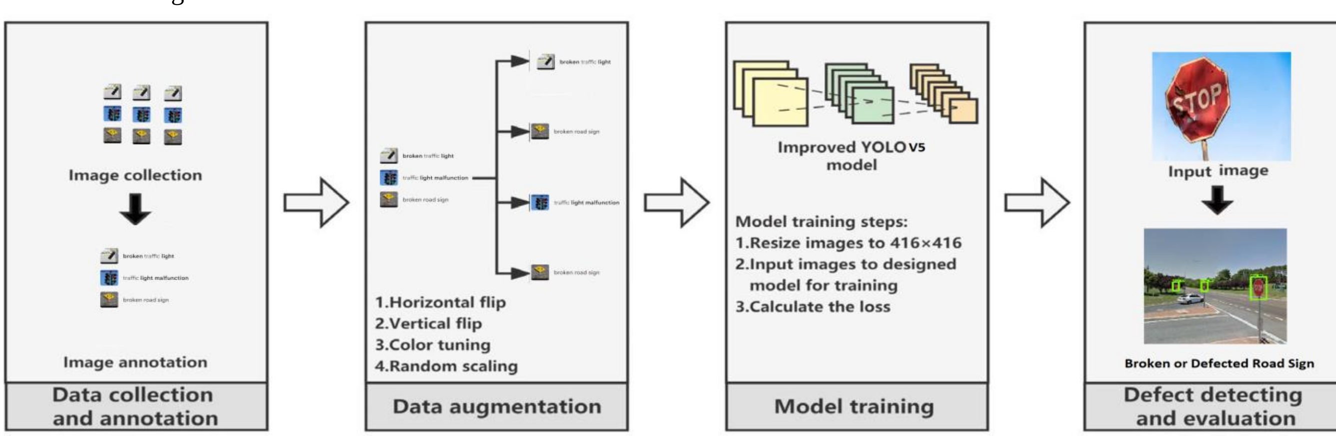

Figure 2 : Methodology.

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A. Data collection

the dataset used in this paper was collected from random website, the images were all collected in a variety of circumstances, such as changes in lighting, color, and shape. A general,2438 image have been captured and divided right into a training set, test set and validation set. The training set consists of 2118 image, the test set consists of 117 image and The Val set consists of image203. Table 3 shows sample from the dataset. The dataset consists of 6 classes 1. Traffic light normal 2. Traffic light damage 3. Manhole normal 4. Manhole damage 5. Traffic sign normal 6. Traffic sign damage.

Table 3 Samples from the Dataset

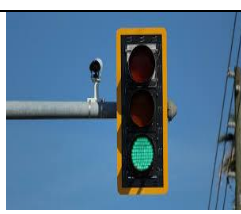
Class	Sample	Number Of Sample
Normal Traffic Sign		234
Normal Traffic Light		138
Normal Manhole		120
Damaged Traffic Sign		966
Damaged Manhole		318
Damaged Traffic Light		342

Figure 3, shows the data distribution, as can be seen, the data is unbalanced (biased towards the damaged traffic sign). because the characteristics of the damaged light signal and the normal light signal are similar in terms of shape and color, so the number of damaged light signal data was increased to increase the distinction between them.

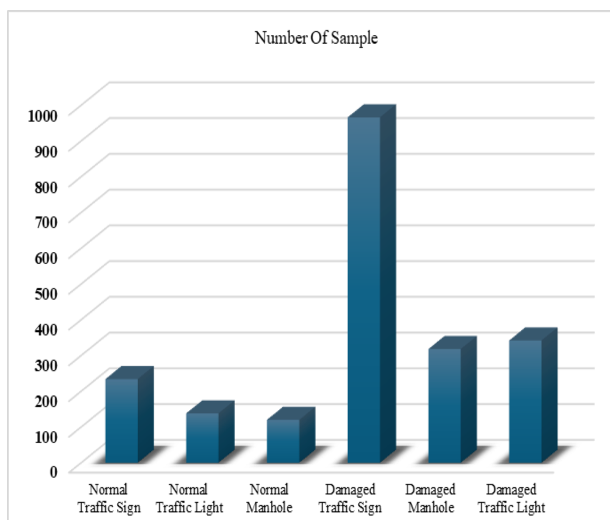


Figure 3: Data Distribution

B. Data Augmentation

to achieve high accuracy , a data augmentation by “image generation” using keras ,Four geometric transformations are used:

i. Shear: ±15° Horizontal, ±17° Vertical.
ii. Saturation: Between -8% and +8% .
iii. Bounding Box Flip: Horizontal, Vertical.

