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# Lane Detection and Traffic Sign Detection using Deep Learning and Computer Vision for Autonomous Driving Research Using CARLA Simulator

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**Abstract**—Lane identification and traffic sign detection is the most challenging and promising problem for self-driving or autonomous vehicles with unintentional lane departure and ignorance of traffic signs being major contributing factors to motor vehicle collisions around the world. To tackle this problem the proposed work aims to detect both lane and traffic signs for autonomous vehicles. This article proposes semantic segmentation and object detection model for implementing Advanced Driver Assistance System (ADAS) applications. The applications are implemented using a variant of Convolutional Neural Networks (CNN) deep learning model such as SegNet and You Only Look Once (YOLO) algorithm. Due to dynamic and adverse environment conditions, devising and testing a system which yields effective performance in all urban driving scenarios is challenging. Hence the environment is set up virtually with the help of the Car Learning to Act (CARLA) simulator. With aid of developed models, lane and traffic signs were successfully detected and tested under various constraints. Obtained results are evaluated with various performance metrics. Models are deployed for separate created datasets. The semantic segmentation model developed for lane detection using SegNet gives a mean average precision (mAP) of 93.33%, an overall accuracy of 94.80%, F-score of 93.42% and a minimal error rate of 5.20%. Model developed for Traffic sign detection, a mean average precision of 93.67%, an accuracy of 95.56%, recall of 92.67%, F-score of 93.16% and error rate of 4.44% have been achieved.

**Keywords**-Convolutional Neural network; You Only Look Once; Semantic Segmentation; Object Detection; Deep Learning; Computer Vision; CARLA Simulator.

## I. INTRODUCTION

Over the last ten years, several attempts have been undertaken to improve algorithmic performance and provide datasets for semantic segmentation and object detection. Deep learning's immense success has had a substantial influence on these algorithms, significantly enhancing their accuracy. Many technical and academic disciplines that demand high-end computer vision capabilities have taken notice of this potential breakthrough. An effective choice in achieving the goal of making self-driving cars recognize its encompassing areas and substituents is done by semantic segmentation based on deep learning(DL). Multi-class discerning abilities and neural networks usage in sensing the surrounding areas with its constituents such as alleyways, pedestrians, traffic signs and signals shows high accuracy when this method is deployed [1]. Hence, this article proposes efficient methods for implementing Lane and Traffic Sign detection applications.

## II. LITERATURE SURVEY

Semantic segmentation is an image classification problem at the pixel level that aims to categorize each and every pixel in the image [2]. Qusay Sellat *et al.,* [3] proposed leveraging two main DL architectures to develop an accurate and real-time semantic segmentation system for self-driving vehicles. The idea of feature pyramid networks (FPNs) and bottleneck residual blocks are combined to create a hybrid model. Mohammad Hosein Hamian *et al.*,[4] proposed a a technique that achieved 81.73% and 76.31% mIoU respectively using post processing methods namely Xception and MobileNetV2 by separating the system into four parts. The use of semantic segmentation has shown promising results in Advanced Driver

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Assistance Systems(ADAS) application and hence extensive research is being carried out in further improvement of these algorithms for autonomous vehicles [3]-[7].

In the last ten years, CNN has made substantial advancements in the area of deep learning, and its performance on CV tasks is bleeding edge [8]-[9]. Among the numerous variants of CNN, an effective model used for semantic segmentation is known as SegNet. The core trainable segmentation engine is composed of an encoder network, a related decoder network, and a pixel-wise classification layer. It is primarily driven by applications for analyzing road scenes, which necessitate the modelling of look, form, and the spatial relationships between various classes [10].

Corrochano *et al.* proposed a method for semantic labeling automatically and tested it using a small-scale car model that learns to drive on a reduced circuit [11]. Zhang *et al.* focuses on classification and localization issues in lane detection using semantic segmentation by proposing a Global Convolutional Network (GCN) model that achieved 57.5875 mean square error [12].

YOLO is a state-of-the-art algorithm used for Object Detection and classification which has given high accuracy rates. It is an efficient model for traffic sign detection because of its regression model that yields the probabilities of the classes of the images detected real-time[13]-[14]. Rajendran *et al.,* [15] proposes traffic sign detection and recognition system consisting of three modules namely- sub-pixel convolution attention module (SCAM), parallel deformable convolutional model (PDCM) and GSConv which were applied to YOLOv5 and achieved 89.2% mAP.

