Abstract—Performance monitoring of object detection is crucial for safety-critical applications such as autonomous vehicles that operate under varying and complex environmental conditions. Currently, object detectors are evaluated using summary metrics based on a single dataset that is assumed to be representative of all future deployment conditions. In practice, this assumption does not hold, and the performance fluctuates as a function of the deployment conditions. To address this issue, we propose an introspection approach to performance monitoring during deployment without the need for ground truth data. We do so by predicting when the per-frame mean average precision drops below a critical threshold using the detector's internal features. We quantitatively evaluate and demonstrate our method's ability to reduce risk by trading off making an incorrect decision by raising the alarm and absenting from detection.

I. INTRODUCTION

Object detection is a crucial part of many safety-critical applications such as robotics and autonomous systems. For safe operation, an autonomous vehicle (AV), for example, needs to accurately locate and identify critical objects like other vehicles and pedestrians on the road. To achieve this goal, there is ongoing research [1]–[10] to improve the speed and accuracy of object detection models. However, due to the discrepancy between training data and deployment environments (i.e., dataset shift [11]) and many other unavoidable factors like sensor failure or degraded image quality, a consistent deployment performance can not be guaranteed. Hence, object detection accuracy can fluctuate without any prior notification while deployed on an autonomous vehicle. A silent failure like this in the object detection model is a significant concern. Due to this failure, the AV can cause catastrophic damage if it operates based on erroneous object detection. Undetected performance drops are a significant bottleneck for the widespread deployment of autonomous vehicles in our everyday lives. Hence, for safety, robustness, and reliability, the importance of performance monitoring of a deployed object detection model is paramount.

The standard practice to prepare an object detection model for deployment is to train and evaluate the model using training and evaluation split of some dataset to measure the accuracy and generalization capacity. Here, the assumption is the training and evaluation data are representative of the real operating environment. However, this assumption does not hold in the context of autonomous vehicles where the operating environment is continuously evolving and might change unexpectedly. Consequently, object detection performance fluctuates without any prior notification. Moreover, the performance might drop below any critical threshold, which can cause a fatal incident. See Figure 1 for an overview.

One possible solution is to develop an exceptionally accurate and domain adaptive object detection system for autonomous vehicles. However, it is impossible in most practical circumstances to account for all imaginable future deployment conditions during training. Another approach is to identify when the performance of the deployed object detector drops below a critical threshold. So without the need to increase the detection accuracy directly, a performance drop identifier can protect the autonomous vehicle by providing crucial alerts during periods of silent failure. However, measuring the performance drop directly during deployment is impractical due to the absence of ground-truth data in this phase. Therefore, we advocate equipping object detectors with self-assessment capability to detect instances of performance drop during deployment.

Self-assessment is becoming a prerequisite for any vision-based efficient, safe, and robust robotic system. This capability is often referred to as introspective perception [12], [13]. For autonomous driving, an introspective object detection system can hand over the control to human drivers when it can predict inconsistency in its operation. There are several works [14]–[17] towards addressing the requirement of providing self-assessment in a deep learning based robotic vision system. However, there are very few works towards introspective systems for object detection. To this end, our paper makes the following contributions:

1) We propose an introspective approach to performance monitoring of object detection during deployment without access to ground truth labels.
2) We propose an internal integrated feature based on the mean, max and statistics pooling techniques for performance monitoring.
3) We introduce the use of per-frame mAP prediction for continuous performance monitoring of object detectors.

The rest of the paper is organized as follows: In Section II we review the related works on introspective perception systems. In Section III, we introduce our framework to find the performance drop for an object detection system. Section IV outlines our experimental setup. Section V presents the results and finally in Section VI we draw conclusions and suggest areas for future work.

II. RELATED WORK

In robotics, the idea of self-assessment was introduced by [13] to achieve reliable performance in a real environment.
They described this self-assessment as the introspection capability of a mobile robot while operating in an unknown environment. Later [14] and [18] adopted the idea of introspection for classification and semantic mapping respectively in the context of robotics. These works examine the output of the underlying system to predict the likelihood of failure on any given input.