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iv. Bounding Box Crop: 0% Minimum Zoom, 20% Maximum Zoom.
v. Bounding Box Rotation: Between -15° and +15°.
The data have been augmentation twice:

First time: The increase number of image using Jupiter Notebook, where it was increased by (X9) for all categories.

Second time: Only the training data augmented using the Roboflow tool, in which the data was incremented by (X3).

Figure 4 shows a sample of the augmentation process, the image is scaled in and out, rotated , and flipped.

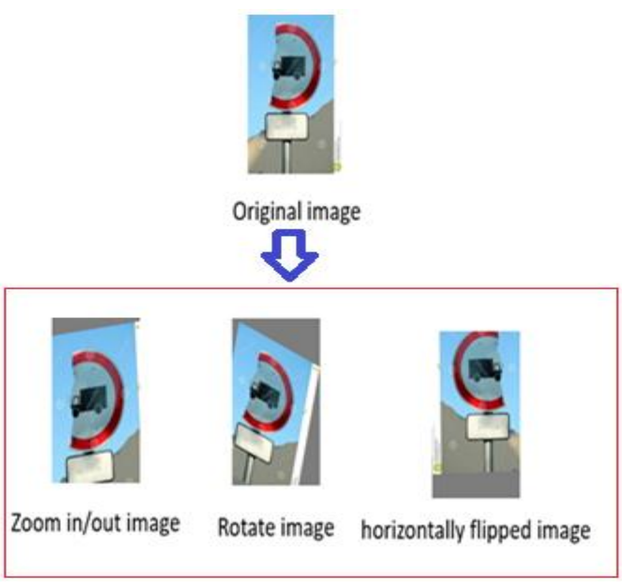

Figure 4: Sample of Data Augmentation

C. Data Annotation

In this part, resize the image to 640*640 and then locate the traffic lights, traffic signs, and sewage manholes by placing a rectangular box (Bounding boxes) that starts at the top left corner and ends at the bottom right corner and gives each image a class name. Figure 5 show Data annotation process.

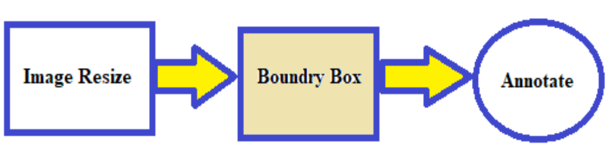

Figure 5 Data Annotation Process.

Figure 6 shows a label image example using Roboflow. Roboflow is an annotation tool to build computer vision applications. The bounding box and the name of the class are determined using AI-assisted[18]. Roboflow is characterized by ease of use and flexibility because it is used GUI. In the right part of the screen, we see the toolbar as shown in the Figure 6. The toolbar consists of 9 small icons, the Drag tool that pan the image or select annotation, Bounding box icon that draw annotation around box, Polygon icon that freeform draw annotation for more precise shapes. Smart polygons use an intelligent assistant to draw your polygon, label assist icon used the prediction from a roboflow train model as a starting point, repeat previous applies all of the annotation from the last image you annotated.

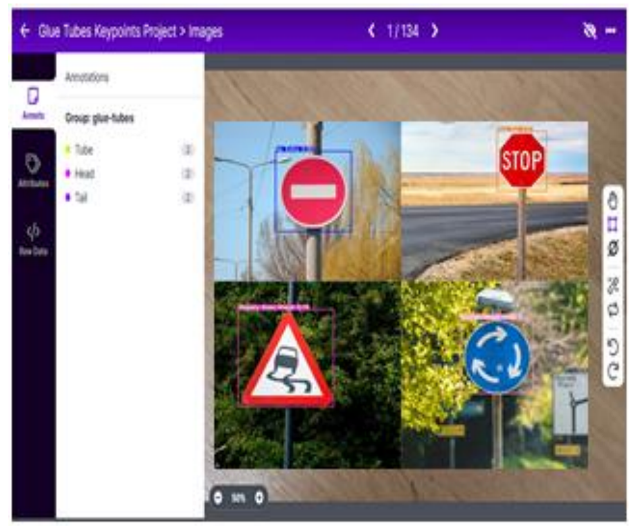

Figure 6: Annotating Images Using Roboflow Tool.

