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ATLAS, AN ALL-TERRAIN LABELSET FOR AUTONOMOUS SYSTEMS

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ABSTRACT

All-Terrain off-road environments are the next frontier for autonomous vehicles to overcome. However, there are many obstacles in the way of this goal. Artificial intelligence has proven to be an invaluable asset in developing perception and path planning systems capable of overcoming these obstacles, but these AI systems fundamentally rely on the availability of data related to the operational environment in order to succeed. Currently, there is no unifying ontology for this data. This has inhibited progress on training AI by reducing the availability of cross-integrable datasets. We present ATLAS: A labeling ontology composed of over 200 labels specifically designed to encompass all-terrain off-road environments. This ontology will lay the ground work for creating scalable standardized all terrain off-road data and will enable future AI by providing an expansive and well labeled ontology that can push the field of autonomous vehicles to new heights.

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1. INTRODUCTION

From military to civilian operations, interest in off-road autonomous robotics has seen a marked increase over the last decade. Applications such as exploration, search and rescue, and supply trains have become notable areas of investigation for the development of autonomous robots in these off road environments. To facilitate these applications, autonomous robots must rely on advanced perception systems to understand the environment around them [1]. Without perception, capabilities such as path planning and decision making are nearly impossible, making perception one of the primary cruxes of any autonomous robot [2]. This is

DISTRIBUTION A. Approved for public release; distribution unlimited. OPSEC#6577 particularly true in outdoor environments where the terrain is largely variable and unstructured.

There have been a wide variety of perception suites that have utilized artificial intelligence (AI) to great effect [3, 4, 5]. However, all of these intelligent systems are heavily reliant on the availability of well annotated data. While there are many extensive and well annotated datasets for structured environments, such as in the case of CityScapes [6] or A2D2 [7], this does not hold true for all-terrain off-road environments. The unstructured and extremely varied environments that compose the vast landscapes of earth make it difficult to develop an extensive and consistently labeled dataset. While datasets do currently exist, many can be found lacking due to those above mentioned difficulties.

Hence, this work presents ATLAS, an All-Terrain Labelset for Autonomous Systems. We seek to provide a unifying ontology for all-terrain off-road datasets that is both detailed enough to provide the necessary depth/expandability of labels for autonomous robots to flourish in these environments, as well as general enough to be easily portable to a wide variety of already existing datasets despite the variance that can be found in different biomes across the earth. By providing this unifying ontology, we seek to streamline a variety of datasets into a format which can be easily applied to a variety of AI aimed towards autonomous off-road environments.

2. BACKGROUND

Unlike common urban datasets such as CityScapes and KITTI, many off-road datasets are often heavily lacking in the number and quality of annotated images. Additionally, these off-road datasets tend to have a large imbalance of classes where some labels are present in less than two percent of the dataset. This is compounded by the fact that the annotation process for images collected in off-road environments is more difficult than that of structured environments due to the unstructured nature and wide variety of outdoor environments. For example, in most U.S. cities a stop sign can be considered a reoccurring structured object of interest that is a consistent size and shape. However, seemingly common outdoor features such as trees will have an incredibly varied appearance depending on species, location, season, and growing conditions. This makes a unified off-road labeling ontology essential to building datasets spanning difficult off-road environments. As seen in Table 1, currently available urban datasets lead off-road datasets in both number of images and number of labeled classes due to the lack of a standardized ontology for unstructured environments.

Table 1: Comparison of the number of RGB image annotation and classes from off-road focused datasets (RELLIS-3D, RUGD, Freiburg Forest DeepScene, and YCOR) to CityScapes and A2D2

Dataset	# of Images	# of Classes
CityScapes [6]	25,000	30
A2D2 [7] via	41,277	38
RELLIS-3D [8]	6,235	20
RUGD [9]	7,456	24
YCOR [10]	1076	8
DeepScene [2]	366	6

Many datasets are also collected from singular environmental biomes, leading to bias in their ontologies that have been tailored for specific locations and are difficult to generalize. Figure 1 even shows how two datasets gathered from a similar biome can produce different ontologies. These factors form what is the primary challenge to be overcome by the creation of this ontology. Once overcome, the amount of annotated data available for training AI will increase, allowing for systems to have more data and become better trained.

