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A Deep Learning–Based Framework for Intelligent Traffic Management

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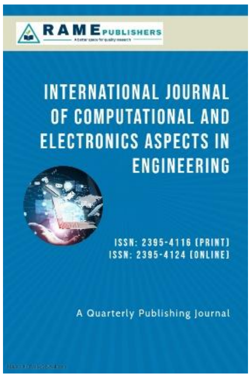

Abstract: This paper explores the potential of the deep learning technique in improving the classification of road signals in transport networks. Traditional methods of observing traffic lights have a strong reliance on observation that is likely to be slow and prone to errors that create delays in acting on traffic changes. The proposed system will be based on the YOLO v7 system to detect and classify traffic lights to improve traffic flow, efficiency, and safety, and minimize congestion. The special data set adapted to this project was. Used as a training and a grading tool. The paper addresses the weaknesses of techniques and emphasizes the need to continue with automated solutions, in order to keep the statuses of traffic signals under control. The proposed system captures images with the help of a single camera and utilizes the deep learning techniques to develop a smart model capable of accurately classifying traffic lights in real-time. Initial results indicate that the proposed model works well in recognizing and classifying traffic signals with high accuracy that presents high precision and recall rates. This study contributes to the development of real-time traffic control systems since the study offers a powerful approach to automatic classification of traffic lights. Besides, the system has been tested extensively to confirm its efficiency and performance in conditions to prove that it is a viable solution, to improve smart transportation systems and future traffic control initiatives.

Keywords: AI, Deep Learning, YOLO, Traffic Light, Artificial Intelligence, Object Detection

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1. Introduction

It is important that in the era of transportation networks the classification of the traffic lights is accurately and efficiently done to ensure that the traffic flow runs smoothly and to enhance the safety on the roads. As cities grow and traffic management turns out to be a complex traditional system relying on manual inspections, the system faces significant limitations [1], [2]. In such systems, delays, inaccuracy and errors often occur and are caused by people which cause congestion and increased chances of accidents. Therefore, it is important henceforth to have improved automated systems that are able to handle the growing traffic flow effectively and efficiently. The advancement of the deep learning methods opens the new possibilities of the automation of the traffic lights classification and monitoring. Convolutional neural networks (CNNs) have proved to be very effective in image processing activities like object recognition and classification [3], [4]. One of such models is YOLO (You Look Once) that has been widely acclaimed because of the capacity to perform specific real-time detection accurately. The recent version of the YOLO vX architecture delivers the best performance through accuracy and speed to the table [5]. Significant potential in traffic signal classification problems in real-time settings as analyzed in this research project in developing an autonomous system, such classification using the YOLO vX architecture [6], [7]. By training the model with a collection of traffic lights images, the system can therefore correctly detect and classify traffic lights according to their colors (red, green and yellow) even under challenging environmental conditions. The proposed study will offer a reliable and efficient methodology as compared to the traditional ways of traffic monitoring by eliminating the failure of the manual verification measures whilst possibly improving traffic movement and security [1], [4], [8], [9].

The paper will be organized in the following manner; Section 2 will explore the studies done to identify traffic signals and the innovations in the field of deep learning technologies. Section 3 outlines the methodology that includes construction of the dataset and model training along with identification of the evaluation metrics and Section 4 presents the experimental results and findings of the analysis as well as Section 5 concluding the research and discussing the ways of further research.

2. Literature Review

The major advancements have been observed in the sphere of traffic lights detection and classification through the implementation of the deep learning approach in the field. Conventional methods of traffic monitoring that were greatly based on the concept of detection have continued to be associated with consistent challenges such as delay in response and traffic misinterpretations. The shortcomings of these systems have been further escalated by the increased urbanization and the pressing need is the automated and intelligent systems that can effectively handle the intricacies of the current traffic control systems.