YOLO 5 ARCHITECTURE

Three parts make up the Yolov5's network architecture: Yolo Layer for the head, PANet for the neck, and CSPDarknet for the backbone. The data are initially sent to CSPDarknet for feature extraction, and then they are transmitted to PANet for feature fusion. Subsequently, Yolo Layer outputs the detection results (class, score, position, size) [19].

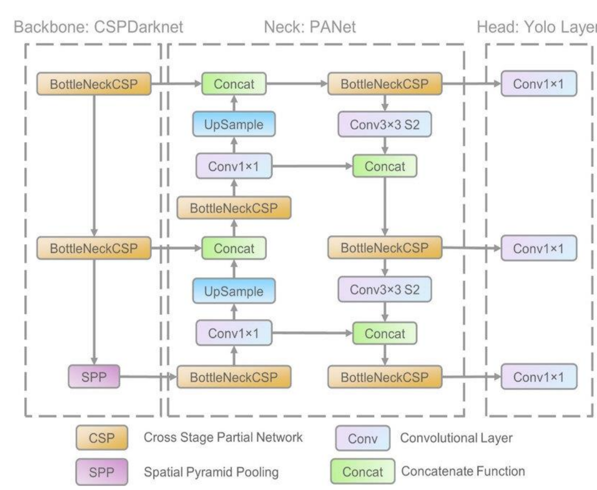

Figure 7 Yolo5 Architecture.

The features of YOLOv5 that were absent from the previous version include: implementing the CSPNet strategy on the PANet model; replacing the SPP block in the model neck with the SPPF block; and integrating the Focus layer to the CSP-Darknet53 backbone. After addressing the issue of grid sensitivity, YOLOv5 and YOLOv4 are now able to recognize bounding boxes with center points in their edges with ease. Lastly, YOLOv5 is faster and lighter than earlier iterations [19].

Shape and color categorization in YOLO is done by dividing the image into an n × n grid. After that, several bounding boxes are predicted by class probability map to give the final bounding boxes and objects classes, as shown in Figure 8 below [20].

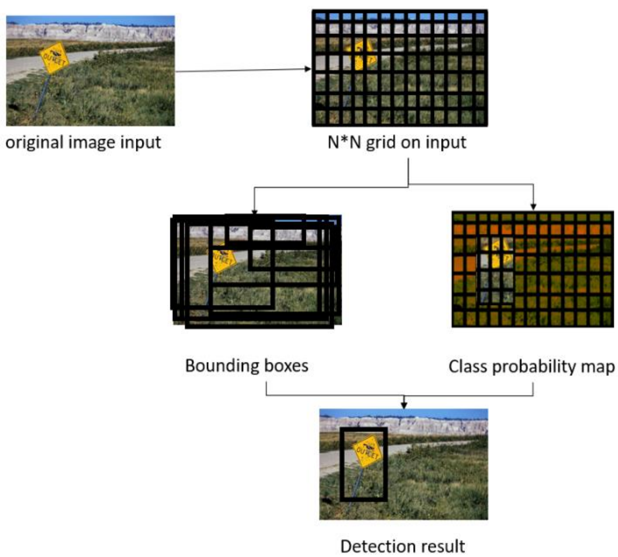

Figure 8 YOLO Detection Process.

Model Evaluation Metrics

For any learning model, evaluating the model is a crucial step. The accuracy score metric is one of the most popular and useful measures for assessing the model. At times, relying solely on the accuracy score statistic is insufficient. As a result, additional metrics like recall, precision, and F1 score were employed. These measures are explained in the following sections [24].

A. *Accuracy*

The most widely used performance metric is accuracy. It is referred to as the ratio of all observations to accurately predicted observations. Only when the dataset is balanced will accuracy provide us with a strong indicator and assessment. We used the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) counts to gauge the accuracy because our data is not balanced [24]. When the dataset is unbalanced, the accuracy based on prior counts is represented by Equation 1, while the definition of accuracy is represented by Equation 1.