Another line of research is to predict the perception system performance from the input itself. In this paradigm, [19] introduced an evaluator algorithm to predict the failure of a human pose estimation model. Zhang et al. [20] introduced the terminology basesys and alert in failure prediction context. They proposed a general framework where alert is used to raise a warning when the underlying system basesys fails to make a correct decision from an input. Daftry et al. [12] proposed an introspective framework to predict an image classifier model failure deployed on a micro aerial vehicle. Following a similar methodology, [21] proposed a model to predict how hard an image is for an underlying classifier. Using a probabilistic model, [22] predicted the probable performance of a robot’s perception system based on past experience in the same location.

Recently, confidence estimation and Bayesian approaches for uncertainty estimation have gained popularity to detect how well the underlying model has performed on the input. TrustScore [23], Maximum Class Probability [24] and True Class Probability [25] are some of the works that measure the confidence of the underlying model for a given task using the confidence estimation paradigm. Using a Bayesian approach, [26] proposed to use dropout as a Bayesian approximation technique to represent model uncertainty. Following their work, [27], [28] have used dropout sampling to identify the quality of image and video segmentation network. Here, all of these works focus on predicting model failure using different approaches for classification and segmentation tasks.

In the context of object detection, [29], [30] have used different approaches to identify the failure of an object detection system. Both of these works are beneficial to identify false positive errors made by an object detector. Whereas, [31] and [32] have proposed different approaches to detect false negative errors made by an object detection model. Our proposed approach differs from these methods in that we can detect images with low per-frame mAP, which covers both false positive and false negative errors as well as poor object localization.

III. Approach Overview

In this section we describe our proposed framework to predict the performance drop of an object detection system during deployment without using any ground-truth data. We assume that the deployed object detection model weight remains frozen during this phase. First of all, we will define the problem.

Assuming we have an object detector $O$ with backbone deep neural network $B$, $O$ is trained to detect a set of objects $T$ from a training dataset, $D_t$. We also have an evaluation dataset $D_e$, similarly distributed as $D_t$. $D_e$ contains a set of images $I = \{I_1, I_2 \ldots I_n\}$ and corresponding annotations $L = \{L_1, L_2 \ldots L_n\}$ per image. After the object detection training phase, $O$ is applied on $D_e$ to detect all the objects from $T$. Thus, we get a set of predictions per image, $P = \{P_1, P_2 \ldots P_n\}$. Using the pairs of annotations and predictions per image $(L_i, P_i)$, we compute the per-frame mAP, $M = \{M_1, M_2 \ldots M_n\}$ following the procedure at [33]. Here, per-frame mAP quantifies $O$’s performance to detect all the existing objects in each image.

We assign each image of $D_e$ into success and failure classes using the Equation 1. Here $\lambda$ is chosen to be the
### IV. Experimental Setup

In this section we will describe the settings that we have used to train the basesys and alert system.

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$k^{th}$ percentile of $M$. The failure class contains the $k\%$ image frames from the $D_e$ where $O$ was not accurate enough to detect the available objects. The choice of $k$ here is application specific. We want to train the introspective perception system alert to predict the images similar to the failure class where per-frame mAP will be lower than $\lambda$.

\[
\mathcal{L}(I) = \begin{cases} 
\text{failure,} & mAP_{\text{per-frame}} < \lambda \\
\text{success,} & \text{otherwise}
\end{cases}
\]  

(1)

To train the alert we use features $F = \{F_1, F_2 \ldots F_n\}$ for each image from $D_e$. Following the failure prediction network proposed by [21] and [25], the final convolutional layer of backbone $B$ is used to extract all the necessary features. Assuming that, there are $N$ channels at the last layer of $B$ and each activation map is of size $W \times H$, we apply Equation 2 on the last layer to extract the mean pooling feature $F_{\text{mean}}$. Here, $f(x,y)$ represents the spatial unit of each activation map.