3. LABELSET ONTOLOGY

3.1. Ontology Overview and Structure

ATLAS was designed using a blend of scientific and visual object classification methodologies to provide a balance between accurately describing complex off-road scenes and optimizing performance of machine learning models trained on these labels. The base labels were adopted from the National Audubon Society Field Guides which provided a great foundation for easily recognizing plants and animals. We then further adapted the ontology by regrouping objects with similar shapes and patterns to maximize performance of machine learning models. This delicate balance between ease of classification and scientific accuracy allows ATLAS to work across a broad range of data that would not be possible with ontologies of currently available datasets.

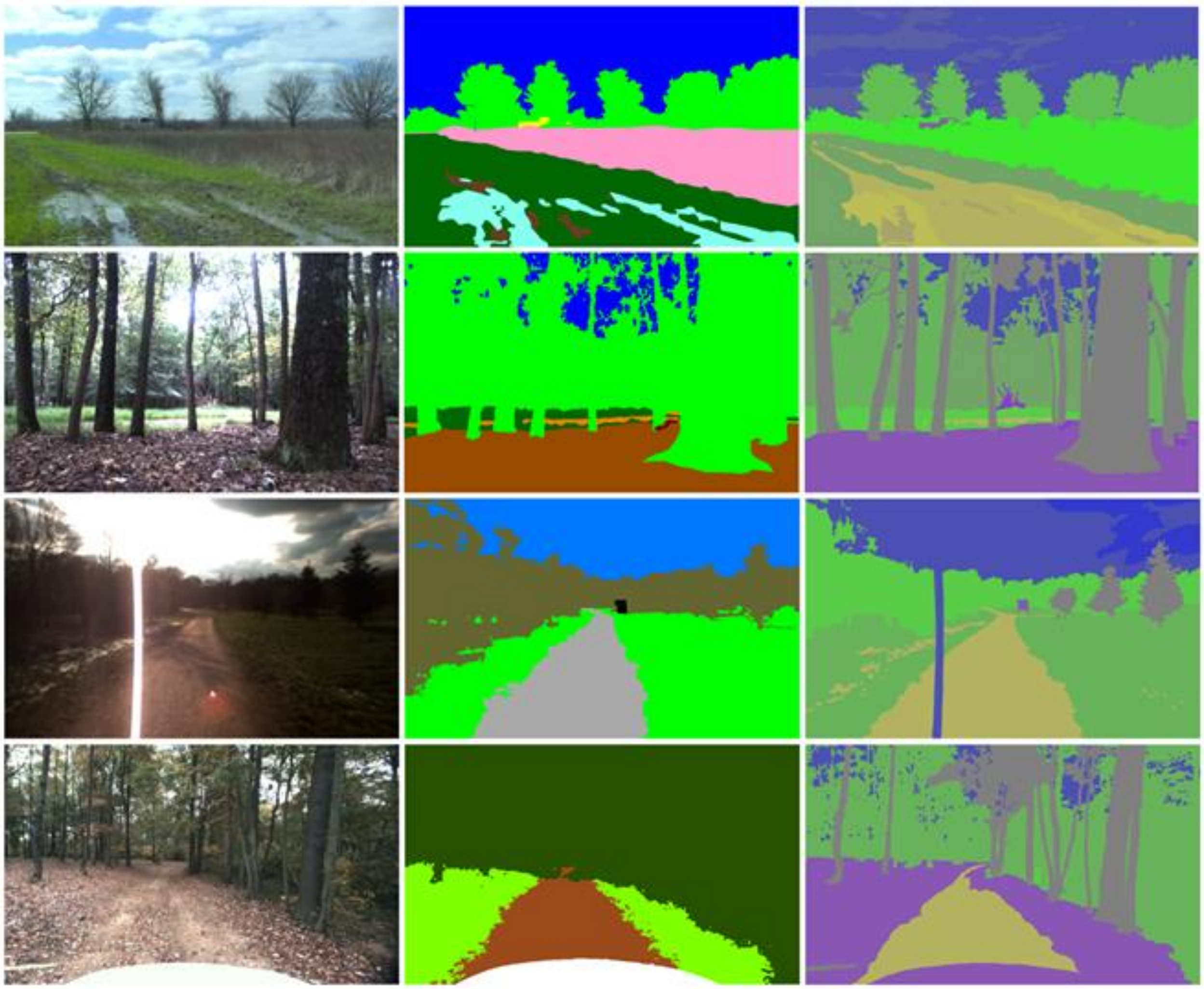

Figure 1: A comparison of state of the art off-road datasets and the ATLAS ontology. The Images from top to bottom are taken from Freiburg Forest [9], Rellis-3D [8], RUGD, and YCMU.

Our label set is structured in an object-oriented manner that allows us to group several objects into a single label and add additional details by branching out from the parent classification. This helps to unify datasets with large variations in label naming conventions as well as make ATLAS backwards compatible with all existing datasets. By providing an inheritance-based mechanism to the labels, additional classifications can be added without changing the overall ontology structure. This opens the door for specialized applications which require high-fidelity labels while still supporting older datasets with high-level ontologies. ATLAS can be further broken down into two main categories: image labels and instance labels.