There are many studies that have addressed how machine learning and deep learning can be employed to detect traffic lights. A deep learning algorithm that integrates feature extraction and classification to deal with traffic analysis was presented in the study by Mohammad Lotfollahi (2018) where the author proposed the concept of Deep Packet. Although the research focused on traffic datasets mainly, it emphasized on the effectiveness of deep learning, in processing live traffic data[10]. Transfer learning tools have been applied to the categorization of traffic signs in a vein to Chunmian Lin work in 2019. The method has been effective in improving accuracy and cutting down the time spent in training by a significant margin. It highlights the efficiency of the learning models, in activities concerning traffic control [8]. H. James Deva Koresh (2019) presents a real-time traffic sign sensing system based on capsule neural network, which performs better than convolutional networks, in both accuracy and resistance to spatial variance [11]. Li (2021) showed a self-driving car system based on learning methods. The system recognizes the traffic lights through changing the light. The study will support the achievement of performance in accuracy and speed. It also has a dataset used to train on the variety of traffic signals in various situations. Recently, it became interested in the system that competently detected traffic lights with a high precision and within a short period [12]. Recently, the trend toward the YOLO (You Look Once) has increased, especially in the environment of a real-time object detection. The YOLO version 8 model has gained a lot of popularity as an efficient and accurate solution to detecting traffic lights. Research by Huang Tran Ngoc (2023) has revealed that YOLO version 8 is faster and more accurate as compared to the iterations such as YOLO version 6 and YOLO version 5. According to their study, the YOLO v8 is effective in difficult traffic scenarios such as various light situations and adverse weather conditions and this is why it is a good alternative, when it comes to using a system that is self-driving and makes use of learning methods. introduced a system that is self-driving and based on the learning methods. The system recognizes traffic lights by switching the lights. The objective of the study is to make the performance speedy and accurate. It also holds a set of training on the variety of traffic lights under various conditions. The findings were that the system was able to identify traffic lights with high precision and within a very short duration of time [2]. Yongsheng Qiu (2023): The article under analysis reports the shortcomings in Convolutional Neural Network (CNN)-based autonomous driving object detection algorithms, namely, their outstanding performance in common datasets. Nevertheless, there is also a significant limitation of the research: these detectors seriously deteriorate performance under low-light foggy weather conditions [13].

Nonetheless, among these developments, there are yet barriers that must be broken particularly where it concerns the difficulties of dealing with unpredictable weather conditions, including fog rain, and dust. Moreover, no data sets that are specifically created to detect and classify traffic lights are available. This paper aims to address these issues by developing a dataset that is tailored to these particular purposes, classifying traffic lights, and using the YOLO v7 framework to improve accuracy and real-time capabilities in different traffic scenarios. It elaborates studies by explaining its flaws, in data source and dependability in challenging situations.

3. Methodology

This part explores the study of traffic lights through an innovative system of identifying the traffic signals. It is revealed by the evolution process which is made up of four deep steps that contribute to the shaping of the efficiency and reliability of the system. As shown in Figure 3 through the illustrated steps, a process that follows the steps aims at achieving accuracy and precision in detection of traffic lights.

3.1 Data Collection

The first step in the process is the data collection. It is the beginning point where it is all about creation of the required data that can be utilized by the system to operate properly. This stage brings out the story of the importance of using training data carefully selected to run in the system. It reveals an expert research methodology that illuminates the issues of collecting images to the systems operations. This is the first stage which emphasizes the need to get data in order to have a good foundation, on which other stages would be grounded. The dataset that was used in the present research work is particular to the determination of traffic lights. A total of 163 images were collected. Sorted into three groups. Traffic signs are red lights, green lights and yellow lights. The variables were the sources that were diverse to present angles of lighting scenarios and environment conditions to capture the images. The pictures were also edited through cropping and resizing them to 640 x 640 pixels to fit the size requirement of the YOLO v7 model input dimension. Samples of the images of each of the classes are presented in Figure1.