Notably in the field of autonomous vehicle driving, other methods and algorithms of interest include Panoptic segmentation [16], Instance segmentation [17], LiDAR segmentation [18]-[19], Bird's Eye View Look-Up-Table estimation [20] and optic flow estimation [21].

Furthermore, applications of DL and CNN are widespread having use cases that include detecting bleeding zones in capsule endoscopy images, point cloud analysis, enabling applications like urban planning and environmental monitoring, for the classification of cloud image patches, crash avoidance and overtaking advice systems to name a few [22] – [28].

## III. DESIGN AND IMPLEMENTATION

Car Learning to Act (CARLA) is an open-source, Unreal Engine-based simulator that has flexible API's and is used for research on autonomous vehicles that enables users to alter and control simulation-related elements. Due to its ability to allow simulations to run on realistic cityscapes and excellent user interaction capabilities, CARLA is being used to implement lane and traffic sign detection. Since the models are being deployed in a virtual environment, there are certain assumptions and constraints that need to be considered.

### *A. Lane Detection*

Lane Detection is the process of obtaining a prerequisite needed to classify the pixels into classes for prior detection of path and planning the movement and control of the autonomous vehicles ahead of time. The implementation of lane detection is inspected in the CARLA environment. Fig. 1 shows the pipeline of the proposed implementation. This system is trained to detect lanes for vehicles to advance on the road.

The CARLA environment is spawned with various actors and pedestrians. The model is then modified and trained using a variant of CNN called SegNet.

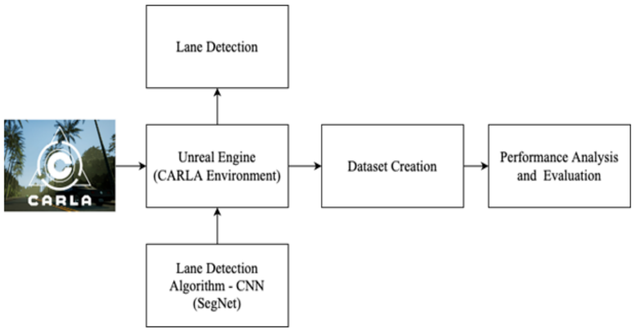


Figure 1. Block diagram of Lane Detection

Lane detection (LD) algorithm performs semantic segmentation on the video dataset of CARLA to determine the lanes. Once the lane is determined it is divided into three planes: center plane, left plane and right plane. These planes enable the vehicle to move in the required path and stay in the lane precisely. As a next step a dataset of total 864 images are created and detailed analysis is performed to obtain the results for evaluation. Fig 2. depicts the flow of lane detection algorithm.

Initially the CARLA simulator is set up to begin. The CARLA module is then imported, and all other various modules required are also imported. Then a virtual world is built and various manual controls to operate the vehicle are provided using the keyboard. Further numerous sensors such as collision sensor, GNSS sensor, lane invasion sensor, camera manager and many other sensors are defined. The heads-up-display (HUD) is a module which displays vital information regarding the collision history, speed, brake, location and other parameters with respect to the vehicle. Subsequently, the lane painting takes place indicating as left lane (turn left) if its lane center is in range (0-318) or right lane (turn right) if its range is in (318-322) or center if it is (greater than 322). Thus, the

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vehicle can move ahead in accordance with the predicted lane. In this way the game loop occurs and finally it can be terminated.

*B. Traffic Sign Detection*

Traffic Sign detection (TSD) is an ADAS technology which enables the recognition of traffic signs present on road. The pipeline of the implementation is illustrated in Fig.3 and the key agents that take part in it: the Speed Traffic Sign Detection Module (YOLO), RGB sensor, Tesseract OCR and the Carla Simulator. Open-source optical character recognition software called Tesseract makes it easier to extract text from photos.

