UNIVERSITY OF MICHIGAN, SCHOOL FOR ENVIRONMENT AND SUSTAINABILITY

Adaptive Resolution Imaging Sonar: Initial Exploration at Shiawassee National Wildlife Refuge

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EXECUTIVE SUMMARY

Shiawassee National Wildlife Refuge (SNWR), located near Saginaw, MI, is a collection of protected wetland, marsh, and flooded forest ecosystems that serve as vital habitat for migratory birds and numerous species of fish. Upon its designation as a National Wildlife Refuge in 1953, staff at SNWR began reconnecting the refuge's wetland habitats to the Shiawassee River and surrounding floodplains, as they had been previously cut off and drained for agricultural and timber development. The refuge is now split into separate units that can be hydrologically managed independently from one another. One of these units, Pool 1A (P1A), is always open to the Shiawassee River and thus remains hydrologically constant. Though staff at SNWR have been able to collect data on fish community composition within and between units, traditional field sampling methods are logistically limiting and insufficient at capturing fish movements. Consequently, SNWR staff incorporated the use of an Adaptive Resolution Imaging Sonar (ARIS) camera, placed at the connection point between P1A and the Shiawassee River, into the ecosystem monitoring plan for the refuge in 2020. The ARIS camera uses sonar technology to generate underwater video footage of fish movements, providing refuge staff with a unique opportunity to study fish migrations unconstrained by traditional field sampling methods.

Working with refuge staff from the U.S. Fish and Wildlife Service and U.S. Geological Survey, our team researched the most efficient means for analyzing data from ARIS footage, the data collection capabilities of both ARIS technology and of refuge staff and resources, and how ARIS data can be incorporated into long-term ecological monitoring plans for SNWR. In collaboration with the University of Michigan Advanced Research Computing Technology Services Group (ARC-TS), we developed a Machine Learning Model (MLM) that can view ARIS footage, count fish, and determine fish directionality with the potential to perform more footage analysis tasks with further development. The following report details the development of this project and the selection of a MLM for data processing, provides an operational procedure for use of our 2021 UM-Shiawassee MLM, and outlines recommendations for expansion of MLM capabilities and for the incorporation of ARIS data into long-term SNWR ecological monitoring.

ACKNOWLEDGEMENTS

TABLE OF CONTENTS

PART 1: INTRODUCTION TO ARIS TECHNOLOGY AND USE AT SNWR

INTRODUCTION

Hydrological reconnection of wetlands to local rivers and lakes is a vital step to achieve ecological restoration. At the Shiawassee National Wildlife Refuge (SNWR), floodplain units have been reconnected to the Shiawassee River via control structures and culverts. Though the refuge was designated as a protected habitat for migratory birds, its wetland and marsh habitats also serve as crucial reproductive and seasonal refuges for riverine, great lakes, and wetland fishes. The refuge is split into separately managed wetland, marsh, flooded forest, and moist soil units, which are periodically connected and disconnected to each other and the Shiawassee River via water control structures. Since 1958, Pool 1A (P1A) has been connected to the Shiawassee River. In 2016, two of the remaining agricultural fields were restored and designated floodplain units Maankiki North (MN) and Maankiki South (MS), which were first flooded in 2017 and 2018, respectively. In 2019, SNWR partnered with the University of Michigan School for Environment and Sustainability to begin conducting post restoration ecological monitoring of P1A, MN, and MS. This research will help refuge staff understand which hydrological conditions are most ecologically beneficial to fish communities.

In-person ecosystem sampling is limited in several ways. First, this type of sampling can only occur when environmental conditions and researchers' availability and resources allow. Second, these sampling methods characterize the fish community at one point in time. Between these two limitations, manual sampling methods cannot gather information regarding fish movement daily timing, volume, and seasonality. Consequently, filling this knowledge gap will benefit SNWR staff moving forward with ecological monitoring of the floodplain units by further characterizing the fish communities moving in and out of the system.

ARIS AT SHIAWASSEE

Monitoring of SNWR floodplain units has been conducted through seasonal field collections using fyke nets and electrofishing (Lugten et al. 2020). However, water depth, high turbidity levels, and staff logistical constraints have greatly limited the capability of these hands-on sampling methods to capture a comprehensive sample of fish communities moving in and out of the refuge units. Refuge staff are particularly interested in describing the character of springtime fish migrations, when many Great Lakes fishes ascend tributary rivers and may use floodplain wetlands for spawning or other purposes. However, water levels in spring are generally too high and too dangerous for in person sampling.

The Ottawa National Wildlife Refuge, another protected, Great Lakes, wetland ecosystem undergoing hydrological and ecological restoration, recently implemented an underwater, hydroacoustic sonar camera to overcome similar issues (Eggleston et al. 2020). SNWR staff incorporated an Adaptive Resolution Imaging Sonar (ARIS) camera into the ecological monitoring plan in 2020. The device sends a sound signal into its field of view and generates an image based on objects that bounce sound signals back ("About Imaging Sonar: Seeing with Sound" *Sound Metrics*). This enables the camera to capture high resolution images and video footage regardless of hydrological and water clarity condition, so it is ideal for capturing fish

movements in and out of the floodplain units at SNWR. By analyzing video data outputs from ARIS, staff at SNWR can begin to understand how fish use the restoration units and rivers throughout the day and during seasonal migrations.

Given that 2020 was the first year using an ARIS camera at SNWR, the physical setup of the camera was experimental and based upon similar usage at Ottawa National Wildlife Refuge in Ohio (Eggleston et al. 2020). An ARIS camera was deployed at the mouth of the connecting culvert between P1A and Ferguson Bayou Channel (Figure 1.1). The camera collects footage continuously, gathering a more holistic sample than traditional methods because it can operate during times of day or seasons when traditional sampling is infeasible. Consequently, data from the ARIS camera has the potential to inform and guide the ecological monitoring of SNWR's floodplain units.

Figure 1.1: An aerial photo of the Shiawassee National Wildlife Refuge. The red circle indicates the location of the ARIS camera placement at a culvert connecting the Shiawassee River to P1A (Image source: Google Maps).

