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Optimizing Semantic Segmentation for Autonomous Vehicle Scene Understanding in Unstructured Indian Traffic through Reinforced Active Learning

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Abstract: Autonomous vehicles (AVs) offer a radical leap in transportation, delivering safer and more efficient mobility options. The capacity to interpret complicated surrounding traffic scenarios in real-time is central to their effectiveness. Scene awareness, especially semantic segmentation, is vital in allowing AVs to successfully comprehend and navigate their environments. However, limited labelled data availability and dataset biases restrict the effectiveness of semantic segmentation models, especially in specific contexts such as Indian driving scenarios. This study presents a novel approach employing reinforced active learning to overcome the aforementioned difficulties. Reinforced active learning integrates reinforcement learning into the active learning framework, allowing the model to select samples for annotation based on model operations and uncertainty estimation. By augmenting the segmentation model with annotation effort, our approach enhances performance in real-world driving scenarios in India. Rigorous testing and validation on the Indian Driving Dataset (IDD) demonstrate improvements in segmentation precision and effectiveness compared to training methods. Reinforcement Active Learning (RAL) using Inception-Unet outperforms Inception-Unet models trained solely on labeled data (DL), achieving a score of 0.615. However, it falls slightly behind the performance of Inception-Unet models trained on fully labeled datasets (DF). Our findings indicate that reinforced learning excels over strategies in selecting samples and substantially boosts segmentation accuracy.

Keywords: Autonomous vehicle, semantic segmentation U-Net, Inception-U-Net, Deep Q learning, Reinforced Active Learning.

1. Introduction

Autonomous vehicles (AVs) have the potential to revolutionize transportation by offering more mobility alternatives, with regard to of efficiency, safety, and comfort [1]. To operate efficiently in real-world environments, AVs must understand complex situations, recognize changing surroundings, and make accurate decisions in real time [2]. AVs depend mostly on visual perception to comprehend and navigate their environment. This encompasses tasks such as identifying objects, semantic segmentation, and estimation of motion [3].

Recent developments in sensor technology, computer vision, and machine learning have significantly enhanced AVs perception of their surroundings. Recent developments in this field opened the path for advanced perceptual systems that can extract important semantic information from sensor data. As a result, autonomous vehicles have a cutting-edge over human drivers in recognizing and comprehending their surroundings [4]. Semantic segmentation plays an essential role in visual perception systems because it allows autonomous vehicles to build a full and interpretable image of their environment from incomplete sensor input [5]. Segmenting an image semantically involves recognizing each pixel. Semantic segmentation is essential for autonomous navigation because it allows visual analysis, object recognition, and avoidance of obstacles. Deep learning technologies, especially convolutional neural networks (CNN), have substantially enhanced semantic segmentation, enabling autonomous vehicles (AVs) to attain new levels of environmental monitoring and awareness of situations [4].

Semantic segmentation models have proven beneficial for a variety of applications [6]; however, they face significant obstacles because of their need on large labeled data sets [7], especially in fields such as driving in India. The Indian Driving Dataset (IDD) is a valuable resource because it incorporates vehicle characteristics unique to India, such as different road arrangements, regional environmental conditions, and driving habits [8]. The IDD, like most real-world data sets, is vulnerable to specific issues such as misunderstandings, class imbalance, and fluctuations in light and weather, all of which can introduce biases and impair model performance. Moreover, manually annotating data is challenging and time-consuming, especially when working at the pixel level, where topic expertise and careful attention to detail are necessary [9].

One feasible solution to these constraints is to increase active learning at the machine learning and data annotation interfaces. In comparison to human annotation, active learning algorithms provide a new and successful method of identifying significant instances from large amounts of unlabeled data, reducing time and money [10]. When reinforcement learning approaches are employed combined with an active learning framework, decision-making becomes more flexible and dynamic [11]. This allows the model to continually modify its decision-making process based on its evaluation of success and uncertainty [12].

While active learning algorithms attempt to identify the most illuminating instances to analyze, passive learning models are often trained using randomly selected data. Active learning approaches are useful for situations with low label data availability, such as driving conditions in India, because they frequently boost model performance while demanding less annotation work [13]. This proactive technique improves learning by reducing the amount of annotation work required, enabling the model to focus on annotating the most difficult and significant data points.