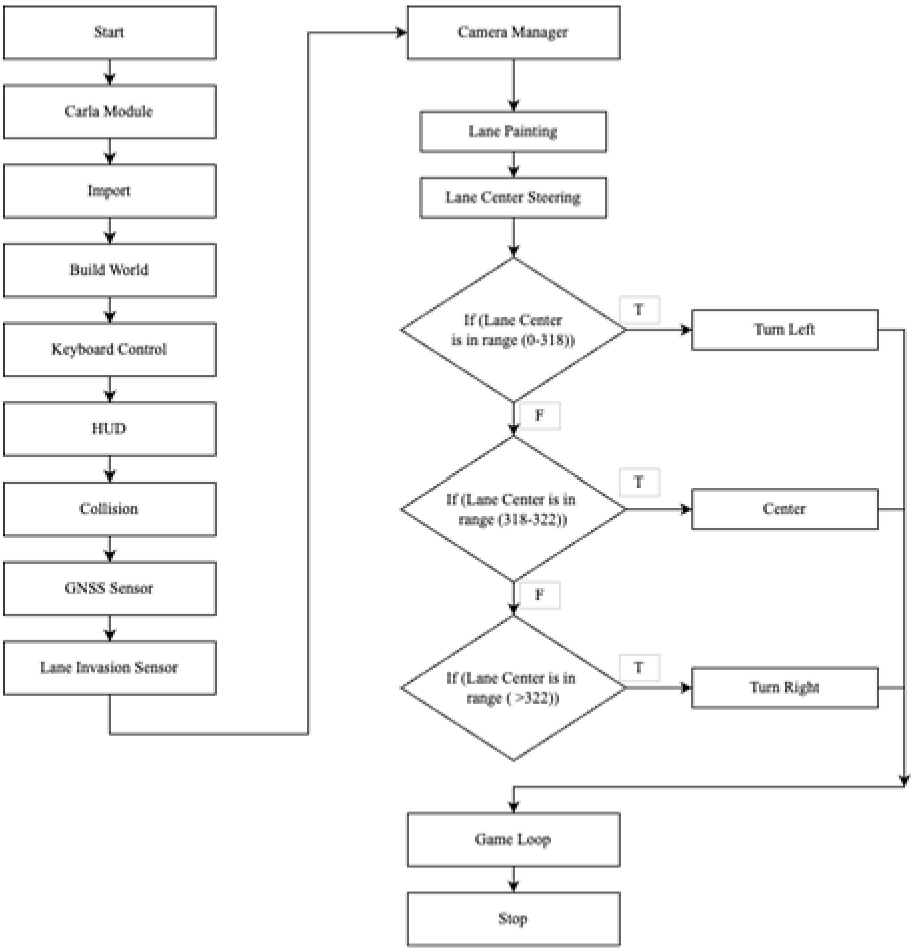


Figure 2. Flowchart of Lane Detection

The system involves two main steps: detection and recognition. In the detection phase the structure of the scene in Carla environment is explored using RGB camera mounted on the dashboard of the car. The YOLO detection module determines the size and location of the frame and examines the regions in the scene to detect the road signs.

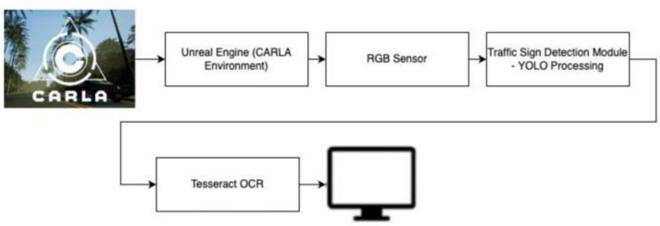


Figure 3. Block Diagram of Traffic Sign Detection

Once the scene's vanishing point (VP) and consequently the ground plane are identified, these regions are defined. Then,

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only within these scene search regions are candidate locations for road signs determined by integrating MSERs with threshold, saturation, and hue colour values (HSV). Based on the movement of these regions in connection to the camera and the scene structure, time information is combined with these regions over subsequent frames to further reduce the detected zones.