Data from multiple ARIS deployments throughout the year will help answer research questions regarding the timing, magnitude, and frequency of fish migrations in and out of the restored floodplain units at SNWR. Additionally, ARIS data can be used to determine future management and ecological monitoring strategies at SNWR. For example, scientists at the SNWR are concerned that the location and size of connecting channels between floodplain units and the four convening rivers may impede fish movement within units. The ARIS camera could monitor fish entering or exiting the refuge unit, so ARIS data would give us clues regarding seasonal fish movements and daily fish movements. Thus, ARIS data may be able to answer questions about

the timing of specific species' migrations, how many fish are using the restored units, and whether fish are affected by the retention and management structures in these units.

The following describes the development of our research and work plan for ARIS at SNWR. This section of the report aims to describe the following:

1. Our ARIS Project Objectives.
2. Details regarding the function of the Machine Learning Model.
3. Details regarding deployment of ARIS at SNWR.
4. Development of our project plan.

ARIS PROJECT OBJECTIVES

We sought to answer the following research questions regarding potential for use of the ARIS camera at SNWR. These questions are designed to help achieve the primary objective for ARIS, which is to explore the deployment of ARIS as a tool for monitoring fish movements and migrations.

1. What is the most efficient way to analyze ARIS data?
2. What kind of data can we gather and what logistics are involved in leaving the camera at one site per season? At multiple sites?
3. How can we incorporate ARIS into the long-term ecological monitoring plan of the SNWR?

TECHNOLOGY BACKGROUND

Other ARIS Projects

Hydroacoustic imaging technology provides fish researchers flexibility to gather data on fish populations and movements in waters with low visibility (Helminen et al. 2020). Additionally, imaging sonar technologies are less invasive than traditional fish sampling methods and can generate images over long-distances, providing researchers with new opportunities for gathering data related to fish abundance, length, and swimming speed (Helminen et al. 2020).

As these technologies grow in popularity, researchers have begun to focus on the accuracy and utility of the data produced. In 2011, researchers at the Ottawa National Wildlife Refuge in Ohio used Dual-frequency Identification Sonar (DIDSON) technology, an older imaging sonar version of ARIS, to compare counting methods and determine the utility of this technology for fish research needs (Eggleston et al. 2020). The study found that manual counting and semi-automated, software-based counting mechanisms provided similar final results, meaning software counting programs were feasible for imaging sonar data analysis (Eggleston et al. 2020). Similar to our work at SNWR, a research team at the Chesapeake Biological Laboratory research pier investigated ways to efficiently and accurately analyze the massive data outputs produced by ARIS technology (Shahrestani et al. 2017). They developed a procedure that accurately performed automated image processing, though researchers noted that their methods and results were location specific (Shahrestani et al. 2017). In 2018, researchers installed an ARIS camera in the Upsalquitch River in New Brunswick, Canada to test the accuracy of ARIS-generated length measurements and found that the technology is promising but is not yet entirely reliable (Helminen et al. 2020). Understanding how imaging sonar technologies generate

necessary fish data, and how accurate that data is, will be particularly important, especially as these technologies become more available.

How the ARIS Camera Collects Data

An ARIS Explorer 3000, a sonar camera produced by the Sound Metrics Corporation, was deployed at SNWR. This camera collects imagery by emitting beams of sound waves with wavelengths that are about 2,000 times longer than visible light wavelengths (Sound Metrics 2021). The length of these sound waves allows them to penetrate farther than light in highly turbid conditions. In total, the ARIS Explorer 3000 emits 128 sound beams that help form the image (Sound Metrics 2021). These emitted sound beams propagate through water until they hit an object with different characteristics than the surrounding environment. The sound waves are then reflected off of the object back to the camera, where these signals are then converted into imagery (Figure 1.2) (Daoliang et al. 2020).
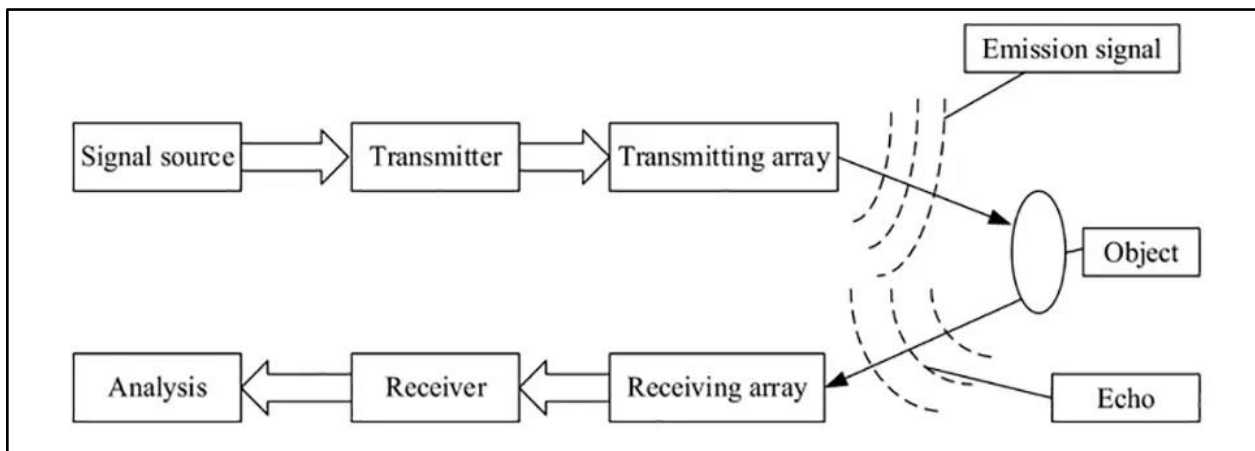
Figure 1.2: Diagram from Daoliang et al. (2020) illustrating the underlying method of how sonar cameras work. The boxes labeled "Signal source", "Transmitted", "Transmitting array", "Receiving array", and "Receiver" all represent the sonar camera, while the "Analysis" box represents the machine algorithm that processes the data.

The resolution of the sonar image is based on the frequency of the emitted sound wave. Higher frequencies allow for easier discrimination between objects in close range of each other; however, resolution is a trade-off for distance, with higher frequencies resulting in a shorter field of vision (Simmonds & MacLennan 2005). In our case, we are using a frequency of 3.0MHz with an image range extending from 1.00 to 3.98m (Bozimowski Personal Communication 2020).