Active reinforcement learning improves the iterative method by adapting data selection strategies based on model effectiveness and uncertainty [14]. Reinforcement-active learning systems continuously evolve and improve through feedback mechanisms in the annotation process, as well as the discovery and selection of instances that enhance the accuracy and generalization of the segmentation model. The model performs better in particular scenarios, such as Indian driving conditions, and is capable of handling the complexity of real-world datasets like IDD due to this iterative improvement method [15].

The following are the main contributions of this work:

We introduce a reinforcement learning-driven active learning strategy tailored for semantic segmentation of complex, unstructured traffic imagery to enhance scene interpretation.

Our framework leverages a Deep Q-Network (DQN) with experience replay, serving as a query mechanism to identify and select the most informative subset of samples from a large pool of unlabeled data.

Experimental findings, both qualitative and quantitative, demonstrate that integrating reinforcement-based active learning with the Inception-U-Net backbone surpasses existing state-of-the-art approaches. In this setup, the Inception-U-Net enhances traditional U-Net by replacing standard convolutional layers with inception modules, enabling the model to extract features at multiple scales through parallel convolutions within each inception block.

This research presents a novel framework for semantic segmentation on IDD using reinforced active learning, aiming to optimize the utilization of existing labelled data while actively selecting samples for annotation. By leveraging the strengths of reinforced active learning, our approach enhances the model's performance in Indian driving scenarios, demonstrating improvements in segmentation accuracy and efficiency compared to traditional training methods. Through extensive experimentation and validation on the IDD benchmark dataset, our method showcases the efficacy of reinforced active learning in addressing the challenges of semantic segmentation in specialized domains, paving the way for more robust and efficient autonomous driving systems.

The rest of the research paper is organized as follows. Section 2 delves into related work in autonomous vehicles and semantic segmentation. Section 3 presents the proposed architecture along with the associated algorithms. The dataset and experimental setup are described in Section 4. The results of the proposed models are presented in Section 5. Section 6 discusses the results; furthermore, section 7 gives a conclusion and future directions.

2. Literature Review

Scene awareness is critical for understanding the behavior of surrounding cars and people to navigate intelligently and safely. Image segmentation is critical in interpreting the scene and its surroundings [16]. Semantic segmentation for scene interpretation is a pre-or post-processing step in many computer vision applications. Handcrafted and graphical models served as the foundation for traditional semantic segmentation approaches. However, the area has changed with the development of deep learning and convolutional neural networks (CNNs), which now allow for end-to-end learning of representations from raw pixels [17]. Initial deep learning-based semantic segmentation models, such as Long et al.'s Fully Convolutional Networks (FCNs) [18], paved the way for further advancements. U-Net [19, 20], SegNet [20], and Deeplab [21] are three systems that have shown very successful in semantic segmentation tasks across different domains. The U-Net architecture, originally presented by Ronneberger et al. in 2015 [22], has proven highly effective for tasks involving biomedical image segmentation. Its design follows an encoder-decoder structure enhanced by skip connections, which help retain spatial information. In a more recent development, Lee et al. (2023) introduced DSUnet, a streamlined variant of U-Net tailored for applications like lane detection and path prediction in autonomous vehicles. DSUnet achieves greater efficiency by incorporating depth-wise separable convolutions [23].

Active learning systems aim to choose the most informative examples for annotation, enhancing learning efficiency while requiring the least labelling effort. Pool-based techniques, such as uncertainty sampling, choose samples based on the current model's predicted uncertainty. Diversity-based techniques choose samples from different portions of the data distribution. Other options include query-by-committee, anticipated model change, and density-weighted uncertainty sampling. Active learning has been used in various fields, including image classification, object identification, and natural language processing [24]. Reinforced active learning combines features of Reinforcement and active learning to dynamically change the data selection strategy in response to model performance and uncertainty. Reinforcement learning agents learn to interact with their environment (in this case, the dataset) by doing actions (such as picking samples for annotation) that maximize a cumulative reward (better model performance). Recent research has examined using reinforced active learning in several tasks, including image classification, object recognition, and semantic segmentation [25].

Some studies combine active learning techniques with semantic segmentation tasks. In order to enhance semantic segmentation, Qiao et al. [26] developed an active learning model based on reinforcement learning. This model trains the agent to selectively annotate appropriate regions of images. Similarly, Liu et al. [27] presented a reinforcement learning-led active learning method for medical image segmentation, which obtained high segmentation accuracy while having low annotation costs.

