Problem Statement for the Automated Image Analysis Pipeline for the Optics Strategic Initiative Working Group
September 2024

Summary:
In marine ecosystems, accurate and timely identification of taxa are critical across a range of natural resource management activities, biodiversity conservation, and ecosystem monitoring. Traditional methods of identification rely heavily on manual observation by trained experts, which are labor-intensive, time-consuming, and prone to errors. Furthermore, with the increasing demand and use of optical sampling methods, there is a need for efficient and reliable automated methods to detect and identify targets from imagery. To that end NOAA Fisheries has funded a suite of Strategic Initiatives with the intent to accelerate the implementation of advanced technology directly into a wide variety of surveys. The Optics Strategic Initiative (OSI) focuses on operationalizing large-scale image collection, processing, and storage; complement, optimize, and replace existing ship- and aircraft-based surveys; automate data processing pipelines; and provide novel, mission-improving metrics. Specifically, OSI will fund projects to increase the accessibility and functionality of machine learning assisted image processing pipelines, and hybrid cloud processing capacity. Upgraded tools will be deployed on a portfolio of surveys. We envision developing a suite of transformational technologies that enable end-to-end automation of optical sampling methods. Those technologies will be implemented in demonstration surveys (i.e. fish, plankton, benthos, aerial/mammals) selected for their topical relevance to the agency and perceived differences in the image analysis problem being addressed.

Internal polling across NOAA Fisheries identified some common barriers to entry and implementation of automated image analysis including: insufficient expertise/personnel, lack of labeled imagery, access to high-speed computing, computational complexity, interpretability of output, poor software interfaces, low programming flexibility, and inadequate administrative and technical support (see attached figures). Results represent a wide spectrum of uses and thus can have varying requirements (e.g. software interfaces). Thus we provide general software requests as well as more domain specific issues for software functionality. Software investments should consider scalable solutions that empower full implementation of automated image analysis into post-processing workflows across domains. Solutions should seek to provide end-to-end solutions across a range of user levels, improve usability and functionality, provide relevant diagnostics for model tuning and evaluation, and generally seek to lower the barrier of entry for this critical toolset.

Desired functionality across modalities.

- Cloud enabled end to end automated detection and classification
- Improved user interfaces and documentation
- Improved and simpler workflows to label images
- Estimates of body size (e.g. using stereo image methods) using multiple measurements of individual animals enabling calculation of precision metrics for individuals and groups (e.g. mean, sd)
- Ability of algorithms to be operable with camera platform upgrades/changes
- Generation of model metadata for tracking deployment in post-processing workflows
- Batch processing for large image/video collections
- Ability to process data to evaluate behavioral response or label behaviors observed

State of the Tech: Fish

There is a wide range of software in use across NOAA Fisheries to automate post-processing of optical imagery for *in situ* fish detection and classification that by-and-large reflect previous NOAA Fisheries investments. We observe highly variable levels of user knowledge/expertise and therefore have a need to be able to provide solutions across a spectrum of user entry points thus software usability is important for this group. Experienced users requested increased flexibility for data inputs and model control, while novice users focused more attention on user interface and accessibility. Common issues expressed for end-users in this group include the lack of labeled imagery, access to high-speed computing, and lack of expertise to create and maintain models. Other issues center on problems associated with varying conditions experienced in underwater photography such as light availability, turbidity, and image quality. Requests include incorporation of stereo-calibrations, and accurate tracking of individuals for measuring fish and estimating vital length data used in stock assessment. Specifically:

- Frame level species specific count data, including classification uncertainties
- Ability to annotate using tracks across multiple frames
- Incorporation of stereo-video calibrations to automate ranging, length measurement, and calculation of precision metrics using multiple measurements of an individual
- Behavioral data such as swimming speed, trajectories, proximity to other individuals
- Solutions for easier creation of labels
- Iterative query/response GUI for rapid model generation and tuning
- Ensuring applications work with varying camera configurations

State of the Tech: Aerial/Mammals

Aerial surveys for marine mammals involve continuous imagery collections for low density populations such as ice seals, circling over animals of interest for individual identification or group size for cetaceans or harbor seals, and collecting clean image sets of complex haulouts of sea lions where animals are piled upon one another. Recent efforts to analyze satellite imagery for marine mammals offers yet another modality requiring machine learning solutions to reduce the image analysis burden. Additionally, underwater imagery is also used to study foraging behavior with the attachment of animal borne camera systems. Many of these approaches have made inroads into machine learning models that have supported the development of semi-automated processing approaches. To realize the true benefits of fine-tuned and applied machine learning models, additional investment in software is required to streamline processing pipelines and reduce the manual components of image processing.

- Species and age-class specific count data
- Bulk processing of image sets from different flights
- Multispectral and satellite imagery support
- Ability to annotate using tracks across multiple frames and multiple passes over the same animals (duplicate identification based on location and habitat - ice floe, reef, etc).
- Use altitude and camera calibration yaml files to automate body size measurements.
- Event detection for animal borne imagery to evaluate diets

- Identification of species from underwater cameras

State of the Tech: Benthic

Existing, image-based survey applications for surveying benthics habitats (e.g. coral), will greatly benefit from platform-agnostic sensor development and the accelerated segmentation based annotation pipeline. For instance, the National Coral Reef Monitoring Program's (NCRMP) Pacific benthic survey is now entirely imagery based, but still dependent on NOAA White Ships, open circuit scuba diver image collection, and human annotation. This application has high potential for rapid application and tangible benefits of new sensor platforms, AI classifiers, and edge bearing imaging systems. Much of this work will focus on classifying sponge and coral but solutions are also sought for demersal epifaunal communities (e.g. Sea Scallops, Conchs, urchins, giant clams, etc). For example, current optical surveys for Atlantic sea scallops require manual annotations of number and size of scallops. Manual annotations are labor intensive and do not allow for processing all viable data collected. This application would allow for increased productivity, streamlining data processes, increase data use for sea scallops, and expand the survey data to other stock and ecosystem applications.

- Species specific spatial distribution and percent coverage data
- Colony/Organism specific segmentation for size, growth, mortality, and recruitment
- Bulk processing of image sets from transects and mosaics.
- API to allow easy and automated deployment of a trained classifier on new images.
- Repository of trained classifiers for different applications to select from.
- Photogrammetric Modeling and Scaling to support 2.5D Annotations
- Enumerating and measuring demersal fish and invertebrates for deriving standardized abundance estimates and size classes
- Automated substrate classification
-

State of the Tech: Plankton

Plankton are microscopic organisms that are incredibly patchy in space and time, and are often sampled with traditional methods such as nets. However, these methods are time consuming and provide a snapshot in time and space. Further, sample analysis involves time consuming taxonomic analysis with a microscope. Advanced imagery methods are quickly becoming more commonplace for quantifying plankton. These instruments include, but are not limited to, *in situ* flow cytobots (IFCB) that image phytoplankton, shadowgraph zooplankton imaging on gliders, towed vehicles (ISIIS, Plankton Scope as examples), autonomous vehicles, and benchtop imagers (Zooscan, Plaktoscope). Each of these methods captures images of plankton across a wide array of sizes- 10 microns for smaller phytoplankton to 13 mm for larger zooplankton. There is a need for automated image analysis across these various size ranges to drastically reduce the time from image acquisition to data in hand. While plankton image classification pipelines exist, non-data scientist user interfaces are needed along with the ability to use shared image libraries.