ARIS Camera Placement and Orientation at SNWR

In late April 2020, the ARIS camera was fitted onto a metal mount installed on the P1A side of the connecting culvert, facing the culvert (Figure 1.3). The camera was submerged and angled downward toward the rocky substrate to capture fish movements throughout the entire water column. The camera remained mounted in this location and position for the duration of the spring and summer until its removal in November 2020.
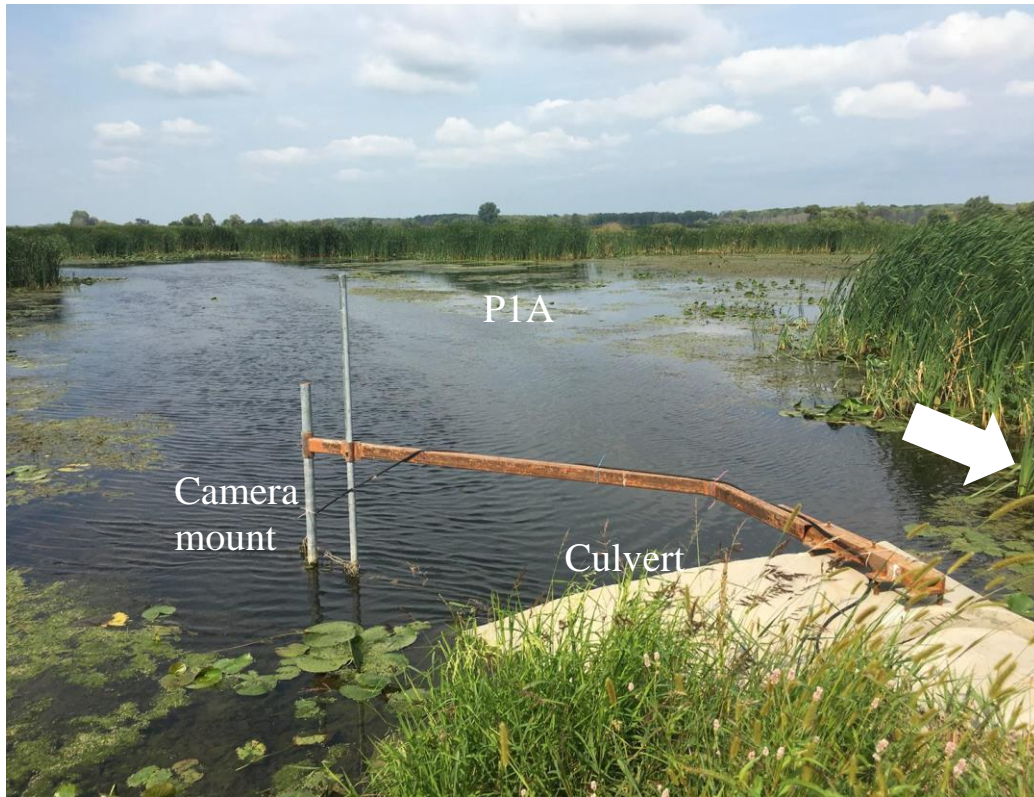
Figure 1.3: Photo of the camera mount at the mouth of the connection culvert. Note the positioning of the camera regarding P1A, which is in the photo background, and the Shiawassee River, which is out of frame, behind the photographer (Photo by Anna Greenberg).

As the camera operates far from any power source, refuge staff installed a gas generator to power the camera and all other necessary electronic equipment. The generator was placed just outside of a large, fully enclosed trailer, which housed all of the more sensitive electronic equipment required to run the ARIS (Figure 1.4). This included a laptop which was connected to a 1TB external hard drive (Figure 1.5). The laptop was set up to receive the camera feed while ARIS was running, and the output files were saved to the external hard drive. As the camera was programmed to run twenty-four hours a day, refuge staff were required to replenish gas in the generator roughly every other day and replace hard drives as they became full.

Figure 1.4: Photo of the trailer located on the dike separating P1A from the Shiawassee River. Note the water in the photo is P1A and the arm of the camera mount is also visible (Photo by Anna Greenberg).

Figure 1.5: Photo of laptop and hard drive setup inside the ARIS trailer (Photo by Anna Greenberg).

DEVELOPMENT OF OUR ARIS PROJECT

Options for ARIS Data Analysis

Though ARIS is a new tool for SNWR, similar technologies have been used by the U.S. Fish and Wildlife Service (USFWS) and U.S. Geological Survey (USGS) for many years. The DIDSON camera, an older version of ARIS, was used by USGS at Ottawa National Wildlife Refuge beginning in 2011, and data outputs from the DIDSON were analyzed using EchoView software (Eggleston et al. 2020). Additionally, the ARIS camera has an accompanying computer software tool, ARIScope/ARISFish, that researchers have used for ARIS data analysis (Helminen et al. 2020). In addition to existing analysis tools like EchoView and ARIScope/ARISFish, we explored crowdsourcing and machine learning as means for ARIS data analysis.

EchoView and ARIScope/ARISFish

Both EchoView and ARIScope are software tools that are capable of analyzing hydroacoustic footage and generating fish counts. EchoView, which was used during the DIDSON trial at Ottawa National Wildlife Refuge (Eggleston et al. 2020), has a costly software license and was consequently dismissed as an option for our ARIS project work.

The ARIScope tool counts fish in ARIS footage and requires that the ARIS footage, which is output in *.aris* file formats, be converted to MP4 file formats for processing. The ARISFish tool is capable of both counting fish and measuring length, a valuable feature for understanding movements of fish in different age classes. ARISFish, however, requires a robust computing device with enough processing power and memory. Due to logistical constraints of the COVID-19 pandemic, we would have had to operate these programs on personal laptops, which did not have the necessary features to efficiently operate the ARIScope and ARISFish programs.

Additionally, the ARIScope and ARISFish programs are proprietary to ARIS technology manufacturers, meaning the capabilities of these programs are static and unadaptable. In exploring the other available options detailed below, we determined that other avenues for ARIS data analysis would provide refuge staff with greater flexibility and logistical freedom than would ARIScope and ARISFish.