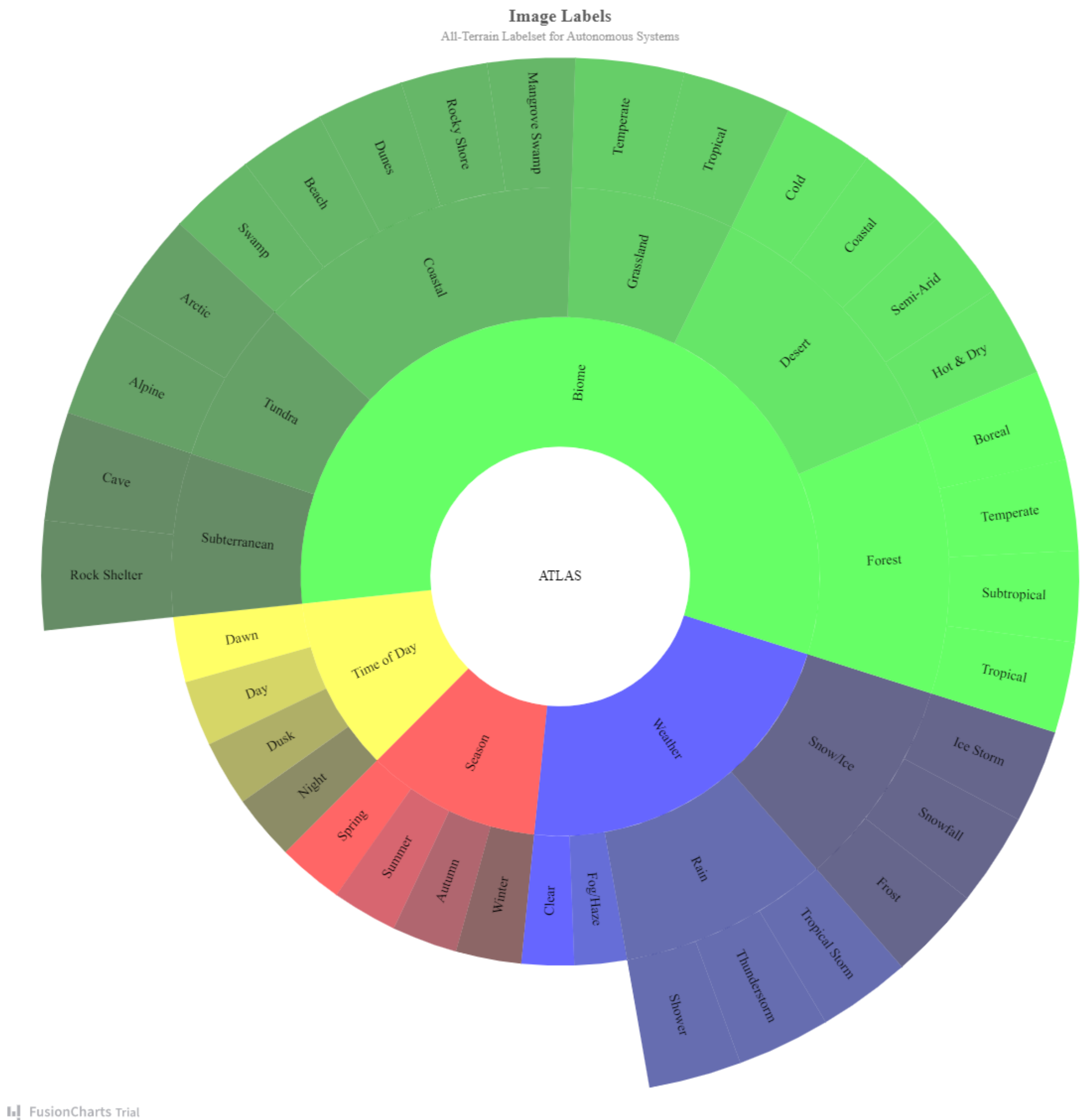

Figure 2: Image labels

3.2. Image Labels

Labels in this category apply to the image as a whole and multiple image labels can be used to describe a single image. This allows datasets annotated with ATLAS to be filtered and create specialized data subsets that are specially tailored to an individual user's application. Although this does not directly impact the performance of machine learning models, by training on specialized data the model will be able to leverage the current environment to better detect objects and understand the scene. The ATLAS image labels are shown in Figure 2.

The image labels help to record the biome, weather conditions, season, and time of day in which an image or video was captured. The weather labels are a simplified version of the National Audubon Society's weather classification [11], which helps to flag images with edge case conditions that could influence the prediction of machine learning models. Biome labels allow off-road data from various regions to be separated to allow for specialized model weights for instance label prediction when working with objects that have high variance and may occur across multiple diverse biomes. Finally, Season and time of day labels ensure that model performance is not biased towards favorable conditions or lighting and provides a method to isolate conditions that may pose additional risk to autonomous platforms.

3.3 Instance Labels

Labels in this category apply to specific objects within the image and may occur zero or more times at any location within any given frame. This provides the bulk of the information captured about the scene and is recorded using polygon segments to preserve spatial information about the object. Based on the instance label, autonomous platforms will need to traverse the area differently depending on its surrounding objects and the fine granularity of the instance labels allow future autonomous platforms to base their action on specific objects rather than just a standard obstacle classification. The ATLAS instance labels are shown in Figure 3.

The instance labels are broken down into 7 primary groups: person, animal, landscape, vegetation, atmosphere, void, and obstacle. The animal labels were derived from the National Audubon Society classification for birds [12] [13], reptiles/amphibians [14], and mammals [15]. Each of these categories was then optimized for machine learning performance by further grouping animals of similar size, shape, color, and pattern into a single label. Similarly, the vegetation labels were also derived from the Audubon Society's classification on trees [16] [17] and wildflowers [18] [19], but in addition to further visual grouping these labels were also refined based on a drivability metric or how likely an autonomous platform would be damaged if it were to collide with the given object. This is necessary, because unlike the animals, vegetation will not react to the presence of an autonomous platform so additional planning is needed to ensure safe operation.