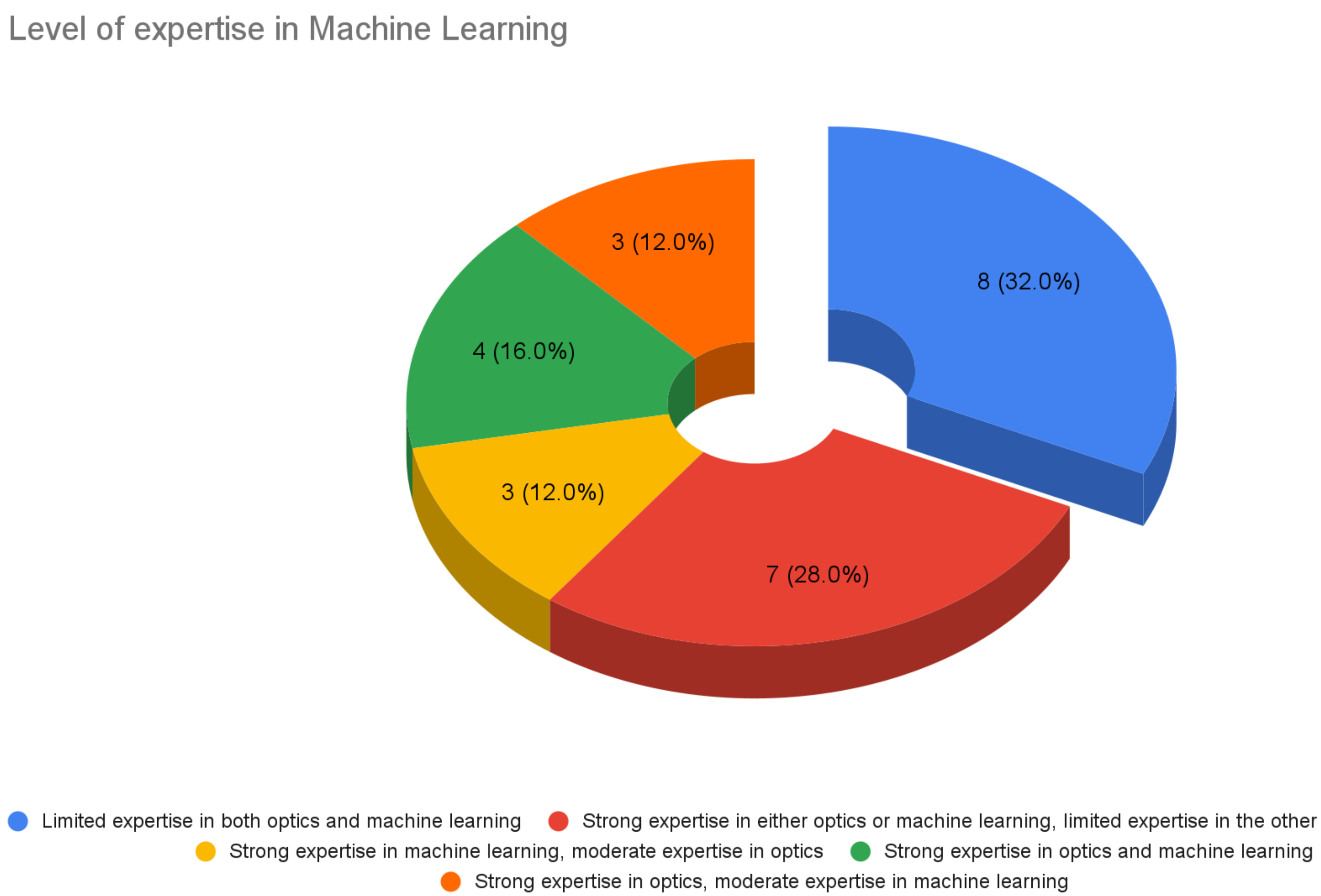
Desired functionality:

- Post-processing of plankton imagery across size classes (10 microns - 13 mm).
- Accessible and discoverable labeled image libraries.
- Target level species specific count and size data, including uncertainties and detritus.
- A custom built SparseConvNet for plankton imagery was built that is very good at IDing plankton but is quite heavy, computationally.
- Ideal system strikes a balance between accuracy and computational cost, and is integrated into a platform that can train as well as test in Cloud environments.

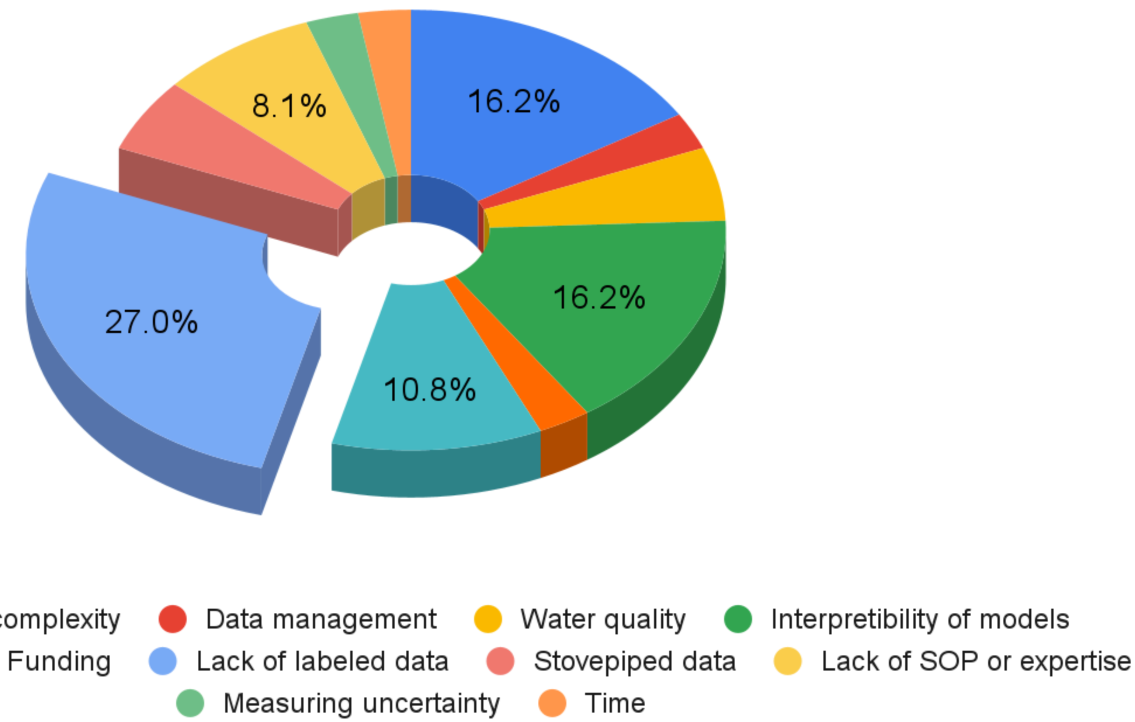
Internal NOAA Fisheries Polling:
Internal polling identified the following companies and software currently in use across NOAA Fisheries. Services range from DIY projects in open source software (e.g. Tensor Flow) to specialty-built software providing end-to-end work flows and project management (RoboFlow). Desired functionality tended to range with user experience with entry level users desiring improved software interfaces and built in workflows. Whereas knowledgeable users tended to identify programming flexibility and open source solutions as important.