Driving in India can be difficult due to the nation's diverse road conditions, inconsistent traffic patterns, and inadequate infrastructure. Because of this, there has been a significant increase in efforts to create useful algorithms for semantic segmentation in all of these fields. In order to improve vehicle awareness and environmental information, multiple studies have focused on semantic segmentation in driving contexts. Full Convolutional Networks (FCN), U-Net, and DeepLab have been chosen as deep learning models for this research [28]. Long et al. [18] demonstrated with data synthesis, how to train an ANN end-to-end for handling semantic segmentation of urban driving scenarios in real-time, with notable outcomes in various cases. The need for methods of active learning has been investigated to reduce the amount of annotation labor necessary to train semantic segmentation models. Uncertain sampling, diversity-based sampling, and committee-based questioning are the three primary methods utilized here. These methods attempt to identify the most valuable regions or trends for annotation in semantic segmentation, resulting to higher performance of models with fewer annotated instances [29]. It was demonstrated that an uncertainty-based active learning system for semantic segmentation may successfully lower annotation costs without sacrificing segmentation accuracy. Annotation efforts can be sped up, and model performance can be improved with limited resources by combining semantic segmentation to drive scenarios with reinforcement learning approaches [30]. However, few studies have been done on this problem, mainly using datasets like the IDD.

Nonetheless, research in related areas has yielded promising results. Despite substantial advances in semantic segmentation within driving circumstances and active learning methodologies, coupling reinforced active learning with semantic segmentation still needs to be explored, especially in datasets such as IDD. Our research intends to close this gap by introducing a unique framework for semantic segmentation in Indian driving terrain, which combines reinforced active learning approaches to expedite annotation efforts and increase segmentation model performance.

3. Proposed Reinforced Active Learning with Inception-Unet as Baseline model

Reinforcement Learning (RL) and Active Learning (AL) are unique approaches that achieve different objectives [31]. RL frequently educates agents on interacting with their surroundings to maximize cumulative rewards. In contrast, AL is used in supervised learning contexts to choose which data points to label to improve model performance. However, it is possible to combine elements of both to develop novel approaches, such as Reinforced Active Learning.

3.1. Reinforced Active Learning for Semantic Segmentation

Reinforced Active Learning (RAL) is a framework that combines RL and AL techniques to select the most valuable data samples for labelling, reducing the labelling effort required to train a model while maintaining or even improving performance [32].

Deep Q-learning (Deep Q) is a popular RL technique for learning to make sequential decisions, typically in discrete action space. It is based on the Q-learning technique [33]. However, it uses deep neural networks to approximate the Q-function, representing the expected cumulative reward for carrying out a specific action in a particular state. Fig. 1 illustrates the detailed architecture of reinforcement active learning.