Crowdsourcing

Crowdsourcing is a growing method that enlists large numbers of volunteers (or less frequently, paid individuals) over the internet to generate or analyze data for research projects (Oxford Advanced Learner's Dictionary). Websites like Zooniverse (https://www.zooniverse.org/), for example, host scientific projects in which volunteer citizens assist in data generation. Volunteers select a project and receive a brief training regarding how to accurately perform data generation tasks ("About" *Zooniverse*). They are then able to assist researchers by, for example, counting the number of penguins in a huddle from remotely gathered video footage, recording the color of birds utilizing remotely recorded feeders, or even characterizing behavior of wildlife in remotely gathered footage.

We strongly considered crowdsourcing on Zooniverse as an ARIS data analysis method. The Zooniverse project would prompt volunteers to watch ARIS video footage and manually mark individual fish to generate fish count totals. ARIS data would need to be stored on cloud storage platforms that were accessible to Zooniverse users, which presented a cost due to the volume of ARIS data that would need to be stored. Another difficulty with crowdsourcing was USFWS and USGS data privacy considerations. ARIS data hosted on Zooniverse would be considered public and would need to be specially approved by USGS, which was uncertain and at best would take several months.

We initially explored both crowdsourcing and a custom machine learning model (MLM) as options for ARIS data analysis and came to realize that machine learning was an inevitability. Though both crowdsourcing and machine learning could generate fish count data, machine learning provides the opportunity for more detailed analysis that, if pursued through crowdsourcing, would require much more intensive volunteer training. We dismissed crowdsourcing as an option for project work, and pursued machine learning as the more viable long-term ARIS data analysis method.

Machine Learning Model

Machine learning is a process in which a computer is trained to independently perform data analysis tasks (Edwards 2014). After data are collected and properly prepared, researchers generate a set of training data that is used to teach the computer model how to perform a task. For example, to teach the computer to count every red car that passes a traffic camera, the researcher would generate a sub-sampled dataset for which they already labeled the red cars. This would be used to teach the computer how to recognize red cars. Once the model has been trained, it goes through numerous evaluations so the model algorithms can be adjusted to increase model performance (Edwards 2014). Machine learning offers great potential for ARIS data analysis.

Selection of Machine Learning

We determined an MLM to be the most appropriate means to achieve our objectives of counting total and directional fish movements. We collaborated with the University of Michigan Advanced Research Computing Technology Services Group (ARC-TS) to lead the programming portion of this project. Our team and ARC-TS generated and signed a Service Level Agreement to outline the product expectations and payment plan for the collaboration (see Appendix 1.1).

The ARC-TS Team implemented a convolutional neural network designed to detect objects in images. The model was trained on proprietary labeled images that were evaluated with a holdout set of testing data. Because we were working with known training sets and classifying objects into known categories, the ARC-TS Team initially identified several supervised learning algorithms that would be capable of counting fish and detecting directionality. Ultimately a supervised residual network (ResNet) model run via Python software was chosen because it is easily modifiable, thus allowing for the possibility of increased capabilities in the future. Additionally, this model is very robust and fast in comparison to others like it. For additional information on the specifics of this model, see the "Machine Learning Model Development and Performance" Section of this report.

While it is useful to quantify how many fish move in and out of units, it is worth noting that this ability is not unique to our MLM. Other software packages, such as ARISFish, which is the standard method of analysis for ARIS camera output, are also capable of counting fish. However, no software package currently exists that can identify fish to species or assess directionality in the ways that SNWR eventually hopes for. For this reason, the development of an entirely novel and modifiable software, such as this MLM was necessary at SNWR. If successful, this model could be a novel tool for ARIS users across the country.

Development of Project Work

Once it was decided that a MLM was the most advantageous way to analyze ARIS footage, we had to decide how to proceed with project work. The majority of our team's time was spent assisting ARC-TS in the creation and training of the MLM. We determined that the remainder of our work would focus on answering ARIS procedural questions, as opposed to biological questions. While using the MLM to better understand fish community composition and migratory behavior in floodplain units is the ultimate goal of the refuge, the highly complex nature of implementing this MLM requires that a thorough procedural groundwork be laid before that is possible.

In this report we describe the technology utilized in the ResNet MLM and detailed logistics of how to operate this model on a variety of different platforms. Additionally, recommendations will be made for future uses of ARIS, expansions of MLM abilities, and data collection and analysis strategies. These recommendations will utilize findings from various other National Wildlife Refuges (NWRs) and restoration projects that have implemented ARIS cameras with similar goals in mind. Ideally, this will allow the refuge to begin to answer the biological questions with ARIS data as soon as 2022.

PART 2: MACHINE LEARNING MODEL DEVELOPMENT & PERFORMANCE

INTRODUCTION

For effective and efficient analyses of the ARIS hydroacoustic data, we created a MLM. We considered alternative methods including crowdsourcing or using existing software but chose the MLM as it could: improve upon the existing software, be used on any operating system, and would be convenient for clients to run. Here we describe the process of creating the 2021 UM-Shiawassee MLM, as well as how it functions.

MODEL SPECIFICS

Model Backbone

The 2021 UM-Shiawassee MLM algorithm is a supervised Residual Network model run in Python. ResNet models work well for research applications such as this one, since they are a deep learning model; one that follows a hierarchical, non-linear set of data transformations that act similar to a human brain (Marr 2018); and that can be used for prediction, feature extraction, and fine-tuning (Keras Team). Specifically, ResNet50, a type of ResNet, was chosen for our MLM because of its flexibility and robustness with images, paired with its relatively quick training time. A robust model can perform effectively, despite alterations to its variables or assumptions.

Coding Language

We chose Python as the coding language because it is an introductory programming language that is easy for beginners to understand, making it feasible for us to pick up and learn model mechanics without needing to dedicate a significant amount of time to learning how to program. Other languages that can be useful for machine learning, most notably C++ and MATLAB, were considered, but those languages have fewer built-in options and more difficult setups. Furthermore, MATLAB was not scalable for the final product, and the university licensing agreements weren't suitable for distributing the product.