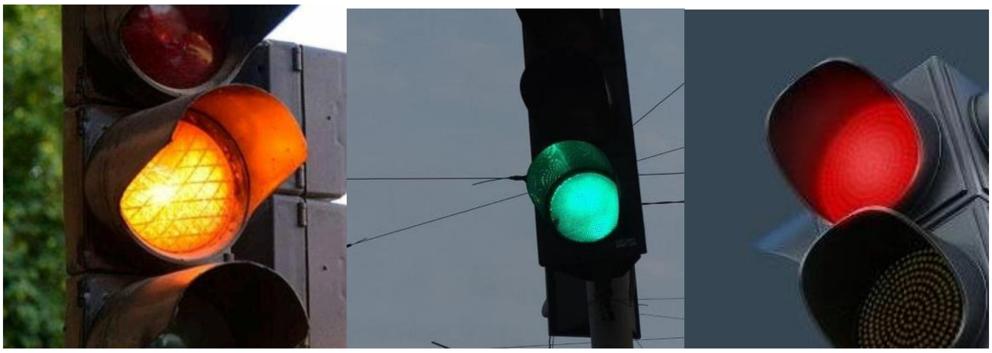

Figure 1. displays examples of reds, greens, and yellows.

a. Data Preparation

The Second stage is the transformation of the aggregate data into model training, which is the noticeable point in the formation of the system. This stage is made possible by the Image Preprocessing as the raw images undergo the metamorphosis process. The auto Orient operation that is the primary one, is the alignment of the orientation of the images collected to a standard format. Meanwhile, the images are resized to a standard image, 640x640 pixels, and it assists in obtaining coherence and similarity among the dataset.

The process of Annotating the Images may be regarded as a well-thought-out project, the feature of meticulousness, which should be attributed to the preparation of the data. The system of manual annotation adds the systematic meaning of context to each image and particular emphasis is made on marking the specific place and the type of traffic lights. The premise behind such an intensive exercise is the ability to produce data labels of invaluable value, which is required in the latter model training efforts.

Classification stage is the one in which the annotated images are created, and the images in it are classified into particular categories based on the color of the traffic lights. The categorization process that leads to the formation of three key classes; Red, Green, and Yellow offers a subtle understanding of the settings of the traffic lights, which are installed on the basis of the advanced model training and inference.

The Classified Images also become the basis of the system development as they are considered to be the background of the traffic light classification data. This well-trained data is the basis of even more model training tasks, and the essence of the actual traffic scenario.

A final culmination of data preparation is the preparation of the Dataset in a systematic manner and partitioning it into training and validation sets. This strategic separation becomes a guarantee of the healthy exchange of images, the enhancement of powerful model training, and strict validation. Considerate allocation enables the researchers to seek the appropriate compromise of the complexity of the model and generalization, which forms the foundation of a highly powerful and reliable vehicle traffic light detection battery.

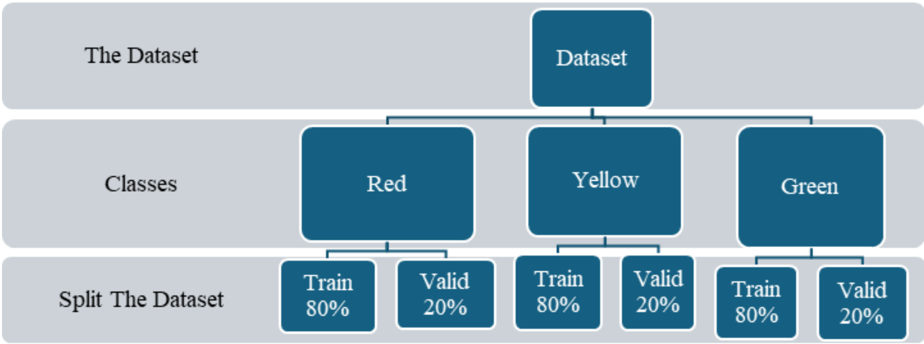

Figure 2. Splitting the dataset

b. Image Preprocessing

The second process is to prepare images that serves as a platform through which the raw data is transformed into useful information that can be used in analysis and subsequently to take actions. Such an important stage is comprised of preparation processes intended to improve and maximize the dataset. Data labelling is useful in generating required data tags to train the model. Moreover, the data should be segmented into divisions within the process because there needs to be a smooth balance between the training and the validation data. Moreover, all the images were resized. There are points, and they are marked with the help of the Labelling tool to indicate the position of the traffic light. The notes were saved as YOLO format (files) and subsequently separated into training and validation groups (80 percent and 20 percent respectively). This was because it had to be such that the model could be trained using a different set of images, to be evaluated. The samples of image cropping process are represented in figure 3.