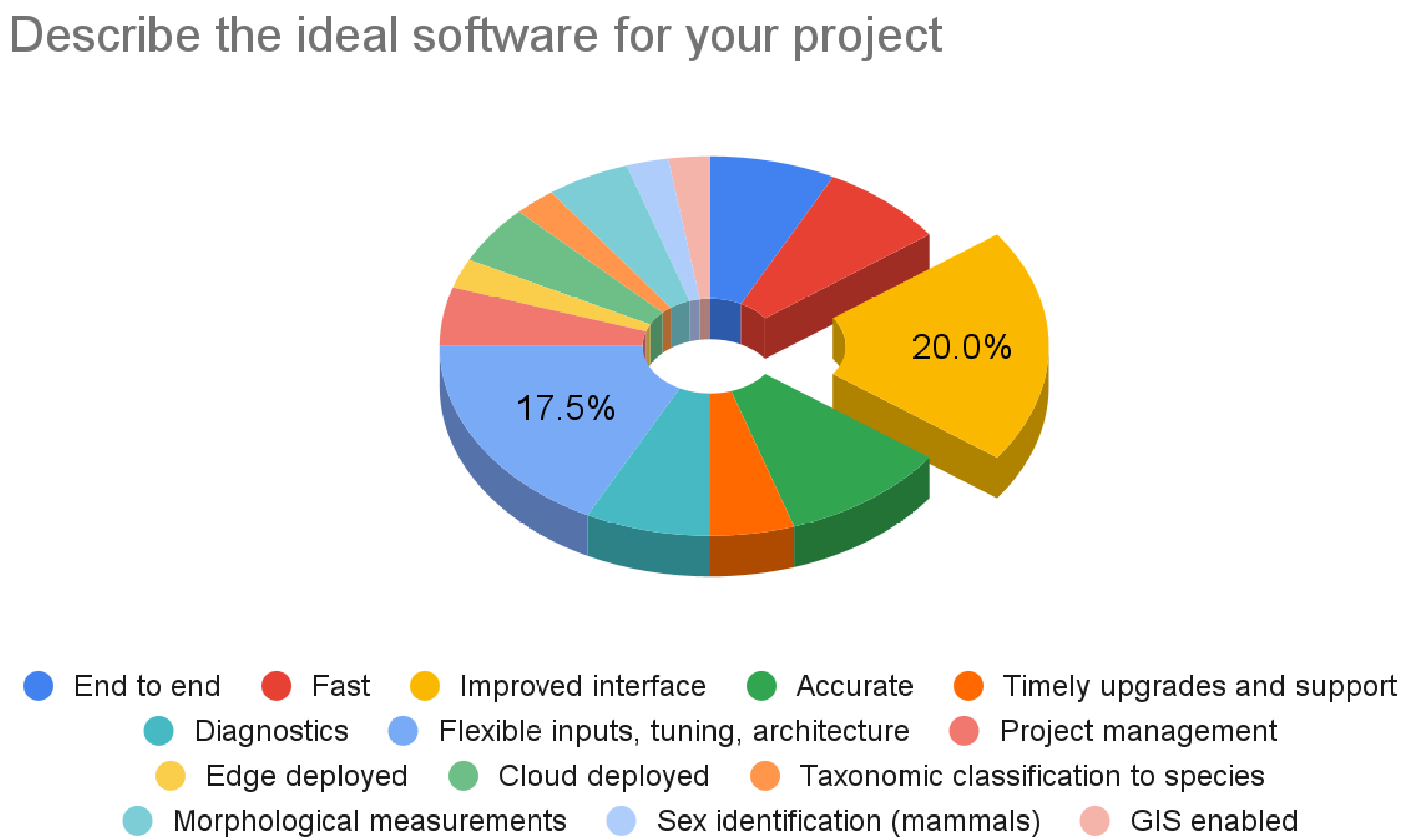
Identified companies/software
Kitware/VIAME - Website
CVision AI - Website
AFID - Website
Enabled Intelligence - Website
Wild Me - Website
RoboFlow - Website
FlukeBook - Website
CI-CIMERS- Chris Sullivan lab
FathomNet.org - Website
Scale - Website
CoralNet - Website

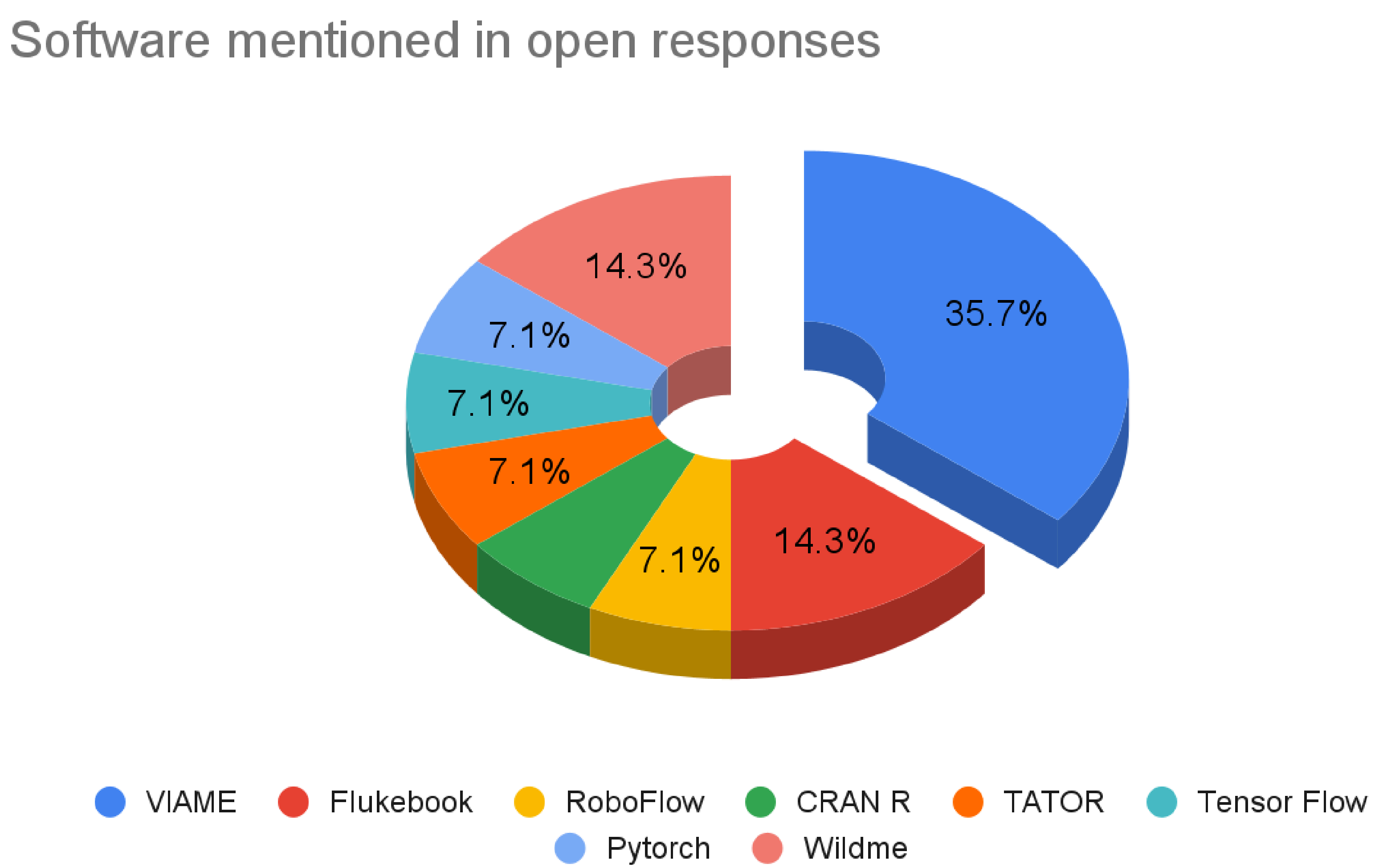
Tensor Flow - Website
CRAN-R - Website
PyTorch - Website