DATA GENERATION & MODEL TRAINING

Machine Learning Method

Machine learning has three phases: training, validation, and testing. In order to train the 2021 UM-Shiawassee MLM, we used the supervised learning method. With the supervised training method, the model analyzes the input of labeled datasets to train algorithms to classify data or predict outcomes accurately (IBM Cloud Education 2020). The labeled datasets provided the model with examples of what objects the computer should be looking for in the data and how to correctly identify these.

Still images were sampled from various months of the unedited video footage, which comes in the form of "*.aris*" proprietary files. We visually analyzed these still images and labeled observed fish by drawing a box around the extent of each individual fish in Python (Image 2.1). Approximately 3,500 total training images were labeled. This number of images should have

enough diversity of fish size and placement in the images that should be representative of all seasons, so further labeling should not be necessary. The 3,500 labeled images were split 80:20 for use in the training and validation steps, respectively. In the training phase, the MLM was shown the subset of training images so it could learn what a "fish" looks like.
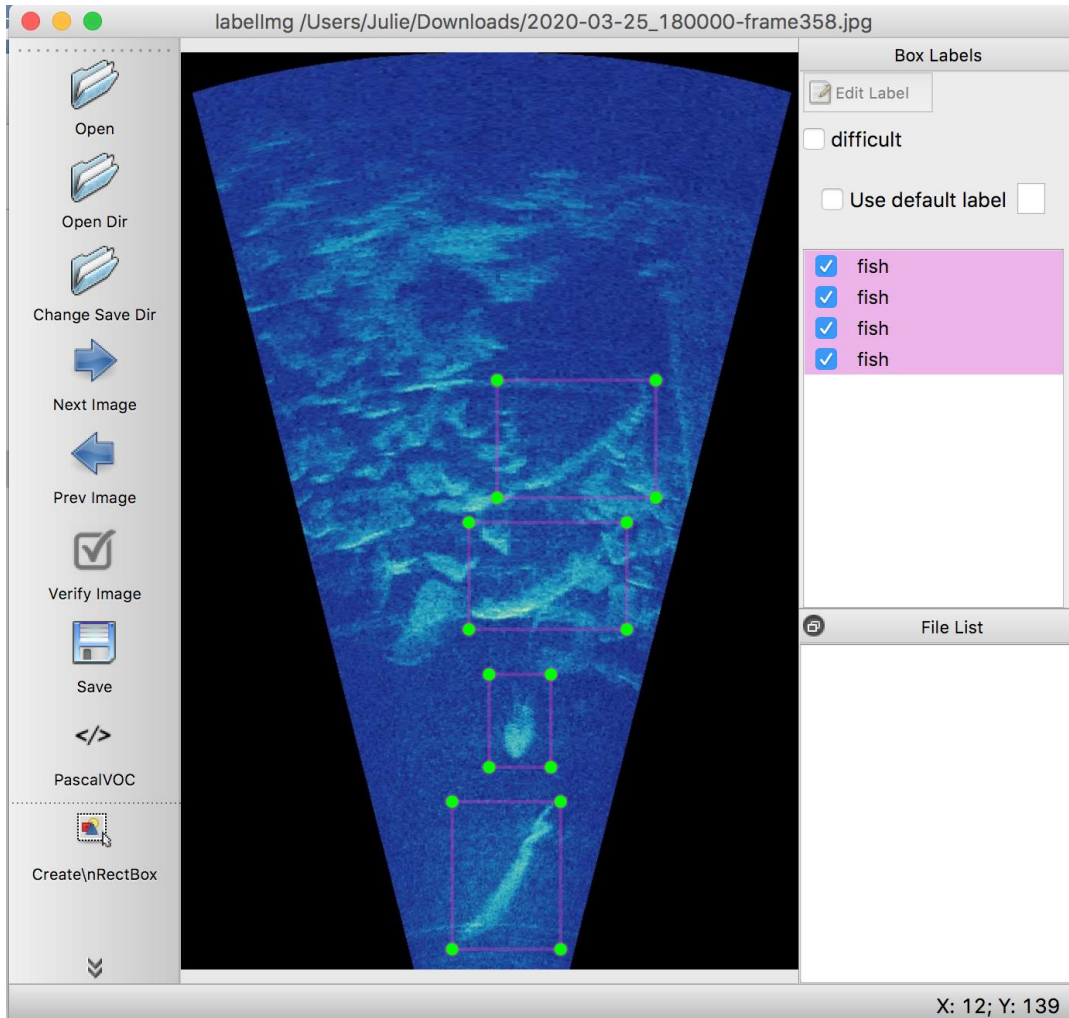
Image 2.1: Screenshot of a single input data image being labeled using the LabelImg Python tool. A single box represents the extent of an individual and is tagged as a "fish."

Training the Model

Throughout the training process, images were fed through the MLM. To do this, all of the training images were put in a randomized order and divided into groups (referred to as "batches"). Batches were run sequentially until 1,000 batches were seen by the model. At this point, all of the images were fed through the model thus completing one "epoch." Then, batches were recreated and the process was repeated for a total of 20 epochs. These 20 epochs should be representative of all seasons and no further training iterations should need to be completed unless the background or coloring drastically change. Having multiple batches and epochs helps the model to fine tune the algorithm parameters, thus improving its performance.

The final step is testing and validation. Images from our labeled training set were selected, duplicated, and the labels removed from the duplicates. These unlabeled versions were shown to the model, which labeled where it identified fish. We were then able to compare the two versions of the same image, the one labeled by the model and the one we manually labeled for the training set. This allowed us to test the model's predictive abilities for accurately identifying fish.

Quality Control

To further increase the accuracy and consistency of the training data, images were cross-labeled by another team member; i.e., two people analyzed each image. Each member was assigned another member's data folder to relabel the camera images. These images were then run through a coding script with the originally labelled images to compare how individuals tagged the footage. This process aimed to ensure consistency across our image analyses.

	Percent of Images
All Fish Matching	72.49%
1 Non-Matching	16.19%
2 Non-Matching	9.10%
3+ Non-Matching	2.22%

Table 2.1: Table of the percentage of fish mismatches divided by count per image for the 950 cross-labeled images.