### *C. Assumptions and Constraints*

The models were provided with a video dataset of CARLA simulator to run. In order to perform analysis of the lane detection model a dataset containing a total of 864 images of 1920 x 1080 pixels were created and extracted at different instances. These images were manually captured in various towns ranging from town 1 to town 5, multiple weather conditions, by spawning several vehicles and pedestrians, different traffic conditions with some of the images containing heavy traffic flow and others containing vacant streets. Some images were captured through manual control of the Carla vehicle and others were captured through the autopilot mode available in Carla simulator. All the images were captured during multiple sessions.

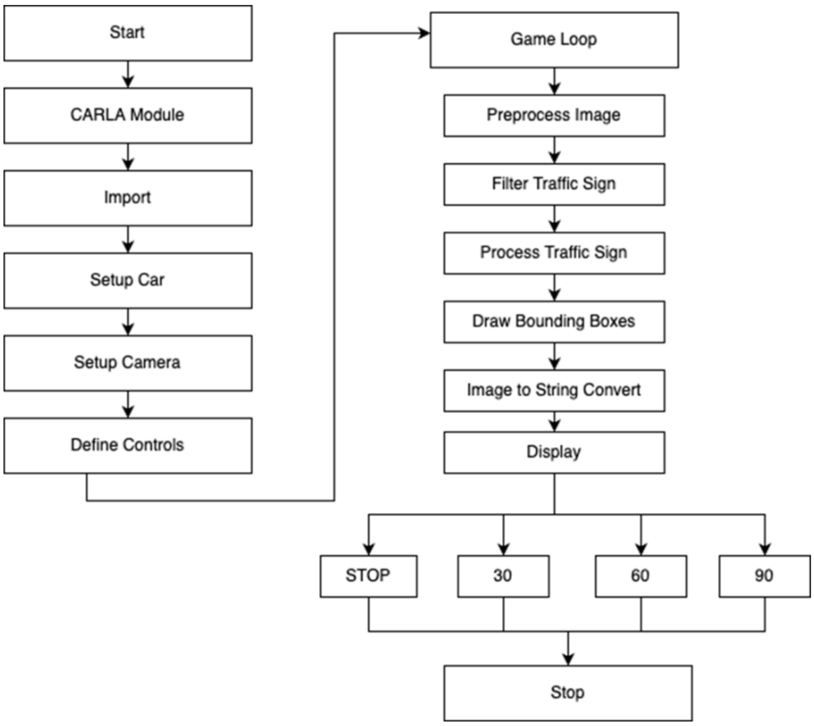



Figure 4. Flowchart of Traffic Sign Detection

The TSD model was executed in towns containing abundant traffic signs. Next, to perform analysis of the model a dataset containing total of 612 images of 1920 x 1080 pixels were created and extracted from the simulator while driving in varied weather conditions, towns, with pedestrians and other vehicles and with vacant streets. It was observed that towns 1, 3 and 5 consisted of a greater number of signs and hence the images for the dataset were extracted from the same. Three classes of traffic signs were identified for the purpose of object detection. The classes are Speed Limit 30 km/hr, 60 km/hr and 90 km/hr. These images were further compared and analyzed to determine the model’s performance.

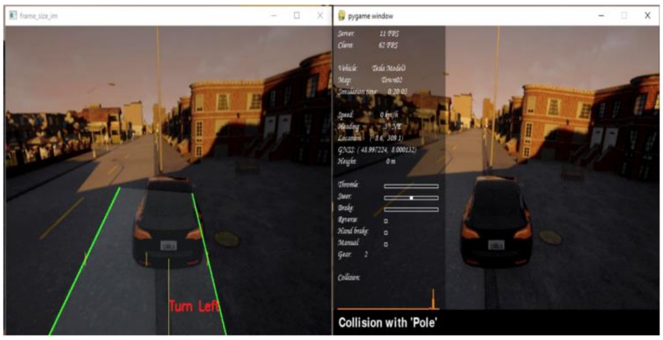
The LD and TSD models were performed under certain predefined constraints and assumptions in the CARLA environment. For Lane Detection, the weather conditions considered were - Cloudy Noon, Cloudy Sunset, Hard Rain Noon, Mid Rain Sunset, and Wet Cloudy Sunset. These weathers were configured in 4 different Urban Towns namely - Town 01, Town 02, Town 03, Town 04. The vehicle used to navigate the environment is Tesla Model 3. For the purpose of detection, various sensors – Collison, Lane Invasion, GNSS and Camera sensors – were utilized. In CARLA, actors refer to the pedestrians and vehicles present on the streets. For the application of lane detection, about 40 to 80 pedestrians and 60-100 vehicles were spawned. It was also carried out in empty streets with no pedestrians. For Traffic Sign Detection, the classes considered are Speed limit (30km/hr), Speed limit (60km/hr), Speed limit (90km/hr). Here, only 3 towns are considered as they have a greater number of traffic signs namely - Town 01, Town 03, and Town 05. The weather conditions here range from Sunny Noon to Heavy Rainfall Sunset.