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

B. *Precision*

Precision was used to test the classifier's capacity to return only relevant examples. Equation 2 represents this measure. To put it simply, it's the ratio of the number of positive outcomes produced by the algorithm to the number of accurately anticipated positive outcomes.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

C. *Recall*

Recall, sometimes referred to as sensitivity, is used to determine how well the classifier can recognize every pertinent event. Equation 3 is the formula that was utilized to compute it. It is calculated by dividing the total number of relevant samples by the number of correct positive outcomes.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

D. *F-Measure*

The F1 score is a crucial statistic in the field of traffic sign recognition and identification since it offers a consolidated value that precisely represents the trade-off between recall and precision. The harmonic mean of two measurements is used to calculate the F1 score, which provides a comprehensive evaluation of algorithm performance. It takes into account the accuracy of positive forecasts as well as the system's capacity to precisely identify all pertinent circumstances. When the datasets are unbalanced or the class distributions are different, this statistic is quite helpful. The F1 score provides scholars and industry experts with a thorough assessment of the model's performance, enabling the creation of resilient and flexible traffic sign recognition systems that optimize precision and recall [24]. The equation that symbolizes F-Measure is given by Equation 4.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

Another important visual metric is the confusion matrix which summarizing the performance of a classification algorithm in a visualized matrix [23].

Results and Discussion

A sample test data was plugged into the model for recognition, Figure 9, shows the recognized tested data surrounded by a boundary box with its class name indicated.

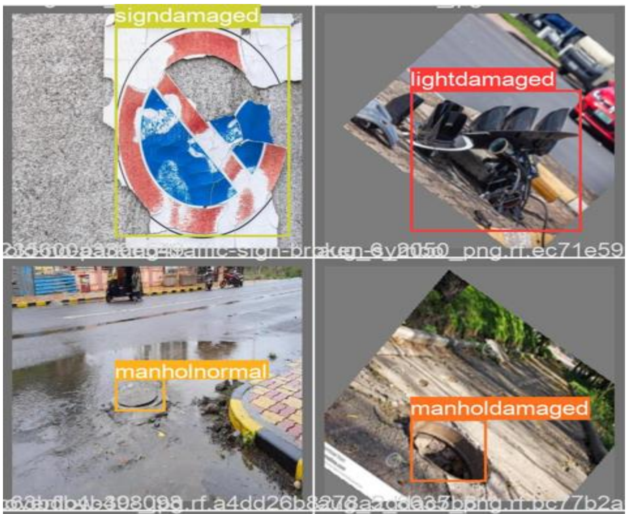

Figure 9 Test Data Recognition Using YOLO 5.

Table 4 below collects the important metrics values for each targeted class, the most precision ratio was in light damage and light normal class, and the less precision ratio was in sign normal class due to the small data size, the most recall ratio was in light normal class, and the less recall ratio was in manholes normal class. Due to the unbalanced dataset even of augmentation, the focus was on the harmonic mean value between metrics, mainly F1-Measure in this case. Taking the F1-Measure as the representative value of all classes, it is clear that the overall accuracy achieved is 85.3%.

Table 4. Measurement Values from Testing Experiments.

Type	Precision	Recall	F1-Measure
All classes	78.40%	93.70%	85.37%
Light damage	100.00%	98.50%	99.24%
Light normal	100.00%	98.90%	99.45%
Manhole damage	85.10%	94.50%	89.55%
Manhole normal	58.30%	87.40%	69.94%
Sign damage	95.80%	93.20%	94.48%
Sign normal	31.20%	89.70%	46.30%

For clear representation of Table 4, a pictorial view for this table is showed in Figure 10.

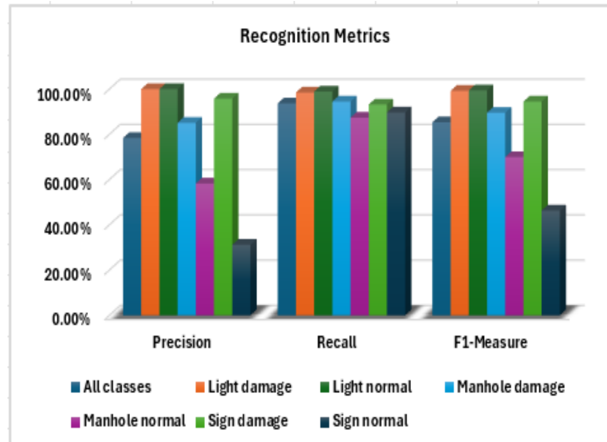

Figure 10. Recognition Metrics of YOLO 5 on Testing Phase.

Using graphical charts, one approach to assess and see how well any machine learning model is performing. The accuracy of training and validation for every epoch is displayed in Figure 11. We stopped training the CNN model at epoch number 40 based on the plot and many experiments, as the model begins overfitting the data beyond these values.