The obstacle labels are reused from the Cityscapes dataset, so that any datasets annotated with ATLAS or machine learning models trained with those datasets would also be compatible with existing urban datasets. Finally, landscape and atmosphere labels provide additional context about the environment to help autonomous platforms navigate rough terrain. These labels are designed to fully encompass elevation changes as well as ground composition, so that off-road platforms will have the ability to dynamically adapt to new elevation grades or soil properties to maintain traction.

3.4 Labeling Rules

In addition to the image and instance label sets, ATLAS also provides a series of rules that outline how the data should be annotated and what to do when encountering edge case conditions. This helps to maintain consistency and quality across all groups and datasets using the ATLAS ontology. Much like the label sets, rules can be added or appended as needed, but the base rules are as follows.

3.4.1 Rule I – Null & Void

Objects that are known but do not fit within another ATLAS label can be marked as 'void' while objects that cannot properly be identified can be left unannotated and marked as 'null.' This provides a means to catch all edge case conditions that do not cleanly fit into the ontology. The void classification is a tier 1 label with no derived attributes; this represents objects of importance that should be considered for future revisions of ATLAS. On the other hand, null is an automated label that can be used to track the proportion of the image that has not been annotated in order to score the overall precision of the annotation.

3.4.2 Rule II - Occlusions

When visibility is reduced due to environmental conditions such as fog or various optical phenomena, all objects that can be identified behind the occlusion should still be annotated. By stacking labels, objects can still be identified in reduced visibility, or the occlusion can be ignored if desired. In the case of a solid object blocking more than half of another object, the blocked object should be marked as occluded to signify that only part of the object can be seen.

3.4.3 Rule III – Panoptic Segmentation

Polygon segments should be used in the form of Panoptic segmentation, where labels are annotated semantically or instance-based depending on the object's relation to the zero-parallax plane. Traditionally, the zero-parallax plane is the point at which two stereo images converge to determine approximate depth from the sensors; in an image annotation perspective, this plane determines the boundary between objects in the near-plane and objects in the far-plane. To find the zero-parallax plane, monocular depth estimation will be used to determine relative distances for each object in the scene. Then, objects in the front 50% of the image will be separated into the near-image plane while the remaining objects are left in the far-image plane. Annotation rules will vary depending on which plane fully encapsulates the object. Instance segmentation ensures that all objects are tracked separately regardless of class and this method of annotation should be used for all labels in the near-plane. However, as objects get further away from the sensor, boundaries become increasingly difficult to find, especially for objects of the same class. In that case, all object in the far-plain will be labeled semantically to show context of the scene while reserving processing power for objects in the vehicle's immediate path.

3.4.4 Rule IV – Transition Zones

When states of image labels cannot be classified using only one of the existing labels, multiple labels can be selected to show transition zones between the existing labels. Transition zones between biomes are often defined by the climate of the area using metrics such as average temperature or rainfall. These time-averaged metrics cannot be measured through data collected a single discrete point in time. Instead, the image labels may be stacked to represent these transition zones for images that contain features from multiple labels within the same category.

4 APPLICATIONS

The object-oriented design of ATLAS allows it to be flexible for a wide variety of applications. The primary labels can be used to update existing datasets and create a path for expansion with more specific sublabels. New datasets can also utilize ATLAS to create a collection of images that will be compatible across both on and off-road environments, allowing advancements in the field of urban autonomy to more easily move into the off-road domain. ATLAS is not just for off-road environments, but rather it is a centralized framework for labeling objects that can be expanded or contracted to suit each user's individual use-case while facilitating the sharing of information that has simply not been possible with the disjoint nature of currently available datasets.