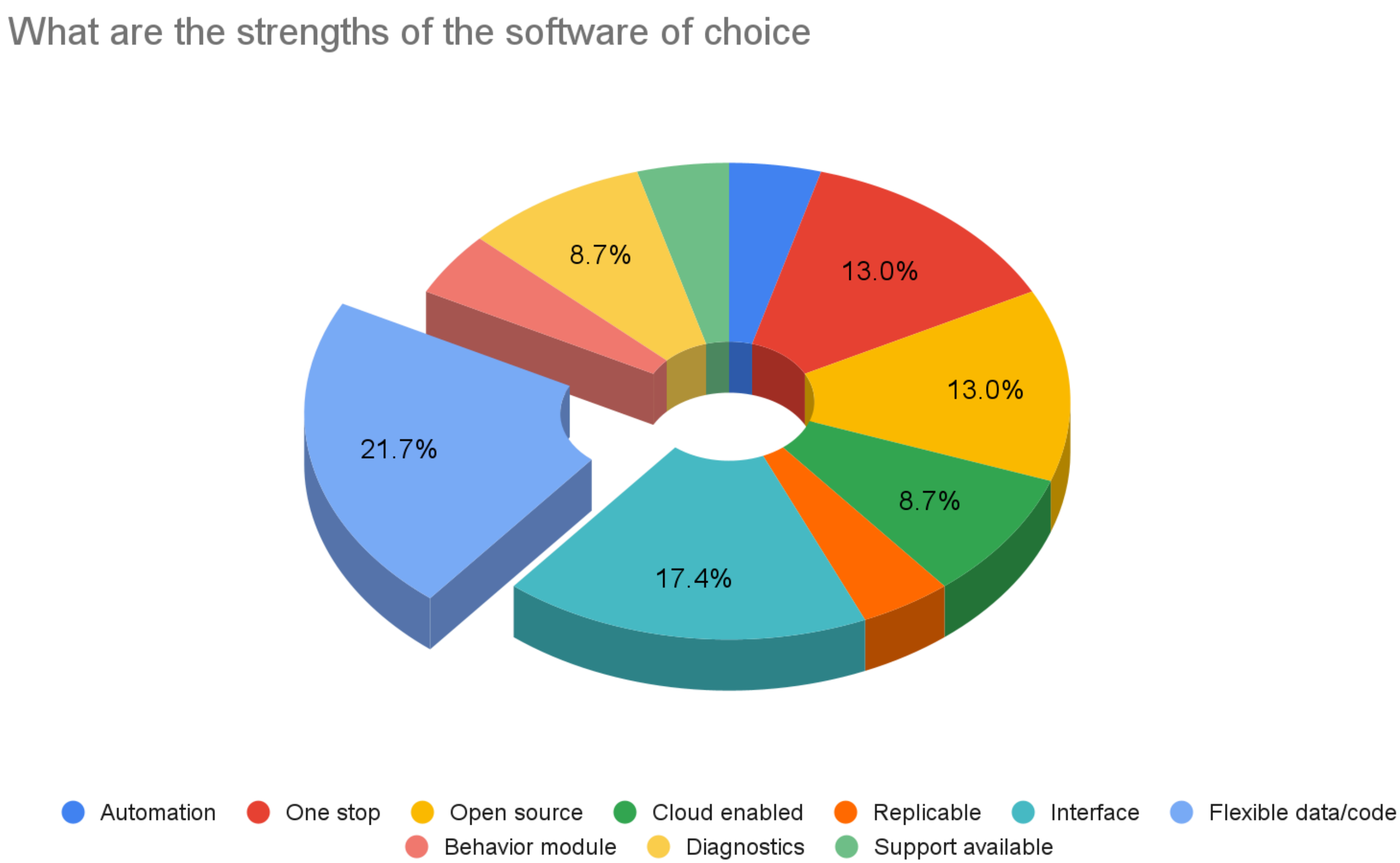

Level of expertise in Machine Learning
8 (32.0%)
7 (28.0%)
3 (12.0%)
4 (16.0%)
3 (12.0%)
Limited expertise in both optics and machine learning
Strong expertise in either optics or machine learning, limited expertise in the other
Strong expertise in machine learning, moderate expertise in optics
Strong expertise in optics and machine learning
Strong expertise in optics, moderate expertise in machine learning

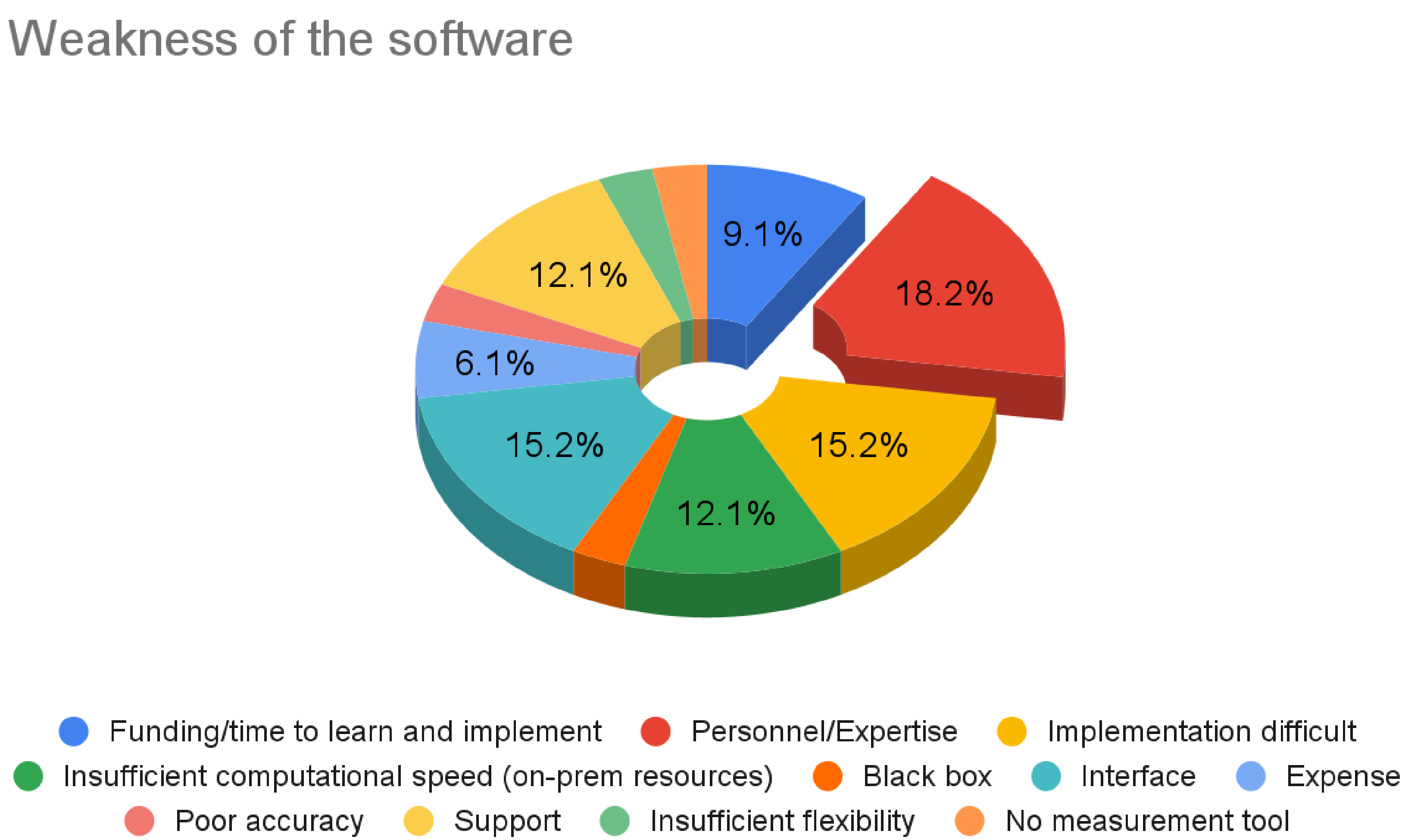
What challenges do you see in the integration of machine learning with optics technologies?