\[
F_{\text{mean}} = \frac{\sum_{x=1}^{H} \sum_{y=1}^{W} f(x,y)}{W \cdot H}
\]

(2)

Applying Equation 3 on the last layer of $B$, we generate the max pooling feature $F_{\text{max}}$.

\[
F_{\text{max}} = \max_{x \in [1,H]} \max_{y \in [1,W]} f(x,y)
\]

(3)

Inspired by [34], we calculate the standard deviation from each activation map to generate the statistics pooling feature $F_{\text{std}}$ following the Equation 4. Here $std(f_i)$ calculates the standard deviation of $i^{th}$ feature map.

\[
F_{\text{std}} = std(f_1) \oplus std(f_2) \oplus \ldots \oplus std(f_N)
\]

(4)

All the features described above are concatenated together to generate the feature $F_{\text{mean,max, std}}$ for the alert system. Equation 5 formulates this process.

\[
F_{\text{mean,max, std}} = F_{\text{mean}} \oplus F_{\text{max}} \oplus F_{\text{std}}
\]

(5)

We train a binary classifier using the $F_{\text{mean,max, std}}$ feature and the corresponding labels from Equation 5 and Equation 1 respectively. The classifier is trained to predict the probability of an image feature to be in the failure class. Following [20], we will refer to the object detection model and its corresponding binary classifier as basesys and alert respectively. Figure 2 shows the incorporation between the basesys and alert system.

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**TABLE I:** Basesys mean average precision (mAP) using ResNet18 and ResNet50 backbone. Here basesys is trained and tested using similar dataset and cross dataset settings. Basesys accuracy drops when trained and tested on different dataset.

| Basesys Training | ResNet18 | | ResNet50 | |
|------------------|----------|-----------------|----------|-----------------|
| mAP (dataset)    | training | testing         | training | testing         |
|                  | kitti    | bdd             | kitti    | bdd             |
| ResNet18         | 0.292    | 0.130           | 0.377    | 0.182           |
| ResNet50         | 0.200    | 0.354           | 0.259    | 0.499           |

**b) Basesys Training:** We have used Faster RCNN object detection network [2] as the basesys in all of our experiments. Basesys has been trained using transfer learning to detect person and car object from both kitti and bdd dataset. Two different versions of Residual Neural Network
TABLE II: Area Under the Precision Recall Curve (AUPRC) and Area Under the ROC Curve (AUROC) score for alert system in the similar dataset settings. Here alert is used to identify basesys performance drop in a known environment. The notation A/B/C denotes that basesys and alert is trained on dataset A using backbone C and alert is used to identify basesys performance drop on dataset B.

| Feature      | kitti/kitti/18 | kitti/kitti/50 | bdd/bdd/18 | bdd/bdd/50 |
|--------------|----------------|----------------|-------------|-------------|
| n_proposals  | 0.130          | 0.128          | 0.136       | 0.110       |
| mean_conf_score | 0.205          | 0.320          | 0.192       | 0.358       |
| classifier   | 0.728          | 0.851          | 0.689       | 0.831       |
| places365    | 0.654          | 0.799          | 0.670       | 0.823       |
| layer        | 0.760          | 0.890          | 0.480       | 0.764       |
| mean         | 0.738          | 0.876          | 0.602       | 0.822       |
| max          | 0.756          | 0.887          | 0.673       | 0.819       |
| mean_std     | 0.747          | 0.879          | 0.689       | 0.855       |
| mean_max     | 0.777          | 0.898          | 0.708       | 0.841       |

TABLE III: Area Under the Precision Recall Curve (AUPRC) and Area Under the ROC Curve (AUROC) score for alert in the cross dataset settings. Here alert is identifying basesys performance drop in an unknown environment. The notation A/B/C denotes that basesys and alert is trained on dataset A using backbone C and alert is used to identify basesys performance drop on dataset B.