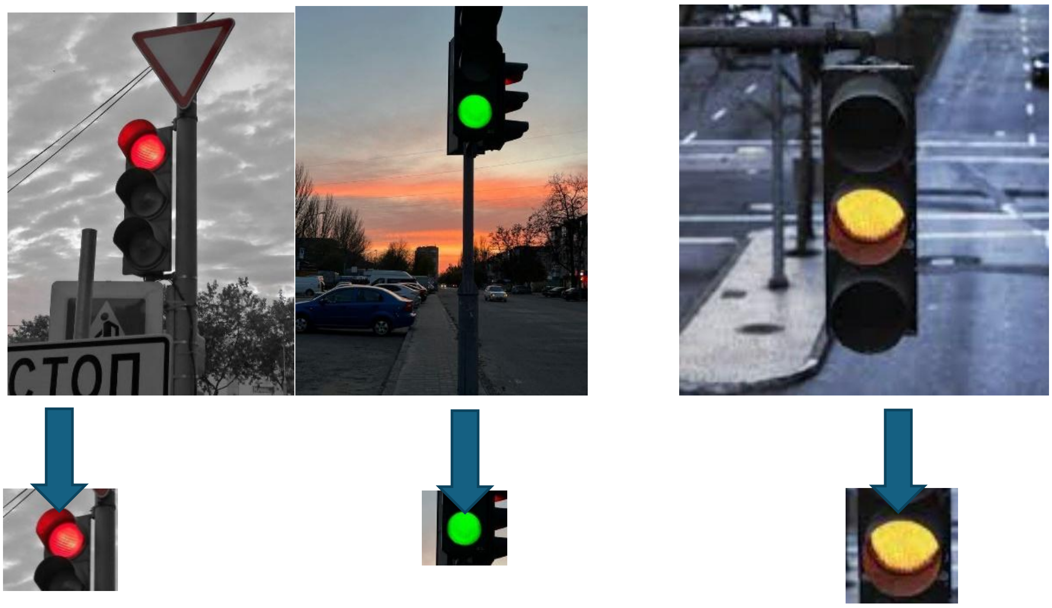

Figure 3. illustrates an instance of cropping. Annotating an image.

c. Model Training

Exploit the potential of the v8 models by capitalizing on the high-end features of the v8s here where a carefully chosen dataset used earlier serves as a substantial starting point to training. The fine-tuning, to v8 models is made in details which enhance performance measures. This step brings together the improvement of algorithms and experience that is acquired through data to increase the complexity of the detection system.

One stage of the process that places the hard work and minute observation at its high point is during the process of selecting the appropriate model to be incorporated into the planned system with the evaluation metrics as a very important factor. One of them is to find out which version of the model is the most effective one to be done by means of testing, using the set of criteria and in the actual conditions. This step is the essence of the assessment that promotes the enhancement and innovation in the field of detection systems.

V7 model was adopted in this project because it is precise in detecting objects in real-time scenario. On the model training to detect and categorize traffic signs, a dataset was employed to adjust the most important parameters like learning rate and batch size to enhance the performance of the models.

d. Evaluation metrics

The trained model was evaluated based on the metrics of mean average precision (alternatively called mAP) precision rates to measure accuracy and recall rates to measure absence of a particular traffic sign and F 1 scores as the overall performance measurement, in different conditions [14], [15].

Accuracy

The precision of categorization indicates the proportion of predictions made.

$$\text{accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad \ldots\ldots\ldots\ldots (1)[16]$$

Where the values shown in the confusion matrix values:

Table 1. Confusion matrix values

		Actual Values	
		P	**N**
Prediction Values	P	TP (True Positive)	FP (False Positive)
	N	FN (False Negative)	TN (True Negative)

Precision

Precision is calculated by taking the tally of positive predictions and dividing it by the overall count of positive predictions made by the model.

$$\text{Precision} = \frac{TP}{TP+FP} \quad \ldots\ldots\ldots\ldots (2)[16]$$

Recall

Remembering something in the context of a classification system (also referred to informally at times, by the term 'sensitivity') involves assessing its capability to accurately anticipate the number of instances.

$$\text{Recall} = \frac{TP}{TP+FN} * 100\% \quad \ldots\ldots\ldots\ldots (3)[16]$$