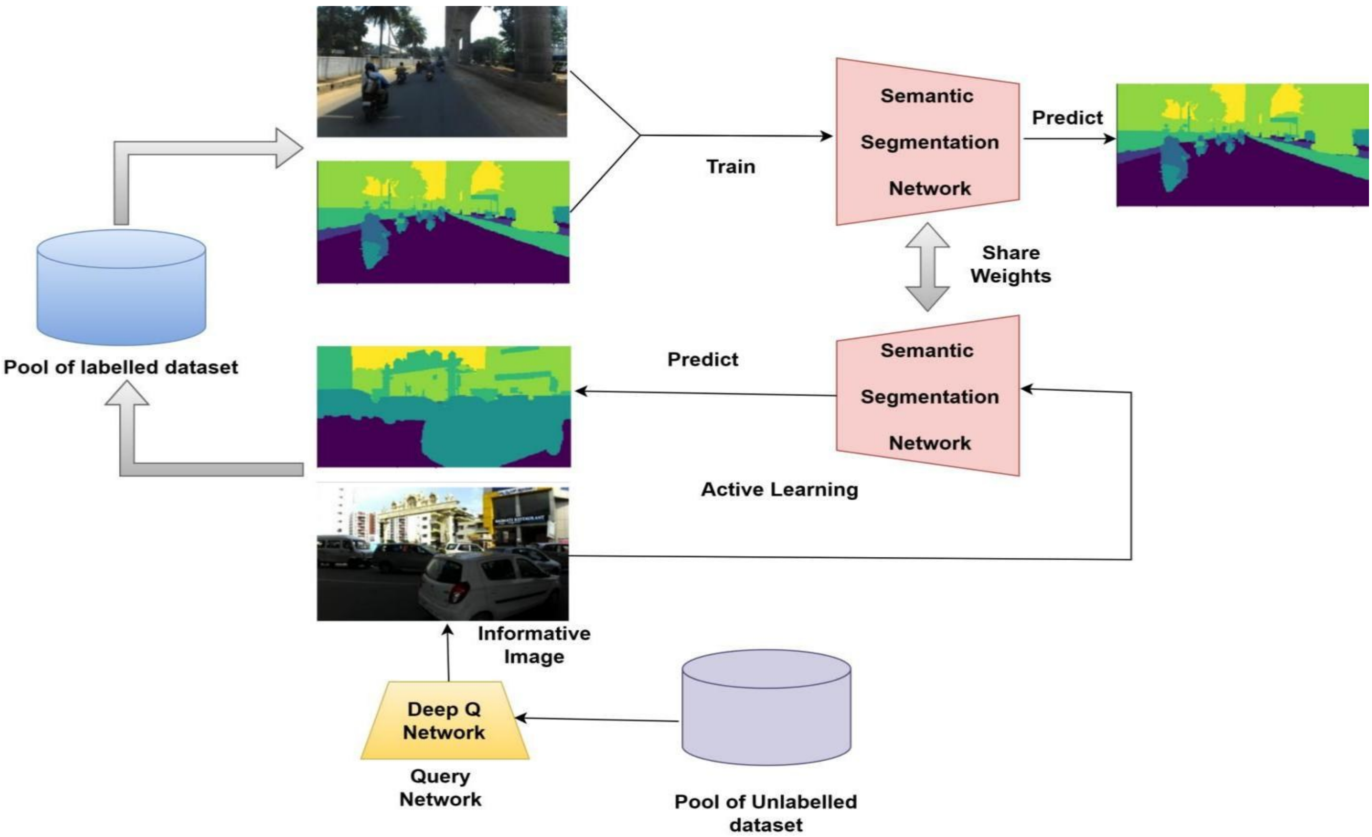

Fig. 1. Detailed architecture of reinforced active learning

The detailed architecture of RAL with Deep Q as the query network is as follows:

Semantic Segmentation Network: In our research, we employ the Inception-U-Net model as the foundation for semantic segmentation tasks on a curated set of labelled datasets within the RAL framework. This model merges two advanced deep learning architectures: Google's Inception network and the U-Net design. Specifically, the traditional convolutional layers in U-Net are replaced with Inception modules from GoogLeNet, enhancing feature extraction. The model retains the U-Net's characteristic encoder-decoder structure, including a central bottleneck, to efficiently capture and reconstruct spatial information.

State Representation: In RAL, the state representation includes vital information about the semantic model's current status alongside unlabeled data. This includes attributes from the model's parameters or representations of uncertainty linked to each unlabeled data point.

Action Space: It defines the set of actions the

RAL agent can carry out. In this context, activities represent a collection of data points to be examined for labelling from an unlabeled dataset. These acts serve as indices for unlabeled data points.

Reward Function: It assesses the goodness of an agent's actions. It indicates the usefulness of the labelled data points obtained by searching a specific data point.

Query Network: The Query Network is a critical component of our active learning framework. It is designed as a convolutional neural network (CNN) capable of processing image data efficiently.

The architecture consists of several layers:

Input Layer: The input layer receives the state representation of the data.

Convolutional layers: These layers extract features from the input image using convolutional filters.

Pooling layers: Pooling operations down sample the feature maps, reducing the spatial dimensions.

Flatten layer: This layer flattens the output from the convolutional layers into a vector format.

Dense layers: Fully connected layers process the flattened features to make the final decision.

The network outputs a binary decision indicating whether to query the label for an unlabeled image or to save it for future exploration.

Epsilon-Greedy Action Selection: To balance exploration and exploitation, we employ an epsilon-greedy strategy for action selection. At each step of the training process, the Query Network decides whether to query the label for an unlabeled image or to save it for future exploration. Probability epsilon selects a random action, allowing exploration of the unlabeled dataset. Otherwise, the action that maximizes the Q-value predicted by the Query Network is chosen, promoting the exploitation of already learned information.

Training and Experience Replay: RAL model trained in two steps namely, training the base segmentation model and training query network.

Training the Base Segmentation Model: The base segmentation model is trained on the labelled dataset during each iteration of the leading training loop. This involves optimizing the model's parameters to minimize a predefined loss function between the predicted segmentation masks and the ground truth labels.