| Feature      | bdd/kitti/18 | bdd/kitti/50 | kitti/bdd/18 | kitti/bdd/50 |
|--------------|--------------|--------------|--------------|--------------|
| n_proposals  | 0.558        | 0.381        | 0.736        | 0.447        |
| mean_conf_score | 0.641        | 0.507        | 0.786        | 0.566        |
| classifier   | 0.783        | 0.629        | 0.818        | 0.483        |
| places365    | 0.781        | 0.624        | 0.821        | 0.493        |
| layer        | 0.780        | 0.684        | 0.815        | 0.580        |
| mean         | 0.754        | 0.665        | 0.809        | 0.563        |
| max          | 0.778        | 0.682        | 0.813        | 0.582        |
| mean_std     | 0.759        | 0.672        | 0.815        | 0.569        |
| mean_max     | 0.786        | 0.692        | 0.822        | 0.586        |

[37], ResNet18 and ResNet50 have been used as the basesys backbone. In our experiments, the basesys, trained using RestNet50 backbone has performed better than the ResNet18 backbone. Table 4 shows comparative performance using the mean average precision (mAP) for all different basesys and dataset combinations.

c) Feature Collection: We experimented with multiple features to find the most suitable one for the proposed alert system. The first set of features are collected from basesys bounding box proposals.
- **mean_conf_score:** This feature exploits object proposal confidence score to determine basesys performance drop. As basesys proposes multiple bounding boxes with corresponding confidence scores and labels during object detection, we use the mean of confidence scores which are greater than 0.5 to build the first feature. Here, a lower mean confidence score indicates a potential performance drop in the basesys.
- **n_proposals:** We assume that a crowded environment might be a factor for basesys performance drop. To evaluate this assumption, we used the number of proposals having a confidence score greater than 0.5 as a performance drop indicator.

The second set of features are collected from two external deep convolutional neural networks.
- **classifier:** Two different versions of Residual neural network, Resnet18 and ResNet50 have been used to extract image features to train the alert system. Both of these networks are pre-trained on ImageNet [38] dataset.
- **places365:** We used ResNet18 and ResNet50 network pre-trained on Places365 [39] dataset to extract features to train the alert system.

In both cases, average pooling has been used at the final convolutional layer to extract the necessary image features.

We use the basesys backbone to extract the third set of features. These will be referred as the internal features.
- **layer:** We applied the mean-pooling operation in all of the convolutional layers of the backbone and concatenated them to create this feature.
- **mean, max and std:** Applying the mean, max and statistics pooling technique described in Section III at the last convolutional layer of basesys backbone, we extracted the mean, max and std features.
- **mean_std and mean_max:** Using the concatenation operation and following the feature generation technique proposed in [34] and [40], we generate two new features mean_std and mean_max using the mean, max and std feature.
- **mean_max_std:** This feature is generated by applying the Equation 5 at the last convolutional layer of basesys.
Fig. 3: Examples of alert prediction to identify basesys performance drop. Here the Green and Cyan bounding boxes show the false negative and false positive errors respectively made by an object detector. Alert prediction is showed at the upper right corner of each image. The first row shows samples from the kitti/kitti/50 experimental settings. The second, third and fourth row show samples from the bdd/bdd/18, kitti/bdd/18 and bdd/kitti/50 experiments.

(backbone.

d) Alert Training:: We used a multi layer fully connected binary classifier with 50% dropout rate to train all the alert systems. Besides, we used binary cross entropy loss with balanced sampling to train the alert network.

V. EVALUATION AND RESULTS

A. AUPRC and AUROC Metrics

This section summarizes the alert accuracy using Area Under the Precision Recall Curve (AUPRC) and Area Under the ROC Curve (AUROC) metric. Here, we will refer all our experimental settings using the notation A/B/C. It means the basesys and alert are trained on dataset A using backbone C and alert is used to identify basesys performance drop on dataset B. Here C can be 18 or 50, resembling the ResNet18 and ResNet50 backbone for the basesys.

Table II summarizes the alert accuracy for similar dataset settings. Our proposed mean_max_std feature achieves 0.781 and 0.902 as AUPRC and AUROC score, and outperforms all other features in the case of kitti/kitti/18. For kitti/kitti/50, bdd/bdd/18 and bdd/bdd/50 experimental settings, features collected from the basesys performs better than all other features in terms of AUPRC and AUROC score.