Approximately 950 images were checked for quality control. We found that labeling was consistent across our team, with 89% of images having zero or one fish mis-matched (Table 2.1). In this context, matching means that the identifying boxes, which were drawn by two separate people, on the same image had more area overlapping than not overlapping. Non-Matching means that there was one case of rectangles drawn in the image that overlapped but did not overlap enough or a rectangle label existed in one image that did not exist in the same image labeled by a different person.

INNER WORKINGS OF THE MLM

To start running the model, one *.aris* data file is uploaded into the terminal. One *.aris* file contains approximately one hour of sonar camera footage and is around 6.5GB in size. This file is then converted from its proprietary *.aris* format into a *.mp4* file using the model's built-in conversion tool. This conversion significantly reduces the size of the raw footage, with the *.mp4* files being approximately 2-4GB in size. The *.aris* file is also processed into individual image frames. Our images were processed every other frame to reduce overall processing time while still getting the most information.

From here, each individual image is run through the model, which outputs predicted fish location within the image and assigns each prediction with an ID number. The location tracking algorithm was provided by the cv2 Python library and was customized with additional code to better meet our needs. This algorithm works by trying to predict the path of where an object will move and then updating the track as the object moves. Every time the algorithm sees something that might be a fish, that it hasn't seen before, it assigns that object an ID number. The ID number is essential in updating the object path. For example, if the object is assigned an ID that has not

been found yet, the model assigns a "trackable object" to it. However, if that object ID has already been assigned, the model will update the previous location if it's a "trackable object." Expanding on this, if an ID already exists in the list of previously IDed objects, but was not identified in the most recent image, then the model will look at how long the fish has not been in frame or "unidentifiable." If the ID has not been seen for more than 10 images, it is considered removed from the image.
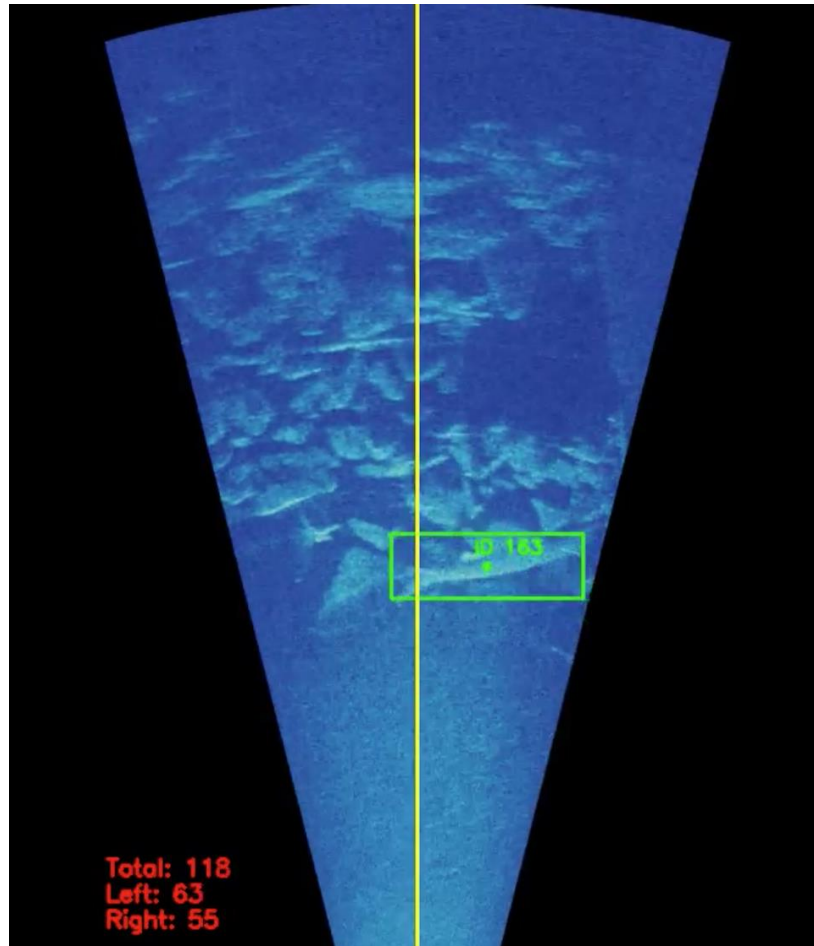
Image 2.2: Screenshot of the .avi output from the 2021 UM-Shiawassee MLM. The green box indicates the extent of the identified fish while the ID number is a possible fish identification. The yellow line down the center is used to determine the directionality of the fish based on analysis of successive frames. Finally, the bottom left is a running total of identified fish and the total count of fish moving either left or right.

File	Total Fish	Total Right	Total Left
2020-03-26_170000.*mp4*	195	94	101

Table 2.2: Example output CSV file from the 2021 UM-Shiawassee MLM describing the number of identified fish and their movement directionality.

Depending on the computer hardware, running the model takes approximately one hour per GB and results in two outputs. The first is a labeled *.avi* video tracking the fish (Image 2.2). The second output is a comma-separated values (CSV) file that summarizes the data from the *.avi*

file. The CSV lists the output data of total fish count and the total count of fish moving either left or right (Table 2.2).

MODEL PERFORMANCE

Model metrics for the 2021 UM-Shiawassee MLM were calculated using various formulas (Formulas 1-5) (Fawcett 2006). The true positives (TP) and negatives (TN) and false positives (FP) and negatives (FN), among other values, were determined in our validation phase. The MLM has a 65.94% precision rate. Precision is calculated by taking the ratio of true positives to the total of the true positives and false positives (Table 2.3) and describes the MLM's proficiency at correctly identifying fish (Wood 2020). So, the higher a precision value is, the less false positives are being identified by the model. In this application, 65% precision is quite good, when compared with the human-to-human validation accuracy of 73%.

$$\text{True Positive Rate (TPR)} = \frac{TP}{P} = \frac{TP}{TP+FN} = 1 - FNR$$

$$\text{Precision/Positive Predictive Value (PPV)} = \frac{TP}{TP+FP} = 1 - FDR$$

$$\text{False Negative Rate (FNR)} = \frac{FN}{P} = \frac{FN}{FN+TP} = 1 - TPR$$

$$\text{False Discovery Rate (FDR)} = \frac{FP}{FP+TP} = 1 - PPV$$

$$\text{Threat Score (TS)} = \frac{TP}{TP+FN+FP}$$

Formulas 1-5: Equations used to calculate metrics for the 2021 UM-Shiawassee MLM.