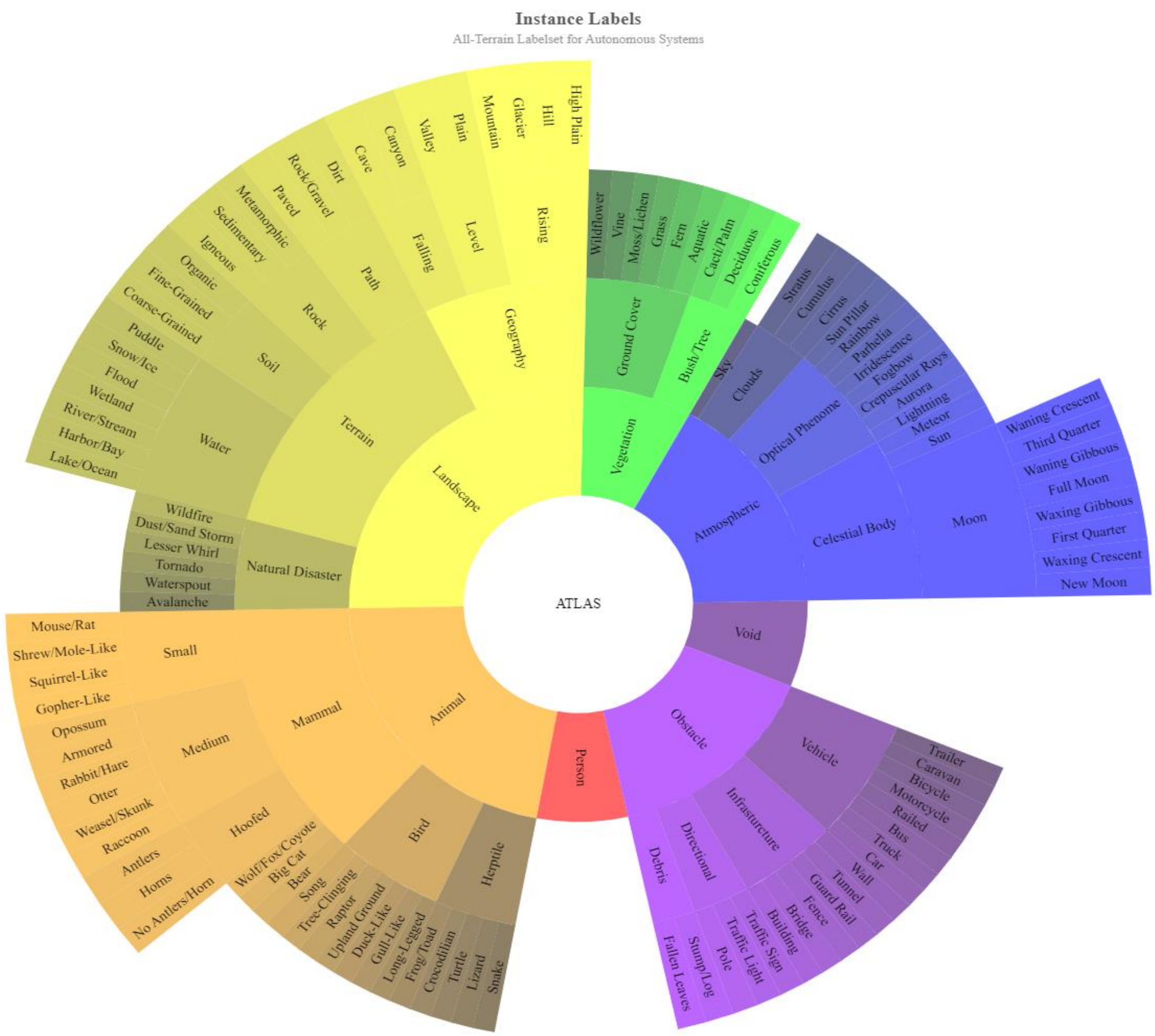

Figure 3: Instance Labels

5 CONCLUSION

ATLAS is just the first step on a road to modernizing off-road perception. Next, we are looking to collect our own data using a specialized multi-spectral data collection rig in order to build the largest and most diverse off-road dataset available. This dataset, using the ATLAS ontology, with be a major breakthrough for robotic perception and will lead to significant advancements in the domain of off-road autonomy. Additionally, we are working on a novel data augmentation system using generative adversarial networks that will allow us to increase the size and variance of existing data to reduce class imbalance based on our image-level labels.

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