## IV. RESULTS AND DISCUSSION

For autonomous vehicles, obtaining the highest levels of accuracy and precision is of utmost importance, since the smallest mistakes could result in unfavorable and catastrophic circumstances. Hence, a detailed analysis was performed to validate the models being implemented. This was done by splitting the created datasets into training and testing data.

### *A. Lane Detection Results*

Initially, when the car tends to deviate from its appropriate path and traverses along the footpath which may result in a collision with a pole, the lane detection algorithm deployed shows a sliding window which pulls each lane from the binary segmentation map after it has been processed to split the lanes, creating the lane instance segmentation image as shown in Fig. 5.





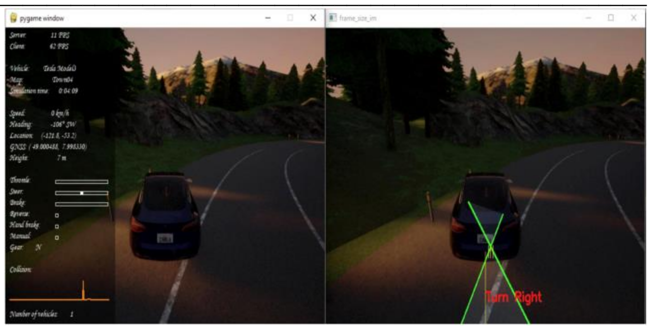



Figure 5. Lane detection for Left, Right and Centre lanes respectively.

The lanes are binary segmented using an encoder-decoder deep learning architecture. Hence the detected lane is shown on the other screen with an indication to turn left for the car in order to avoid collision with the pole. This result not only shows the lane of the CARLA simulator detected but also a warning with a statement about what to do next for collision avoidance. On the dataset captured, this strategy was validated, and it produced results that were competitive. The results were compared for several scenarios in which the vehicle was deliberately driven into barriers to see how accurately the lane detection algorithm would identify and suggest a left turn as seen in Fig.5. Similarly, if the car deviates from the right lane or the center lane the algorithm displays the required path to be traversed by the car along with direction. In this way the car is assisted and monitored to traverse along the correct lane and avoids any collisions with pole, other vehicles or pedestrians.

### *B. Traffic Sign Detection Results*

The YOLO model employed is able to recognize the 90 km/hour traffic sign as seen in Fig. 6, which is a significant advantage for autonomous driving vehicles since the speed detected on the traffic signs will allow the car to either slow down or speed up depending on the number and ensure a safe driving. Based on a regression system that gives classes and bounding boxes for photos of traffic lights, traffic signs, cars, people, and objects at speed during the execution of the algorithm, the YOLO model is capable of detecting items in real time. The CARLA vehicle was equipped with an RGB camera sensor, which collected environmental data in each frame and prepared them for analysis by the trained model. Following the creation of the trained model, every vehicle navigating the lanes of the CARLA Environment is capable of recognizing traffic signs for the specific range of speeds.

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Figure 6. Traffic sign detection for speed limit of 90km/hr, 60km/hr and 30km/hr

The speed ranges include 30 km/h, 60 km/h and 90 km/h, and is separated into three categories here for the regression model's intended identification. The recognized texts of different speed limits are displayed on the bottom left corner of the monitor as shown in Fig. 6.