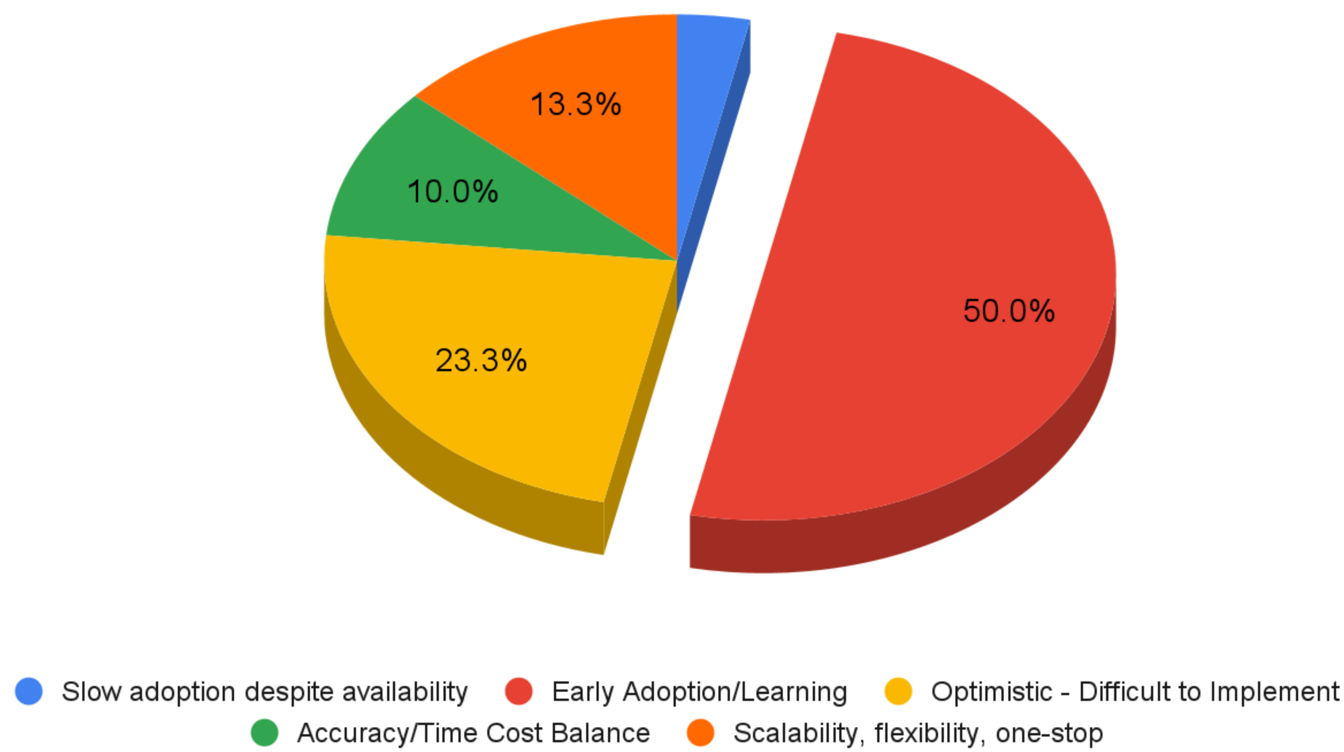

Describe the ideal software for your project
20.0%
17.5%
End to end
Fast
Improved interface
Accurate
Timely upgrades and support
Diagnostics
Flexible inputs, tuning, architecture
Project management
Edge deployed
Cloud deployed
Taxonomic classification to species
Morphological measurements
Sex identification (mammals)
GIS enabled


Software mentioned in open responses
35.7%
14.3%
7.1%
7.1%
7.1%
7.1%
14.3%
7.1%
VIAME
Flukebook
RoboFlow
CRAN R
TATOR
Tensor Flow
Pytorch
Wildme

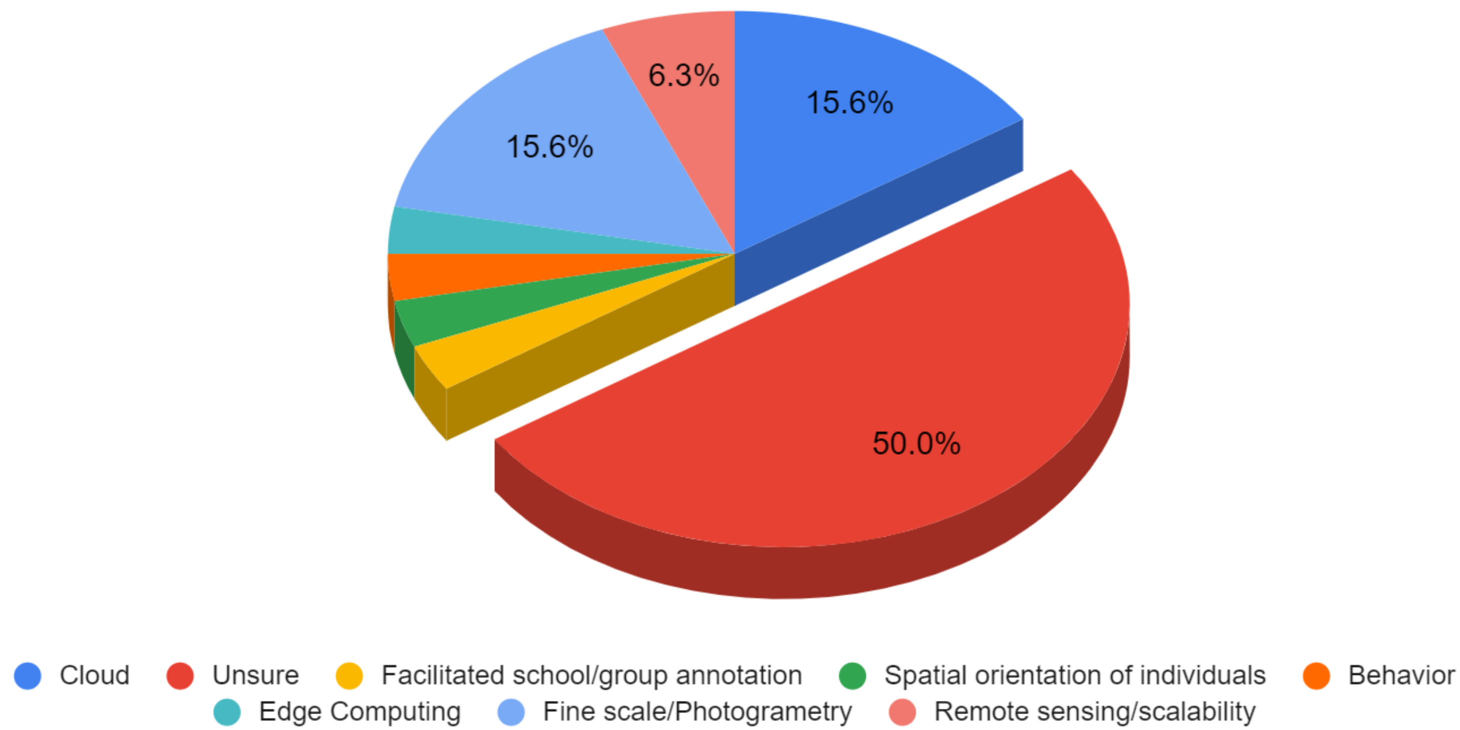

What are the strengths of the software of choice
8.7%
13.0%
13.0%
21.7%
8.7%
17.4%
Automation
One stop
Open source
Cloud enabled
Replicable
Interface
Flexible data/code
Behavior module
Diagnostics
Support available