Furthermore, the 2021 UM-Shiawassee MLM has an average 85% confidence value for all of its predictions. Confidence relates to how sure the model is that it identified a particular fish. This value is determined by behind-the-scenes actions in the neural net but is essentially based on how similar the area of the image is to the model's understanding of a "fish" versus how similar the area is to the background. If the neural network looks at an area and decides that it is similar to the background, but still with a few differences, the network might predict a fish with a low confidence value. Likewise, if it finds an area that has distinct differences from the background and similarities to a fish, it'll predict a fish with a high confidence. Our MLM automatically discards any predictions below 30% confidence. With the incorporation of a neutral background, as mentioned in "Recommendations for Future ARIS and MLM Use" section of this paper, it may be possible to increase both the confidence and precision of the MLM.

Metrics	ResNet50 Model
True Positive Rate (TPR)	57.13%
Precision/Positive Predictive Value (PPV)	65.94%
False Negative Rate (FNR)	42.87%
False Discovery Rate (FDR)	34.06%
Threat Score (TS)	44.11%

Table 2.3: Table showing the rates of discovery for the 2021 UM-Shiawassee MLM.

PART 3: ARIS 2021 MACHINE LEARNING MODEL OPERATING PROCEDURES

INTRODUCTION
We focused on creating a usable and transferable ARIS data analysis tool for the USFWS, USGS, and future Shiawassee project teams. The MLM can be used and adapted by future users to meet their logistical and data analysis needs. For example, the MLM can either be used remotely by project team members working from home or internationally, or by refuge staff at SNWR offices and facilities.

The following describes the operating procedures for setting up, using, and troubleshooting the ARIS 2021 MLM.

TWO METHODS FOR RUNNING THE MLM
The MLM is a package of computer code that must be "attached" to an operating system in order to run. Users can think of the MLM like a lamp that doesn't work unless it is plugged in. There are two primary methods for "plugging in" the MLM.

Using Method 1, the MLM is "plugged in" on a virtual desktop in XSEDE: Jetstream, which is essentially a computer that exists in the virtual cloud environment on the internet (Figure 3.1). Camera footage must be uploaded to the Jetstream platform. Uploads are faster and rely less heavily on computing resources of the user's machine using the Globus Connect Personal (GCP) tool. Since this method relies on a "virtual computer", the computing capabilities of the researcher's computer are irrelevant. The ARC-TS team recommends you use a Windows machine for this method.

Method 2 houses the MLM on a local desktop computer and does not require an internet connection (Figure 3.1). Camera footage can be loaded directly into the model from the hard drives that directly collect footage outputs. The MLM algorithms use the computing resource of the machine in which it is housed, so the machine needs a Central Processing Unit (CPU) and memory (RAM) that are large enough to efficiently run the MLM. The program that runs the code was designed by ARC-TS for a Windows machine. If it is necessary to use Method 2 on a Mac/Linux machine, ARC-TS can provide the appropriate program and code.

METHOD 1   METHOD 2
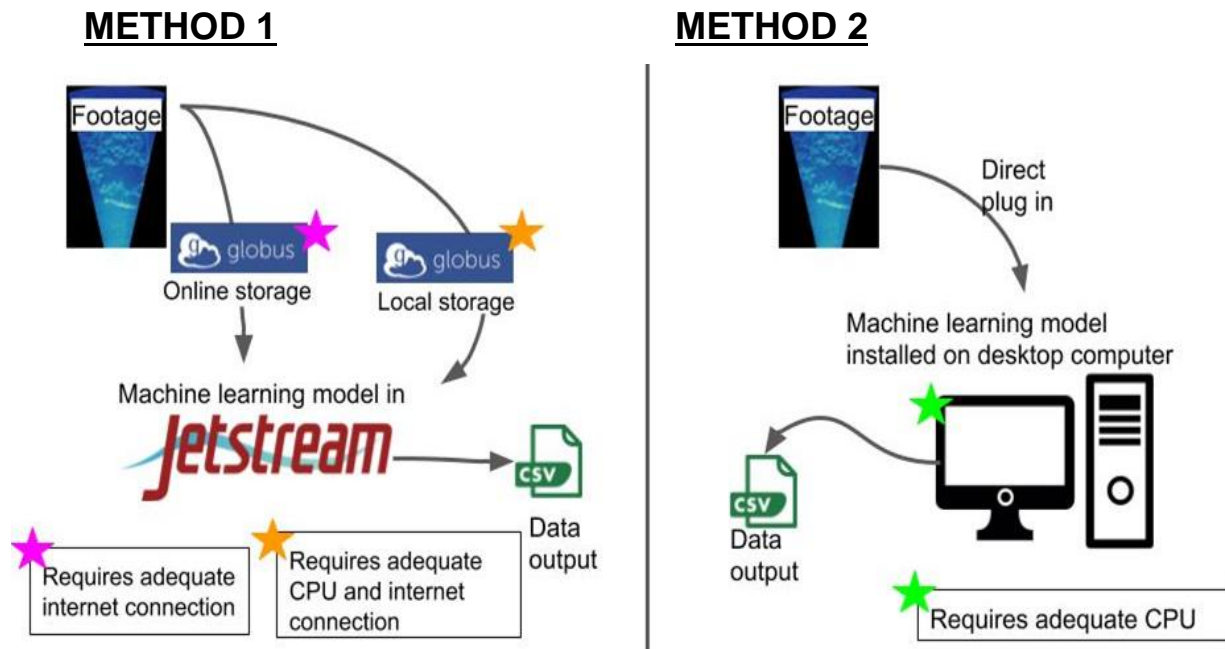
Figure 3.1: Visual representation of the two methods for housing the MLM. Note the stars which indicate computing and internet considerations for each method.

Advantages and Disadvantages of Each Method

Each method for running the MLM comes with advantages and disadvantages (Table 3.1). It is likely that some combination and joint use of both methods will be the most efficient use of time and resources for analysis of ARIS footage and data production.