The proposed alert system is beneficial for cross dataset settings too. Table III shows the AUPRC and AUROC scores for alert when it is used to identify basesys performance when deployed on an unknown environment. For bdd/kitti/18 settings, alert achieves 0.790 and 0.696 as AUPRC and AUROC score respectively when used with the mean_max_std feature. In all cross dataset experimental settings, mean_max_std features outperforms all other features for identifying basesys performance drop.

B. True Warning Rate

Using the best performing feature, mean_max_std, we use the true warning rate metric to determine the quality of the alert system in raising a warning against basesys performance drop. Here, warning rate is the ratio of correctly raised warning vs the total number of frames with per-frame mAP below the critical threshold. Table IV shows the true warning rate raised by alert system.

The results in Table IV show that in cross dataset settings the true warning rate is higher than the similar dataset settings. As basesys accuracy drops in cross dataset settings
Fig. 4: Risk-Averse Metric for the proposed alert system. (a) Point per image earned by basesys with and without considering alert warning when trained and tested on similar dataset. (b) Point per image for basesys with and without alert system when trained and tested on different dataset. In both cases, basesys earns more point per image when associated with alert.

(Table I), alert becomes more useful in these cases by identifying the critical cases. When the detector with ResNet50 backbone is trained on BDD and tested on Kitti, alert can identify 81.4% of the frames where basesys per-frame mAP is lower than the critical threshold. Figure 3 displays multiple samples of alert raising the alarm and flagging frames where basesys performance drop below a critical threshold of 0.5. The frames show conditions such as night, rain, cluttered environments.

C. Risk-Averse Metric

In Risk-Averse Metric (RAM) [20] we evaluate alert’s capability to trade-off the risk of making an incorrect decision with not making a decision at all. RAM gives basesys +1.0 and −0.5 respectively for a correct and incorrect prediction. basesys will get 0 point if it does not make any decision considering the warning raised by alert. For crucial system like self-driving car’s object detection we expect basesys to trade-off incorrect decision for no decision. In such case, basesys can handover its control to some more competent systems. Figure 4a shows the point per image earned by basesys when it operates with and without considering the warning raised by alert in similar dataset settings. In all cases, basesys earns more point per image if it abstains from making an incorrect decision taking alert’s warning in consideration. Figure 4b shows the RAM metric for cross dataset settings.

D. mAP vs Declaration Rate Metric

In this section we evaluate the basesys accuracy score for different declaration rate (DR) [20]. Here, declaration rate is the proportion of images on which basesys operates. The rest of the images are discard assuming that basesys per-frame mAP will be lower than the critical threshold on those images. To calculate this metric we first sort the images in the ascending order of alert confidence. Next, mAP of top DR percentage of images are computed to plot the mAP vs DR metric. For a perfect alert the mAP for low DR images would be very high and decrease gracefully as DR approaches to 1.0. In Figure 5a we show the mAP score for four different declaration rate in similar dataset settings. The mAP score drops gradually with the increasing declaration rate. Figure 5b shows the mAP vs DR metric for cross dataset settings. In both cases, we use mean_max_std features in alert to identify basesys performance drop.

VI. CONCLUSION

Deep learning-based object detection is a critical component of a wide variety of robotic applications, from autonomous vehicle to warehouse automation due to its accuracy and efficiency. However, its performance is a function of the deployment conditions and could drop below a critical threshold leading to increased risk. Although there is always room to improve accuracy and speed, safety is still a significant concern that should not be overlooked. To this end, we presented an introspection approach to performance monitoring of deep learning based object detection. We showed that our approach can improve safety by raising an alarm when per-frame mean average precision is detected to drop below a critical. We also showed that internal features from the detector itself could be used to predict when per-frame mAP degrade. Our results showed quantitatively the ability of our method to reduce risk by trading off making an incorrect detection with raising the alarm and abstaining from detection.

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