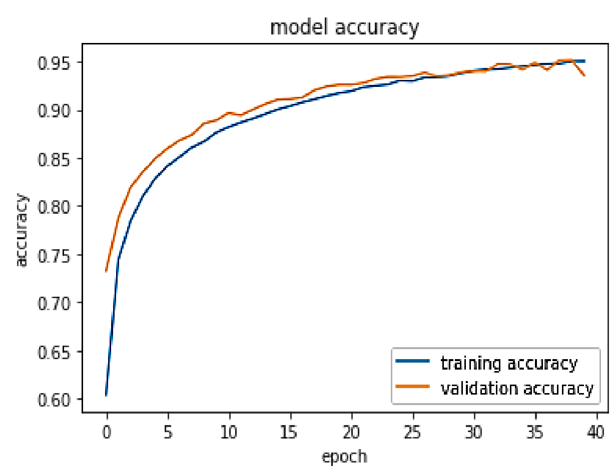

Figure 11. Training and Validation Accuracy

The training and validation losses for every period are shown in Figure 12. While the CNN model is operating at tell epoch number forty, the validation and testing loss is getting smaller. Additionally, it is evident that the validation loss begins to rise after 40 epochs, necessitating the termination of CNN training.

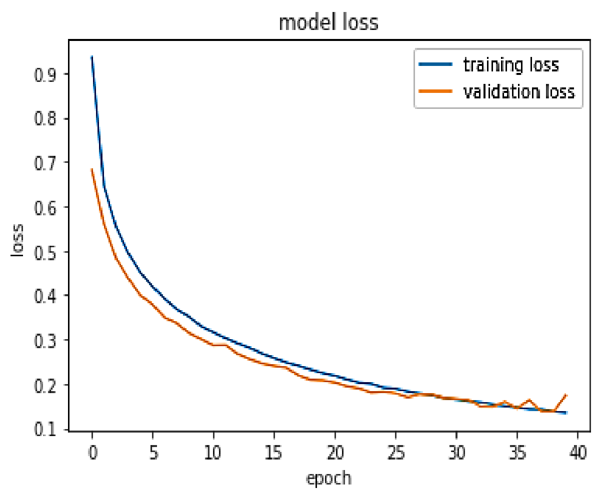

Figure 12. Training and Validation Loss

Confusion matrix, which characterizes a classifier's performance on test instances, often the test portion of a dataset, was a significant result. The majority of the classifications from Figure 13's confusion matrix was centered on the main diagonal, indicating that the classification had a high degree of accuracy.

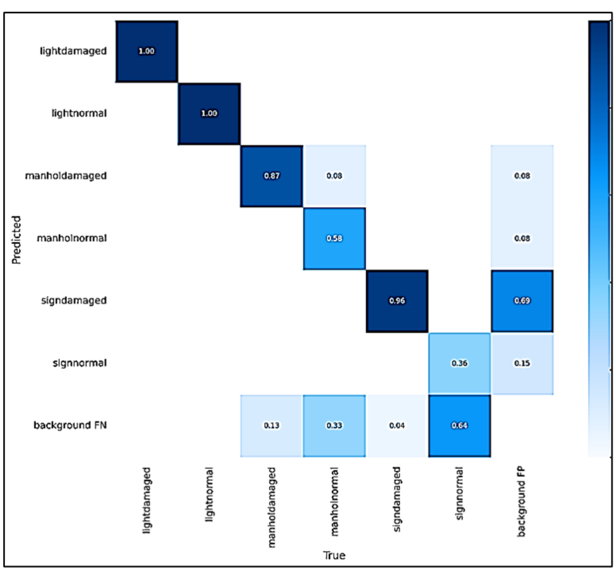

Figure 13. Confusion Matrix

CONCLUSION

This research presents a real-time detection of YOLO5-based damage to traffic signs, traffic lights, and sewage manholes. This research introduces a multi-task convolutional neural network architecture for autonomous identification of urban infrastructure problems. It can identify malformed traffic signs, faulty traffic lights, and sewage abnormalities simultaneously from street-level imagery. An extensive dataset of annotated photos of metropolitan scenes shot in a range of lighting conditions is used to train the model. Our approach's efficacy is proven by thorough testing and evaluation on real-world datasets. Results show that the model outperforms current techniques in detecting the specified abnormalities with high accuracy and robustness. We also go over the possible ramifications of our research for urban management, such as increased commuter safety, cost savings for municipal authorities, and more effective maintenance operations.

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