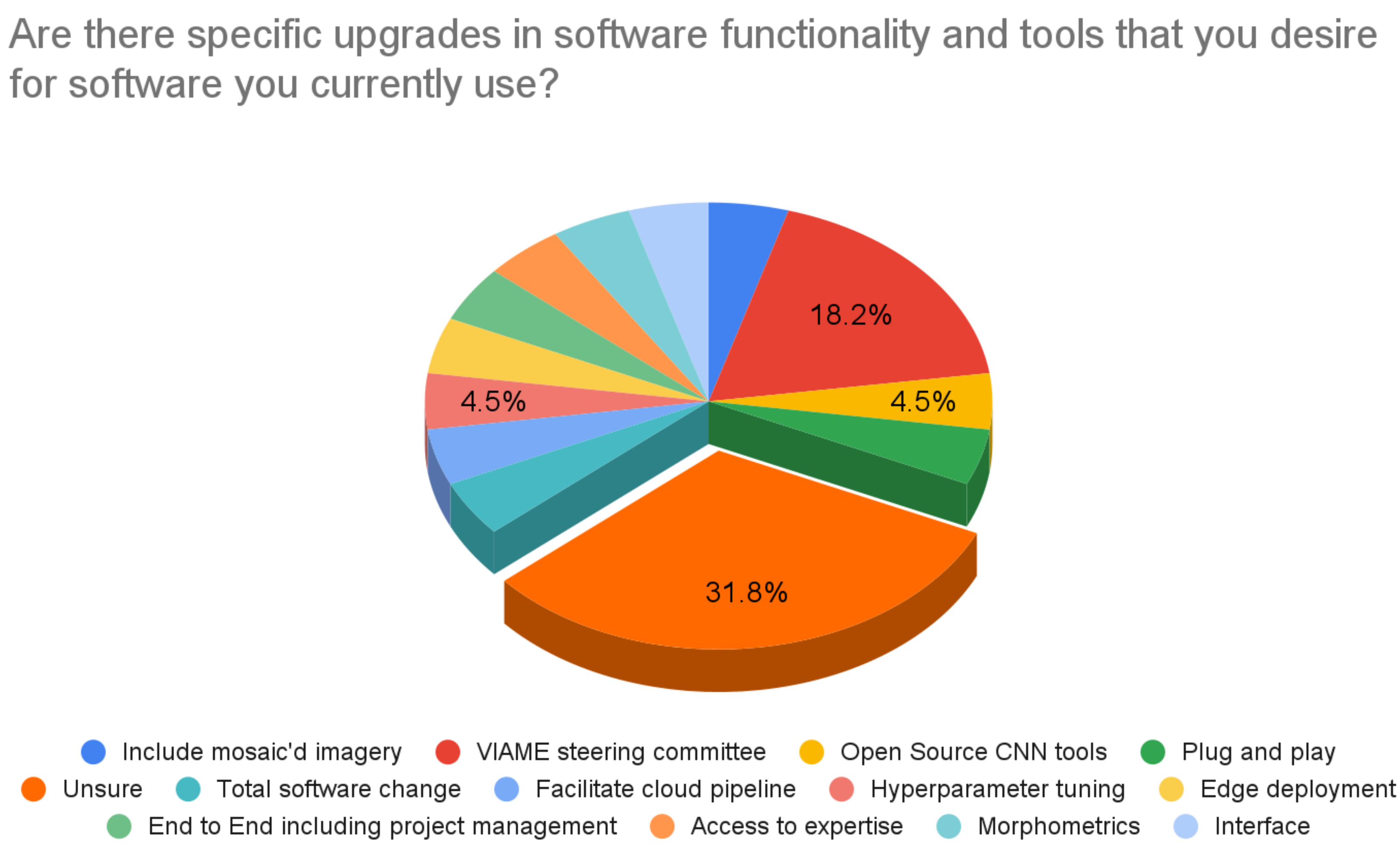

Weakness of the software
9.1%
18.2%
12.1%
6.1%
15.2%
12.1%
15.2%
Funding/time to learn and implement
Personnel/Expertise
Implementation difficult
Insufficient computational speed (on-prem resources)
Black box
Interface
Expense
Poor accuracy
Support
Insufficient flexibility
No measurement tool

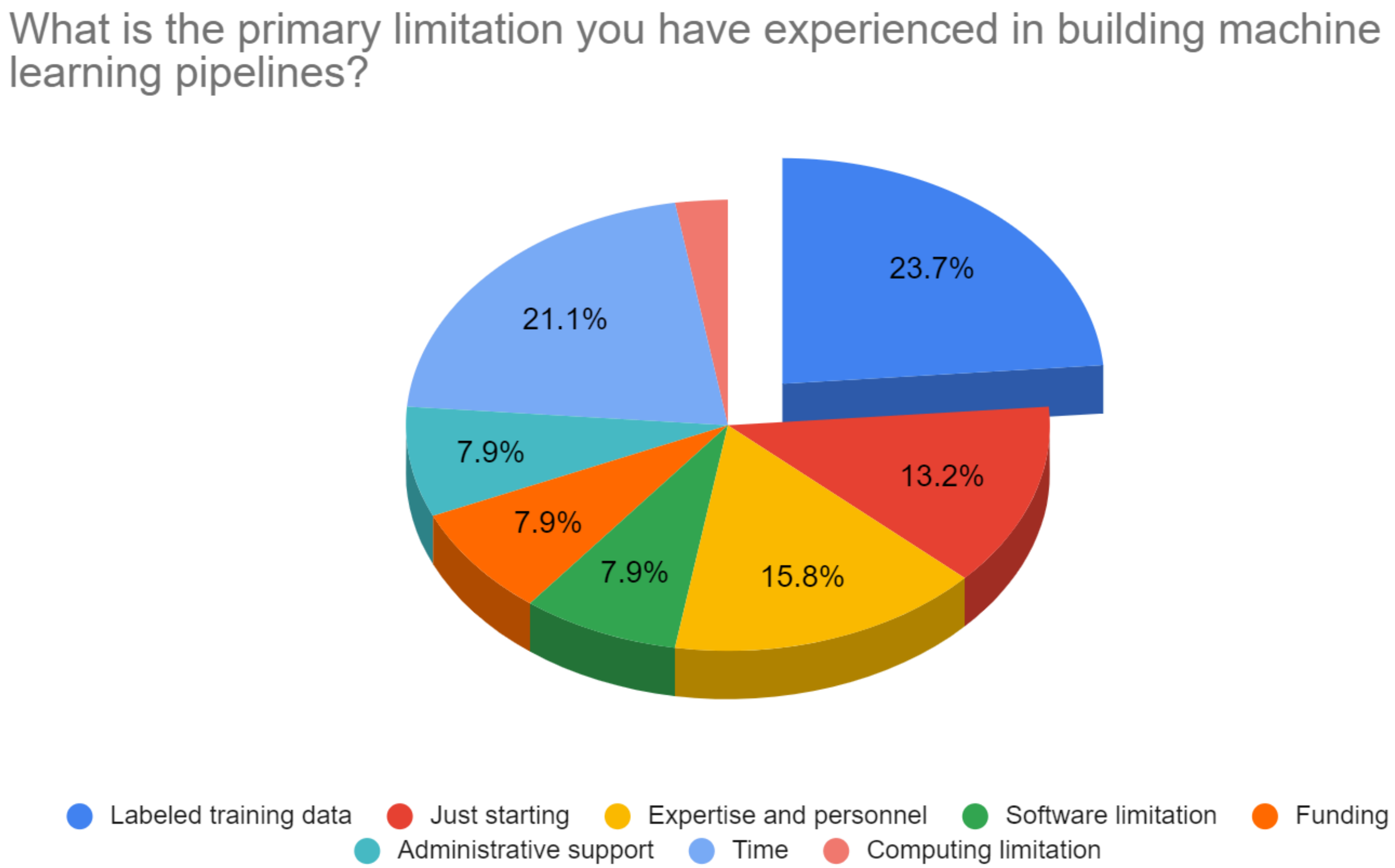
How has the choice of machine learning software impacted the outcomes of your research projects? Are there specific tools that you find particularly well-suited for