Training the Query Network: Simultaneously, the Query Network is trained to learn a querying policy that determines whether to query the label for an unlabeled image or to save it for future exploration. During interaction with the environment (unlabeled dataset), the Query Network predicts actions based on the current state (image) and updates its parameters to improve decision-making. The training objective for the Query Network is typically formulated as a reinforcement learning problem, aiming to maximize a cumulative reward signal over time. In our case, the reward signal could encourage the Query Network to select informative samples for labelling while minimizing labelling efforts.

Experience Replay: Experience replay is commonly used in reinforcement learning to improve sample efficiency and stabilize training. During exploration, samples (states) that are not immediately labelled are stored in a replay memory. Periodically, a batch of samples is randomly sampled from the replay memory to train the Query Network. By replaying past experiences, the Query Network can learn from diverse states and actions, leading to more robust and efficient decision-making.

Updating the Models: Both the base segmentation model and the Query Network are updated iteratively throughout the training process. The base model is updated to improve segmentation performance on the labelled dataset, while the Query Network is updated to learn an effective querying policy for active learning.

Balancing Exploration and Exploitation: Throughout the training, the exploration rate (epsilon) is gradually annealed to balance exploration and exploitation. Initially set to a high value, epsilon encourages exploration by selecting actions randomly. Over time, epsilon decays to a minimum value, promoting exploiting the learned knowledge.

The proposed Reinforced Active Learning (RAL) framework combines Deep Q-learning with active learning to boost semantic segmentation in data-starved environments. Unlike traditional approaches that rely on static uncertainty-based selection, RAL uses a dynamic, reward driven querying policy to select the most informative samples to label. This reduces annotation cost while maintaining high segmentation accuracy. Designed specifically for unstructured Indian traffic, the model is trained on the IDD-Lite dataset which mimics the diverse and chaotic nature of Indian roads. RAL is well suited for such environments where traffic is non-lane disciplined and highly variable. Also, the Inception-U-Net backbone captures multi-scale contextual information so the model can handle scenes with occlusions, mixed traffic and poor infrastructure. This targeted design ensures better generalization and robustness in real world driving scenarios found in developing countries. Together these innovations make RAL a scalable and context aware solution for semantic segmentation in unstructured traffic.

4. Experimental Setup

This section discusses the dataset utilized, model training parameters, and hyperparameters used. The performance measures used to compare the proposed model's performance against state-of-the-art (SOTA) models are discussed in detail in section 4.3.

4.1. Dataset

In our study, we meticulously evaluated the performance of the proposed architecture using IDD Lite [34], a downscaled variant of the IDD explicitly tailored to facilitate efficient computational processing in resource-limited environments. The significance of utilizing IDD Lite lies in its focused representation of unstructured driving conditions, a critical aspect, especially in countries like India, which are characterized by diverse and challenging road environments. IDD Lite gained widespread recognition when it was featured in an online semantic segmentation competition held in December 2019, coinciding with the 7th National Conference on Computer Vision, Pattern Recognition, Image Processing, and Graphics (NCVPRIPG).

Fig. 2. Original Images with ground truth

The dataset depicts frequent obstacles in irregular traffic scenarios, such as difficult-to-cross muddy terrain and obscured road borders. IDD Lite is home to many cars and people who are carelessly placed and violate traffic restrictions. The dataset, which includes 1404 training shots and 204 validation images, correctly simulates driving scenarios in India, replete with complicated barriers, hazy road markings, a diversity of cars and pedestrians, shifting lighting, and disregard for traffic rules. Its semantic segmentation consists of seven categories: driving region, live beings, non-driving area, roadside objects, autos, sky, and distant objects.

To facilitate the implementation of reinforced active learning, we partitioned the IDD Lite training dataset (DF) into two distinct subsets: a labelled dataset pool (DL) and an unlabeled dataset pool (DU). The DL subset, which constitutes 80% of the DF, comprises annotated images used for model training. In contrast, the DU subset, comprising the remaining 20% of the DF, consists of unlabeled images awaiting annotation. This partitioning strategy balances leveraging existing labelled data and maximizing the potential for active learning-based annotation strategies to improve model performance. Fig. 2 depicts examples of unstructured traffic situations and the multi-label segmentation ground truth for these images.