F1 Score

Another way to classify data merges sensitivity and accuracy in what's called the F score also known as the F measure or F_β score, where β is a positive value that weighs precision and recall differently; they are both considered important and should not be overlooked when evaluating models performance indicators like accuracy or memory usage, in machine learning applications.

$$\text{F1 score} = \frac{2*\text{precision}*\text{Recall}}{\text{precision}+\text{Recall}} \quad \ldots\ldots\ldots\ldots (4)[16]$$

e. Mean Average Precision (mAP)

One commonly used metric is the Average Precision (often abbreviated as mAP) which is determined by calculating the average of the Average Precision values, for all categories/classes considered.

$$\text{MAP}=\frac{1}{n}\sum_{i=1}^{n}\text{API} \quad \ldots\ldots\ldots\ldots\ldots (5)[17]$$

4. Result and discussion

Here, the results of data collection and preprocessing are presented, as well as the results of training the six YOLOv7 models using the collected dataset. The results are then compared to select the best model to be used as a proposed traffic sign detection system. The comparison is made using the following evaluation metrics: (average mean accuracy, precision, recall, and F1 score). After performing the following operations in order:

a. Resize the images

The dataset utilized for this thesis comprises images of varying dimensions that need to be adjusted to align with the requirements of YoloV6 used in the model proposed here. Which specifically calls for a size of 640x640 pixels.

b. Annotating the Images

Each picture is accompanied by a TXT file with matching names. In total there are 383 images, in one folder labeled "images" and 383 TXT files stored in a folder called "labels " creating a unique dataset.

c. Split the dataset

The dataset was split into two parts. A training set and a validation set. Using algorithm 4. The training set accounted for 80% of the dataset and was utilized to train the suggested model; meanwhile, the validation set constituted 20% of the original dataset and served for model evaluation purposes as depicted in Figure 4.

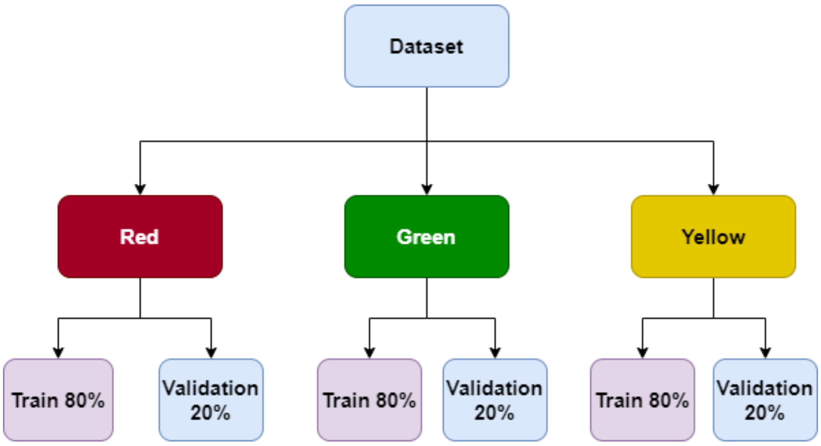

Figure Error! No text of specified style in document.**.** Dataset Splitting

In this experiment, the YOLOv7X used to train the collected data. The results of using the YOLOv7X are shown in Table (4.1).

Table 2. Results Obtained by YOLOV7x

Classes	mAP0.5	precision	Recall	F1-Score
Red	98.4 %	96.9%	96.3%	96.6%
Green	97.1 %	97.8%	89.2%	93.3%
Yellow	96.6 %	92%	88.3%	90.1%

1. The table outlines an in-depth evaluation of the performance of a traffic light detection system of specific classes, i.e., Red, Green, and Yellow. All classes are carefully checked regarding different performance indicators, which would explain the effectiveness of the system in identifying traffic lights of different colours.
2. mAP0.5 (mean Average Precision at IoU 0.5): This value is probably one of the most significant indicators of the accuracy of the detection system since it considers the mean accuracy of object detection at a given Intersection over Union (IoU) 0.5. Increased mAP0.5 value implies an increase in the accuracy of the correct recognition of objects in all classes [14], [15].