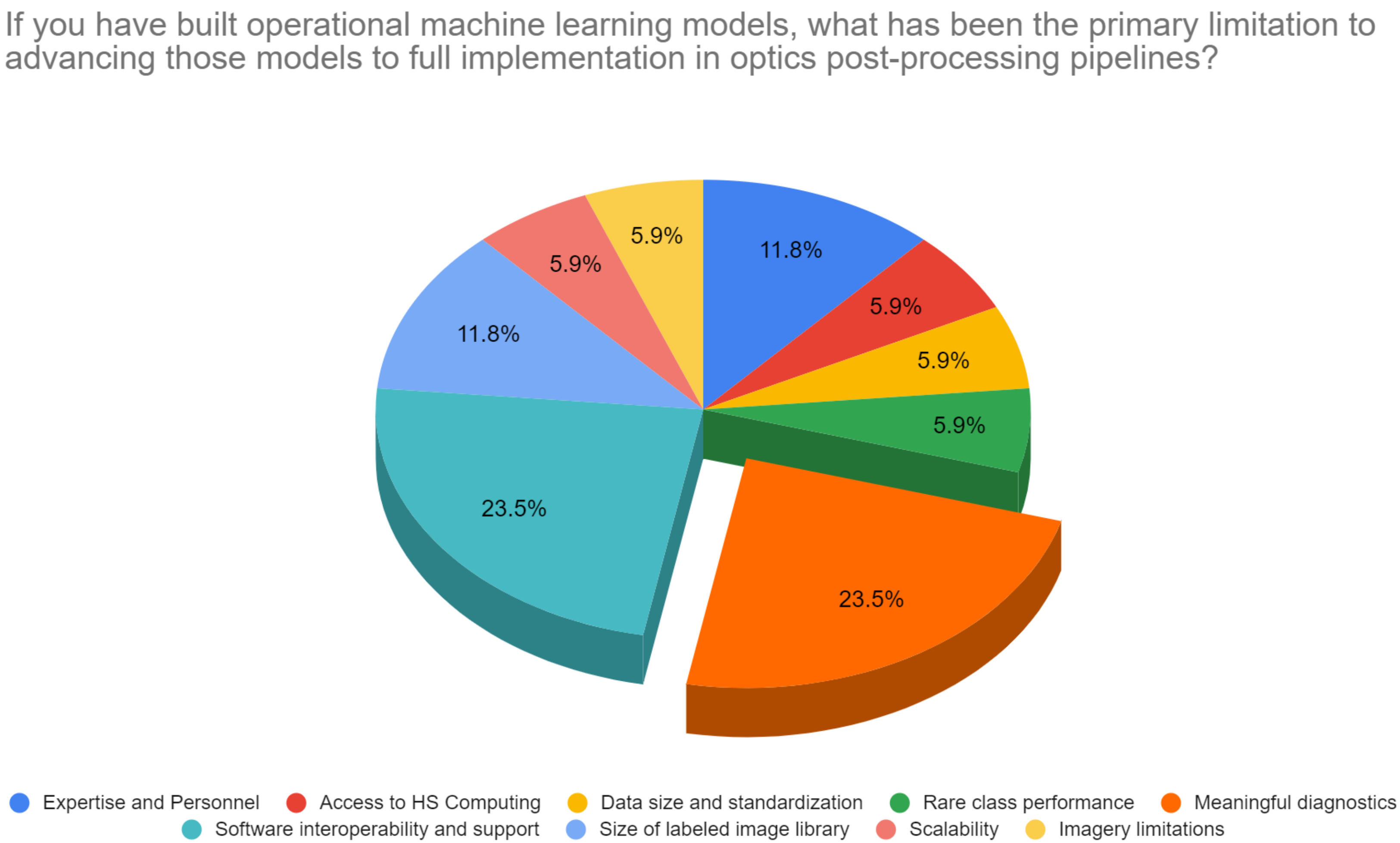


Are there specific areas or subfields within advanced optics where machine learning, combined with certain software tools, could significantly push the boundaries of current knowledge?