4.2. Model Training

The proposed model was trained on 1120 labelled data, and 280 unlabeled samples and tested on 204 samples. The Adam optimizer [35] was then utilized to improve the categorical cross-entropy loss functions. We used the ReLu activation function [36] except after the final convolutional layer to avoid the vanishing gradient problem. After the final convolutional layer, the SoftMax activation function is used to provide pixel-level categorization.

4.3. Performance metrics

Mean intersection over union (mIoU), accuracy, sensitivity, specificity and F-score are the performance metrics used to evaluate the performance of multi-label semantic segmentation models [37]. All performance metrics are listed below.

$$\text{Accuracy}=\frac{(TP+TN)}{(TP+FP+FN+TN)} \quad (1)$$

$$\text{Sensitivity}=\frac{TP}{(FN+TP)} \quad (2)$$

$$\text{Specificity}=\frac{TN}{(TN+FP)} \quad (3)$$

$$\text{F-Score}=\frac{2\times TN}{(2\times TN+FP+FN)} \quad (4)$$

$$\text{IoU Score}=\frac{\text{Area of overlap}}{\text{area of union}} \quad (5)$$

The intersection over the Union (IoU) metric is widely used to evaluate the performance of semantic segmentation models [38]. Accuracy, sensitivity, specificity and F-Score are the performance metrics mainly used for classification problems. As semantic segmentation is achieved using pixel-level classification, this performance metric also helps to evaluate the proposed model's performance accurately.

5. Results

The proposed RAL method utilizes baseline models, Inception-Unet, to carry out multi-label semantic segmentation from single images of unstructured roadways. The method contains two crucial steps:

Training of baseline models: In the beginning, the proposed baseline models are trained employing the whole training dataset (DF) and a subset of the training dataset's labeled samples (DL). This stage attempts to provide an elementary understanding about the semantic segmentation challenges by using data that is both labeled and unlabeled.

RAL Training: The learnt baseline models are subsequently used with a pool of labeled and unlabeled data to perform reinforced active learning (DL/DU). This method continually picks suitable samples for annotating based on the model's predictions and uncertainty estimations, continually improving model performance and reducing annotation costs.

Table 1. Performance of proposed models on IDD-Lite dataset

Model	Training Dataset	Mean IoU	Accuracy	Sensitivity	Specificity	F-Score
Inception-Unet	DL	0.609	0.957	0.705	0.974	0.726
RAL with Inception-Unet	DL+DU	0.615	0.958	0.708	0.974	0.732
Inception-Unet	DF	0.622	0.958	0.728	0.975	0.740

Table 2. Performance evaluation of state-of-the-art-models (SOTA) on IDD-Lite validation dataset

Model	Proposed Model	U-net [34]	DRN ResNet18 [38]	E-Net [34]	ERF-Net [38]
Mean IoU	0.615	0.603	0.598	0.566	0.554

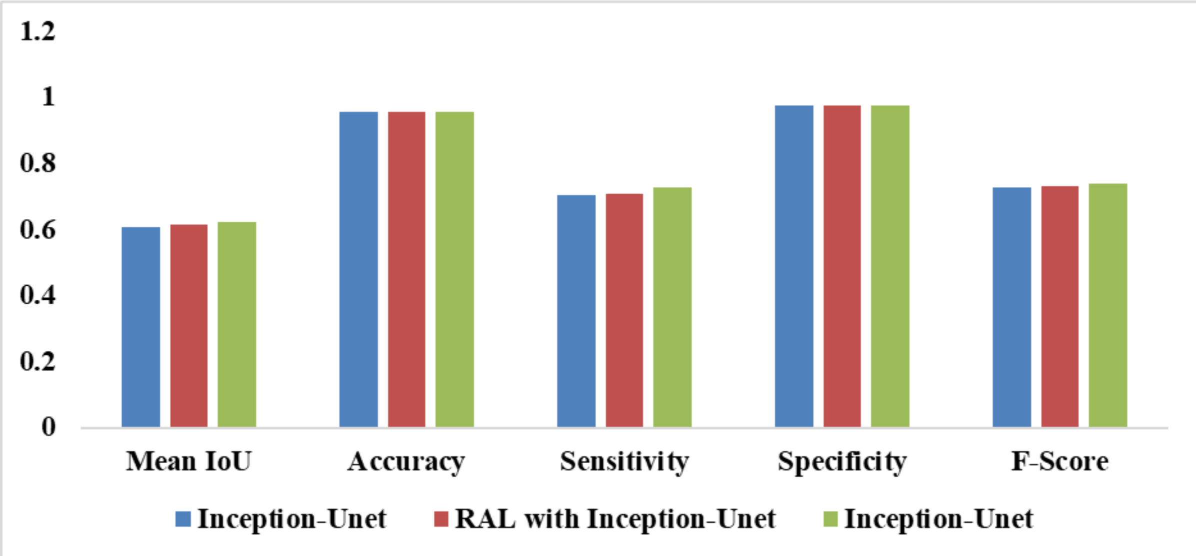

Fig 3. Illustrates the comparative segmentation results of multi-label semantic segmentation using RAL with the Inception-Unet model