3. Precision: is a metric of system ability to differentiate things and displays the probability of correct positive identifications, among all the positive identifications that the model makes.
4. Recall: Recall is also known as sensitivity, it is a measure of its ability to detect all positive instances, of a certain type.
5. F1-Score: it is a harmonic mean of recall and precision and represents a balanced assessment of the model.

Red Class Evaluation:

- As can be seen, the Red class records a significant mAP0.5 of 98.4 which indicates a praiseworthy overall accuracy in identifying red traffic lights.
- ; The accuracy level is, 96. 09 (and this indicates that most predictions are correct).
- Recall is impressively high at 96.3, which means that the system is very proficient in capturing a good proportion of the real red traffic lights.
- The F1- Score, of 96.6, means that it was accurate and complete in recognizing red traffic lights.

Green Class Evaluation:

- Green traffic lights demonstrate an admirable mAP0.5 of 97.1 showing that they are accurate in identifying green lights.
- • Precision has a score of 97.8 which is considered a Highlight, indicating that it is accurate in detecting green traffic lights.
- A significant recollection of 89.2, in particular, explicitly demonstrates its effectiveness in the provision of a number of genuine cases of the issuance of the green light.
- The F1-Score at 93.3 supports a balanced score between the precision and the recall, which confirms the ability of the system to detect green light.

Yellow Class Evaluation:

- The Yellow class has a good mAP0.5 of 96.6, This shows that it is accurate, in the recognition of yellow traffic lights.
- Precision 92 Precision shows that there is an ability to positively predict the light group of yellow color.
- This makes the system record a high degree of the actual cases of the yellow traffic light which is 88.3 percent of the total number of recalls.
- F1-Score F1-Score = 90.2: It means that this system is comprised of the balanced measure of precision and recall, and it means that the system will be able to see yellow lights.

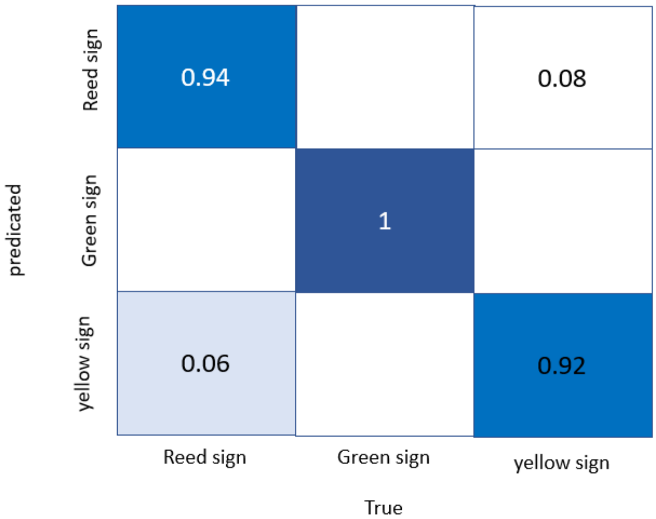

Figure 5. illustrates the confusion matrix depicting the classification of traffic signs using YOLO v7.

Based on the values of confusion matrix, the classification accuracy values are 0.84,1 and 0.92, which are of red sign, green sign and yellow sign. The results are depicted in figures (6a-6d) with the use of YOLO V7X:

Figure 6a. Detection Using YOLO V7X

Figure 6b. Detection Using YOLO V7X

Figure 6c. Detection Using YOLO V7X

Figure 6d. Detection Using YOLO V7X

5. Conclusion

The paper examines the complexity of traffic light detection in terms of its relevance to the contemporary transport industry. The researchers employed the deep learning models, like the YOLOv7, to train powerful models and perfect them to navigate traffic scenes. Such measures as a mean average precision, precision, recall, and F1 score became the metrics by which optimal model selection should be measured. The results indicate that there is a possibility of the traffic light detection systems to transform transportation management to enhance efficiency, safety, and sustainability. They are saying their goodbyes to this chapter and hope to keep going on and finding new ways, as they strive to change the limits and build a future with technology driving human advancement and success. The paper finally gives its view of optimism in further study and exploration in the area of traffic light detection, which will lead to a future where technology will be a catalyst to societal growth and development.

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