### *C. Performance Evaluation*

The performance of the algorithms in the CARLA environment is analyzed using various performance metrics. These include Accuracy (ACC), Error Rate (ERR), Precision (PRE), Recall (REC), F-Score (F1), True Positive Rate (TPR) and True Negative Rate (TNR). The semantic segmentation model developed for lane detection using SegNet gives a mean average precision (mAP) of 93.33%, an overall accuracy of 94.80%, F-score of 93.49% and a minimal error rate of 5.20%. It was also observed that class Right yielded the maximum Recall, F-score, Precision and lowest FPR.

Model developed for TSD, a mean average precision of 93.67%, an accuracy of 95.56%, recall of 92.67%, F-score of 93.16% and error rate of 4.44% have been attained. Speed limit Class 30 achieved the highest level of accuracy at 97.66% with least percentage of false positives. Table 1 shows the performance of each test class and along with the average values in terms of percentage. Table 2 shows the performance comparison of proposed implementation with different existing models for both the applications.

With reference to lane detection, there is a significant improvement in performance of precision and recall by 3.26% and 2.10% respectively [29]. Comparative models were tested on DeepScene dataset whereas designed system was deployed on the created CARLA dataset. For Traffic sign detection, the proposed YOLO architecture outperforms SegU-Net, R-FCN and faster R-CNN by a large margin [30] as observed in Table 2. Another point to notice is that the compared models do not detect the individual speed limit sign values. An additional step of recognition is performed by the proposed model to detect the text which is an added advantage of the model developed over the existing methods.

TABLE I. PERFORMANCE OF LANE DETECTION AND TRAFFIC SIGN DETECTION

| **Application** | **Class** | **ACC** | **ERR** | **PRE** | **REC** | **F1** | **TPR** | **TNR** |
|---|---|---|---|---|---|---|---|---|
| Lane Detection | Left | 95.63 | 4.47 | 96.00 | 96.00 | 96.00 | 88.83 | 96.45 |
| | Center | 94.07 | 5.93 | 89.00 | 88.00 | 88.49 | 83.67 | 77.21 |
| | Right | 94.70 | 5.30 | 95.00 | 97.00 | 95.98 | 97.21 | 96.72 |
| | **Overall** | **94.80** | **5.20** | **93.33** | **93.67** | **93.49** | **89.90** | **90.13** |
| Traffic Sign | 90 kmph | 94.92 | 5.08 | 97.00 | 89.00 | 93.00 | 96.55 | 89.36 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Detection | 60 kmph | 94.10 | 5.90 | 89.00 | 93.00 | 91.00 | 89.28 | 92.59 |
| | 30 kmph | 97.66 | 2.34 | 95.00 | 96.00 | 95.49 | 92.20 | 96.00 |
| | **Overall** | **95.56** | **4.44** | **93.67** | **92.67** | **93.16** | **92.68** | **92.65** |

TABLE II. COMPARISON OF PERFORMANCE OF LANE DETECTION AND TRAFFIC SIGN DETECTION WITH EXISTING MODELS

| Application | Model | PRE | REC |
|---|---|---|---|
| Lane Detection [29] | FCN | 87.38 | 85.97 |
| | ParseNet | 90.07 | 91.57 |
| | $\text{Ours}_A^{D40}$ | 88.12 | 89.52 |
| | **Proposed Model - SegNet** | **93.33** | **93.67** |
| Traffic Sign Detection [30] | R-FCN | 53.31 | 44.48 |
| | Faster R-CNN | 58.17 | 46.03 |
| | SegU-Net | 91.13 | 70.71 |
| | **Proposed Model - YOLO** | **93.67** | **92.67** |

## V. CONCLUSION

Robust detection of lanes and traffic signs using DL techniques have proven to exhibit favorable results. Considering this, semantic segmentation and object detection models were implemented in CARLA's Unreal environment to recognize lanes and traffic signs. SegNet and YOLO architectures, respectively, were successfully used to create these applications for autonomous vehicles. Two distinct datasets were produced and analyzed in order to evaluate these models. The results of lane detection obtained an overall accuracy of 94.80% and mAP of 93.33%, along with performance measures like recall, F-score and error rate. The object detection model recognizes 3 classes of traffic signs and obtained a mAP of 93.67% and an accuracy of 95.56%. These promising results strengthen the idea that the proposed models and algorithms can be successfully utilized to keep up with the increasing demand for accurate algorithms in the field of autonomous vehicles.

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