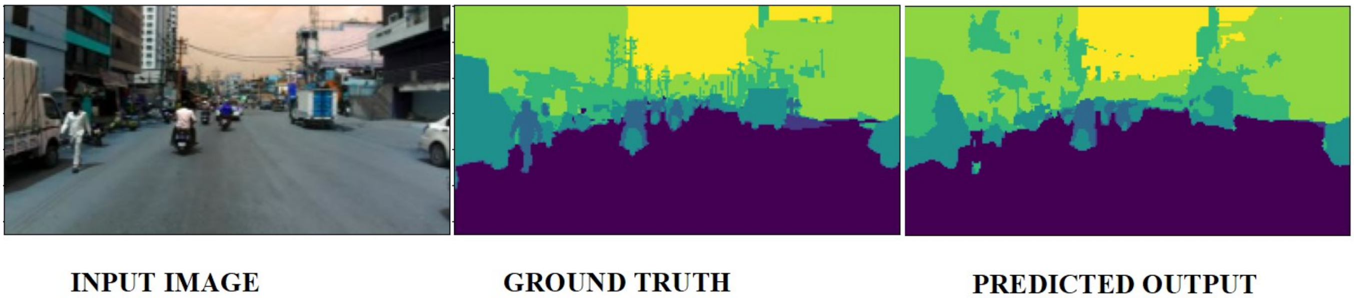

Fig 4. Segmentation result of multi-label semantic segmentation using RAL with Inception-Unet model

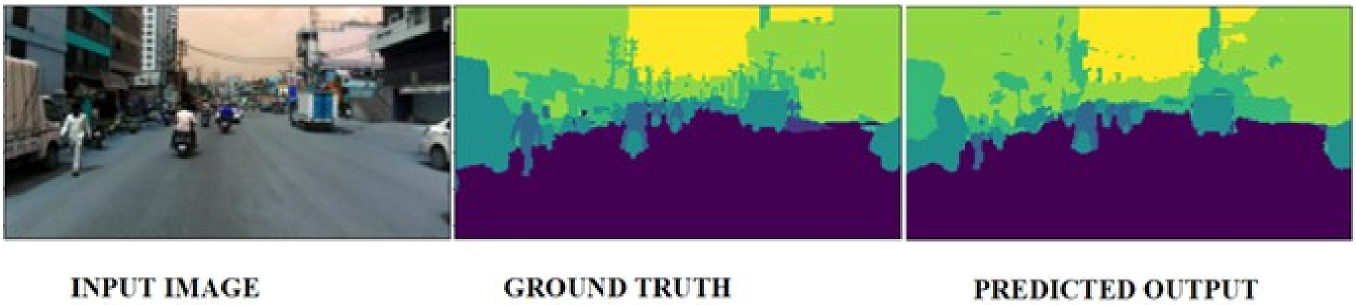

Fig 5. Segmentation result of multi-label semantic segmentation using Inception-Unet model on full dataset

To evaluate the effectiveness of RAL models vs baseline models, we utilized the intersection over union (IoU), accuracy, specificity, sensitivity, and F-score measures. Table 1 and 2 compares the performance of RAL models with the baseline models as well as state-of-the-art models. Fig. 3 illustrates the comparative analysis of semantic segmentation results of RAL with Inception-Unet model. The proposed RAL with inception-Unet baseline model's mean intersection over union (mIoU), accuracy, sensitivity, specificity, and F-score are 0.615, 0.958, 0.708, 0.974, and 0.732, respectively. The RAL with Inception-Unet's intersection over Union (IoU) is 0.615, which is higher than Inception-Unet models trained on a pool of labelled data (DL) but lower than Inception-Unet models trained on whole training samples (DF). The sample input images and their corresponding multi-label semantic segmentation output and ground truth of the RAL with inception-Unet baseline model are presented in Fig. 4, while the results from the Inception-U-Net model trained on the full training dataset are shown in Fig. 5.