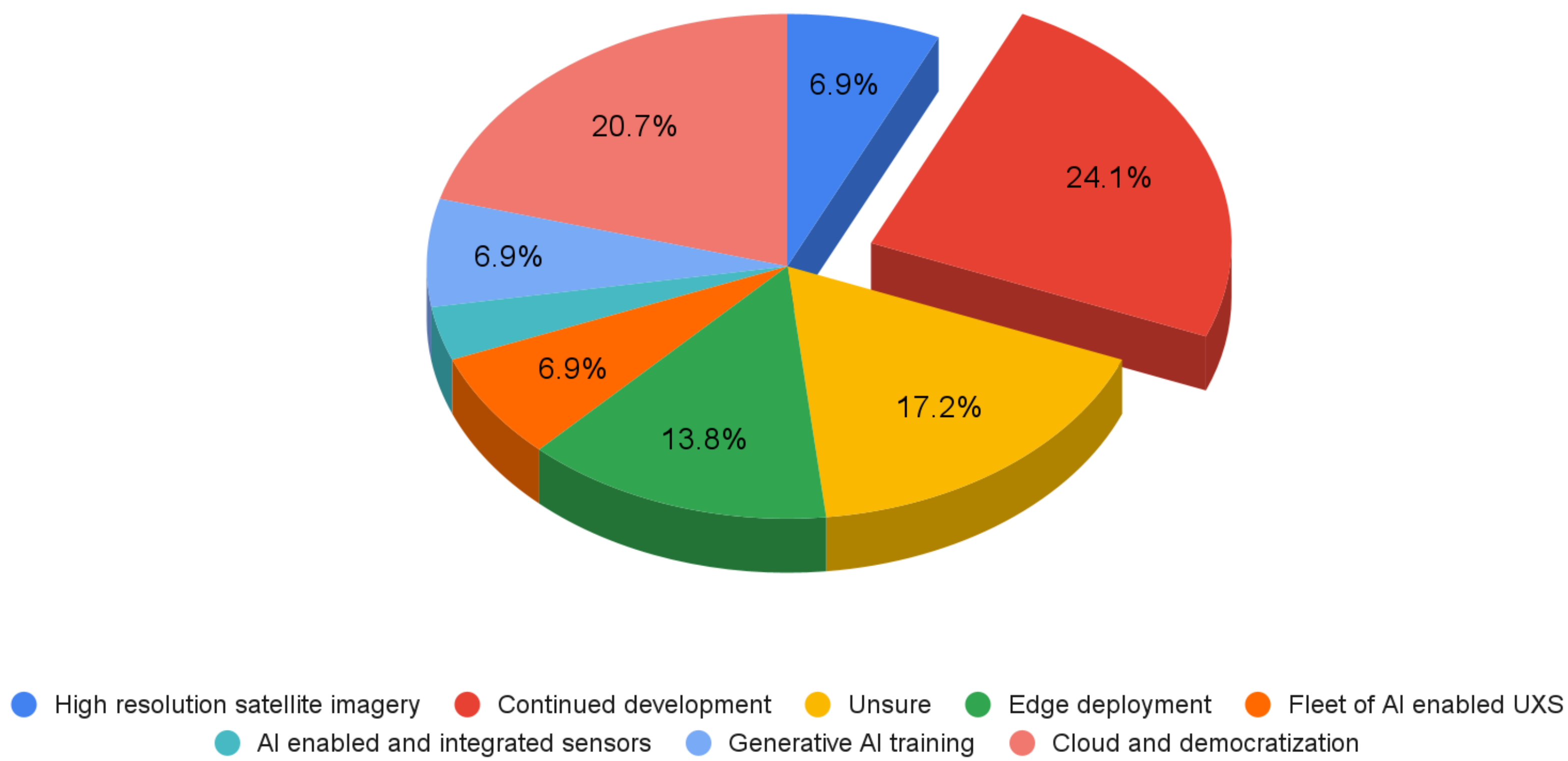


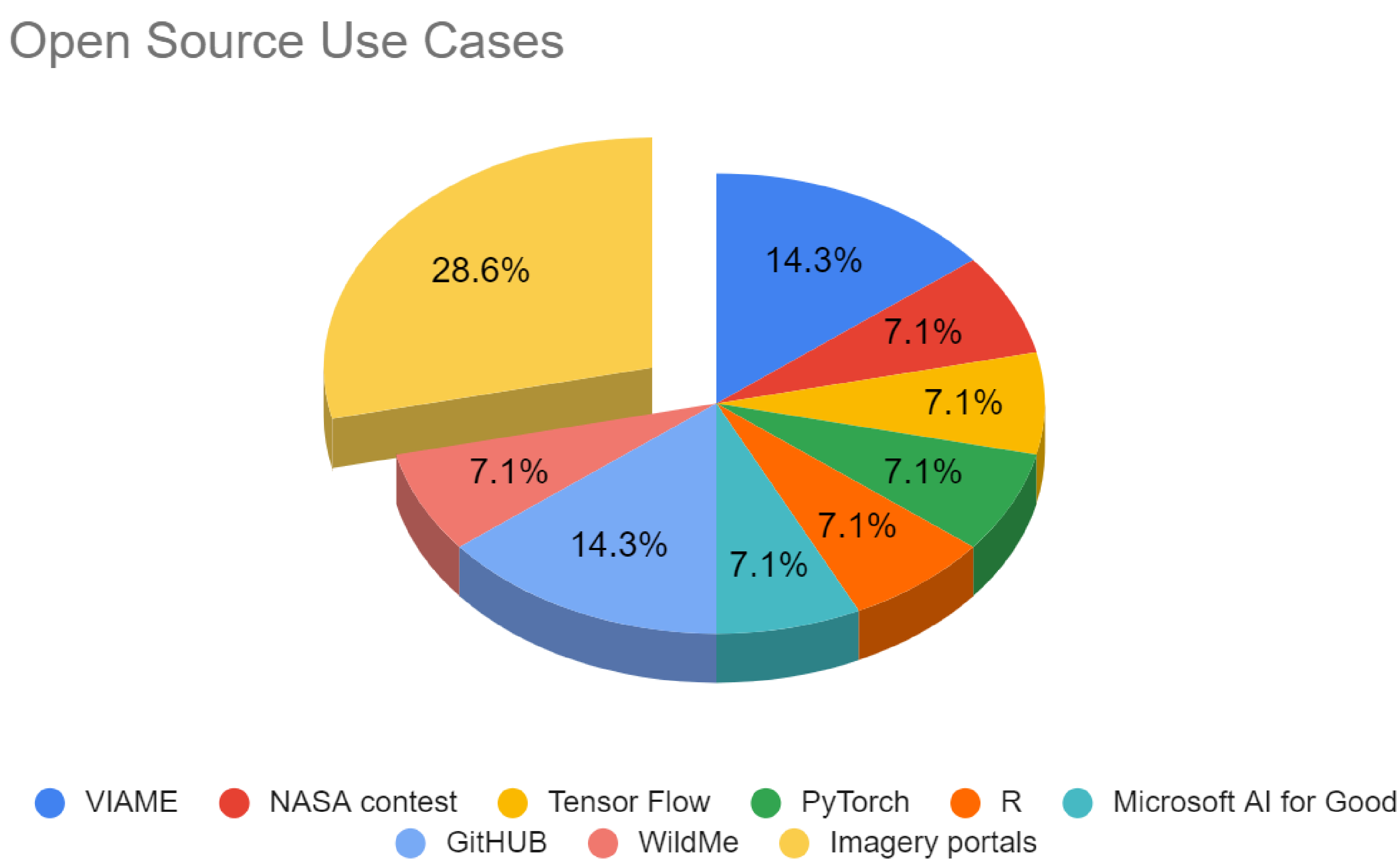

Are there specific upgrades in software functionality and tools that you desire for software you currently use?
18.2%
4.5%
4.5%
31.8%
Include mosaic'd imagery
VIAME steering committee
Open Source CNN tools
Plug and play
Unsure
Total software change
Facilitate cloud pipeline
Hyperparameter tuning
Edge deployment
End to End including project management
Access to expertise
Morphometrics
Interface


What is the primary limitation you have experienced in building machine learning pipelines?
23.7%
21.1%
7.9%
13.2%
7.9%
7.9%
15.8%
Labeled training data
Just starting
Expertise and personnel
Software limitation
Funding
Administrative support
Time
Computing limitation

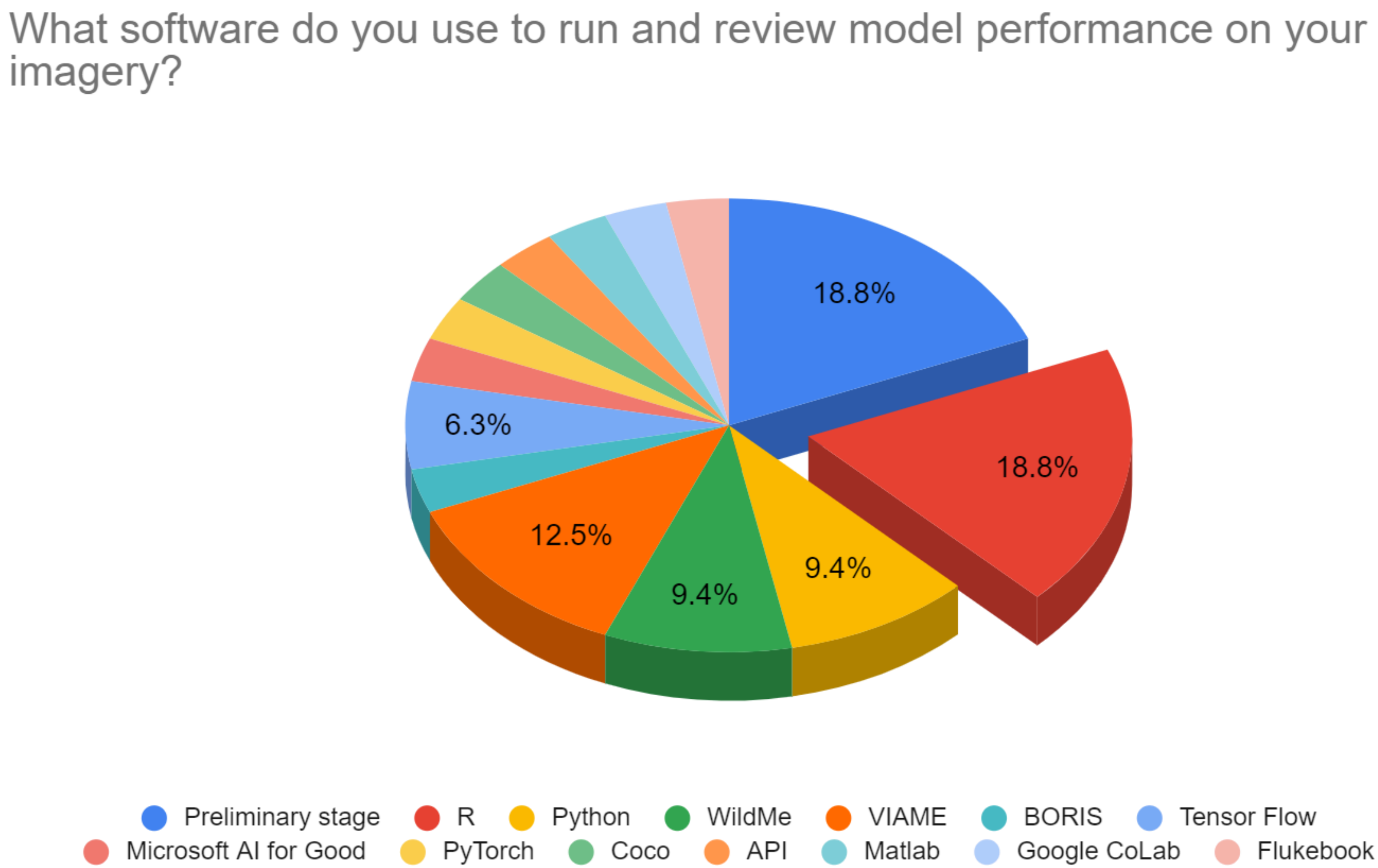

If you have built operational machine learning models, what has been the primary limitation to advancing those models to full implementation in optics post-processing pipelines?
11.8%
5.9%
5.9%
5.9%
23.5%
23.5%
11.8%
5.9%
5.9%
Expertise and Personnel
Access to HS Computing
Data size and standardization
Rare class performance
Meaningful diagnostics
Software interoperability and support
Size of labeled image library
Scalability
Imagery limitations

What emerging trends do you foresee in the integration of machine learning with advanced optics research over the next decade?





Open Source Use Cases
28.6%
14.3%
7.1%
7.1%
7.1%
7.1%
7.1%
7.1%
14.3%
7.1%
VIAME
NASA contest
Tensor Flow
PyTorch
R
Microsoft AI for Good
GitHUB
WildMe
Imagery portals


What software do you use to run and review model performance on your imagery?
18.8%
18.8%
9.4%
9.4%
12.5%
6.3%
Preliminary stage
R
Python
WildMe
VIAME
BORIS
Tensor Flow
Microsoft AI for Good
PyTorch
Coco
API
Matlab
Google CoLab
Flukebook