6. Discussion

Multi-label semantic segmentation is essential for scene understanding of unstructured traffic environments [39], especially in nations that are developing where traffic trends are very random and unpredictable. These algorithms assure the safety of autonomous vehicles on unstructured roads by understanding the scene and predicting the behaviors of nearby traffic users [40]. Researchers studying traffic conditions in developing nations can utilize the Indian Driving Dataset Lite (IDD-Lite) to better recognize and tackle particular challenges in these contexts. This article offers a unique technique for multi-label semantic segmentation on the IDD-Lite dataset that utilizes Reinforcement Active Learning (RAL). We aim to improve segmentation results in unstructured traffic circumstances, which are frequent in developing countries, by employing an Inception-Unet baseline model. The RAL approach increases model performance while decreasing the amount of time and resources required for annotation [41].

Despite these advantages, several limitations should be noted. RAL works well with small to medium sized datasets but might bottleneck when applied to larger datasets due to sample selection and model retraining complexity. Also, IDD-Lite dataset is specific to Indian roads and traffic behavior, the trained model might not generalize well to other geographies without domain adaptation. Incorporating domain adaptation techniques and evaluating the framework on datasets from different regions would improve its robustness and allow broader applicability in global traffic scenarios. Enhancing the model’s ability to generalize across diverse environments would significantly strengthen its practical relevance in real-world autonomous systems.

The proposed RAL with inception-Unet baseline model's mean intersection over union (mIoU), accuracy, sensitivity, specificity, and F-score are 0.615, 0.958, 0.708, 0.974, and 0.732, respectively. The mean intersection over the union (mIoU) of the the proposed RAL with inception-Unet is 0.615 which is better than inception-Unet when trained on inadequate quantity of labeled data (DL) and smaller when trained on full dataset.

The evaluation of our proposed approach produced promising results. The intersection over union (IoU) method accurately predicts semantic segmentation effectiveness. These results demonstrate an important advancement over the default model trained on an inadequate quantity of labeled data (DL). However, it is also important to highlight that although RAL significantly enhances performance under low-labeling conditions, it still falls short of models trained on the full dataset (DF). This indicates the potential need for further data augmentation or more generalized feature learning approaches. It is important to recall that, despite their outstanding results, the RAL models fall short of those trained on the whole dataset (DF), emphasizing the potential benefits of more data improvement. Finally, we demonstrate how reinforced active learning enhances semantic segmentation on the IDD-Lite dataset. We acquired significant improvements in segmentation performance through combining RAL techniques with cutting-edge baseline models, enabling intelligent vehicle safety systems to tackle the unique difficulties of developing rural roads.

7. Conclusions

Semantic segmentation plays an important role in computer vision, particularly for systems such as autonomous vehicles, where safe and secure navigation needs an in-depth understanding of the surroundings at all times. Reinforced Active Learning (RAL) proposes an alternative to these problems by automatically recognizing suitable instances for annotation, improving annotation efficiency and model performance.

We recommend using RAL in this work to carry out semantic segmentation on the Indian driving dataset, that provides different obstacles due to constantly changing challenging driving conditions, road design, and ambient issues. We were able to automate the process of selecting samples for annotating by employing a reinforcement learning method that assesses each sample's informativeness and potential impact on model performance. Using this approach, we can develop reliable segmentation models that respond to the driving variables in developing countries in order to address the issues that come with them.

The main contributions of this work include the integration of a Deep Q-learning-based querying mechanism within the RAL framework to enable more effective sample selection, enhancing the efficiency of the active learning process. Additionally, the study employs Inception-Unet as a strong baseline model, leveraging its capability for multi-scale feature learning to improve segmentation performance. Finally, the approach demonstrates substantial performance improvements on a real-world, unstructured dataset (IDD-Lite), all while significantly reducing the overall labelling effort required. Our results showed that, on the Indian driving dataset, RAL increases semantic segmentation effectiveness. The intersection over union (IOU) statistic is a vital factor affecting segmentation accuracy. RAL with Inception-Unet surpasses the Inception-Unet model trained solely using labeled data, with an IOU of 0.615. This is less than models trained on the whole training dataset (DF).

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Data Availability Statement

The data used in this study are available at https://idd.insaan.iiit.ac.in/dataset/details/.

Conflicts of Interest

The authors declare no conflicts of interest.

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