	METHOD 1	**METHOD 2**
Description	MLM is housed in a virtual environment.	MLM is housed on a local desktop computer (must be Windows).
Advantages	Does not include any computing requirements. Greater applicability to remote work. Multiple researchers can work simultaneously.	Simplifies workflow for moving ARIS footage into MLM. No internet connection required. Can theoretically be run on any computer, but the program that runs the code was designed by ARC-TS for a Windows machine.

Disadvantages	Requires adequate internet connection. Requires adequate computing allocation in virtual environment account. Requires more complex workflow and use of GCP to upload ARIS footage into a virtual environment.	Limits number of researchers who can use MLM at any given time.
Considerations	The Jetstream (or other virtual desktop) allocation is typically limited in processing power usage and in memory. Researchers are not able to rely on Jetstream for data storage. Applying for a Jetstream allocation takes time (3-6 weeks).	Most desktops do not have adequate-enough CPU to efficiently run the MLM. More CPU can be purchased for a desktop computer. Code package associated with the following sections applicable to a Windows machine. Consult ARC-TS for code applicable to a Mac/Linux machine.
Time for *.aris* → MP4 file conversion	6.5GB file (equates to ~ 1 hr footage) will convert in ~30 minutes in Jetstream.	
Time for MLM processing of converted hour of ARIS footage	1 hr of footage takes 6-7 hours to be processed through the MLM **at 12CPUs** in Jetstream.	Footage MLM run time is directly proportional to the CPU of the platform. If the computer has 12CPUs, 1 hr of footage will take 6-7 hours to be processed through the MLM. If the computer has 4CPUs, 1 hr of footage will take 18-21 hours to be processed through the MLM.

Table 3.1: Summary of comparisons between MLM Methods 1 and 2.

METHOD 1 DESCRIPTION: XSEDE - JETSTREAM

Jetstream is a cloud computing resource from XSEDE that acts like a virtual super-computer. Future student teams will have to work with their faculty advisor and ARC-TS to set up a Jetstream allocation with adequate memory and CPU capabilities.

Using Jetstream to house the MLM is advantageous because it does not require the student to have physical access to a computer with adequate computing capabilities. Each student will have their own Jetstream account, but the student team will all be working with the same computing resource allocation. This means that multiple students can work in Jetstream at the same time off the same allocation.

PLEASE NOTE: file names, account names, storage platforms, lines of code, etc. listed in this procedure document were used by our team. These may change depending on the version of the MLM and on the student team's relationship with ARC-TS. All file names, account names, lines of code, etc. in this procedure document that may change in future years are written in red text.

PLEASE NOTE: other computing resources, like the Great Lakes Cluster, are also usable for mounting and using the MLM. This guide is written for Jetstream users because that is what we used. Future student teams should consult with ARC-TS and their faculty advisors regarding the best cloud computing platform to meet their research needs.

How to Get Started on XSEDE - Jetstream

This section outlines steps to set up Method 1 for ARIS footage analysis. Once you complete these steps, you will NOT need to complete them again.

Startup Allocation Application

1. Every member of the student team and their project advisor will create an XSEDE user account (https://portal.xsede.org/#/guest).
2. The student team will need to write an application for a larger Jetstream allocation.
   a. Information and policies about the application can be found here: https://portal.xsede.org/allocations/policies#61.
   b. NOTE: there are periodic deadlines for these allocation applications.
3. The application will ask for the following information:
   a. Project Title
   b. Abstract
   c. Keywords
   d. Principal investigator
      i. NOTE: you will put in your project advisor for this section.
   e. Field of science
   f. Documents
      i. NOTE: this will be your advisor's CV (2-page limit).
   g. Resources
   h. Resource disclosure
      i. This refers to other resources at your team's disposal.
      ii. NOTE: the 2021 UM-Shiawassee Team listed "UMich Box" here as a place to store our extra video
      iii. NOTE: please see Appendix 3.1 for the application submitted by the 2021 UM-Shiawassee Team, which includes the resource request (that was developed with help from ARC-TS).
4. The student team advisor will need to submit the application.
   a. This is done by copying/pasting application materials into the application page which can be found on the following page:
      i. Login to XSEDE → Allocations → Submit/Review Request → Startup → Start a New Submission
5. The application may take several weeks to be approved.

Launching Instances

Your "Instance" is your virtual machine within Jetstream.

1. Create a new project in your Jetstream account.
   a. Click "Projects" at the top of your Jetstream homepage.
   b. Select "Create New Project".
   c. Name your project (example: Shiawassee2020).
2. Select your Project.
3. Click "New" and "Instance".
   a. Select "Show All" and enter "UMICH" into the search bar.
   b. Select the most up-to-date instance: "Shiawassee Team UMICH V6"
   c. Confirm the following information before launching the instance (see Image 3.1):
      i. Project: should be your project that you created
      ii. Allocation: should be the SEAS Shiawassee Allocation (TG-BIO200001).
      iii. Instance Size: set to m1.Xlarge
         1. This is very important! Size selection determines the amount of memory and CPU associated with your instance. It basically determines how powerful your virtual machine will be.
      iv. Provider: Jetstream TACC.
   d. Click "Launch Instance"
      i. It will take between 10-20 minutes for your instance to fully launch.
      ii. You will receive an email when it has launched successfully. You can also check its status on the homepage of your Project.
         1. To confirm that your instance has successfully launched, check that the Status says "Active" and the Activity says "N/A".
4. Once your instance is fully launched, it is available for use. This means it is using up some amount of your Jetstream allocation "in the background" (even if you are not actually using the instance, it is still running and using up allocated CPU).
   a. PLEASE NOTE: Whenever you are NOT using your Jetstream instance, you need to "Suspend" or "Shelve" the instance to stop it using up your allocation.
      i. If you do not Suspend or Shelve your instance, it will run "in the background" and use up allocated CPU while not in use. That means there will be less available for you to use to run the MLM.
      ii. Click on the Instance in your Projects.
         1. On the right-hand side, select either "Suspend" or "Shelve".
         2. This process will take several minutes.
      iii. Whenever you need to use your Jetstream cloud computer, you will need to "Unsuspend" or "Unshelve" your instance.
         1. This process will also take several minutes.
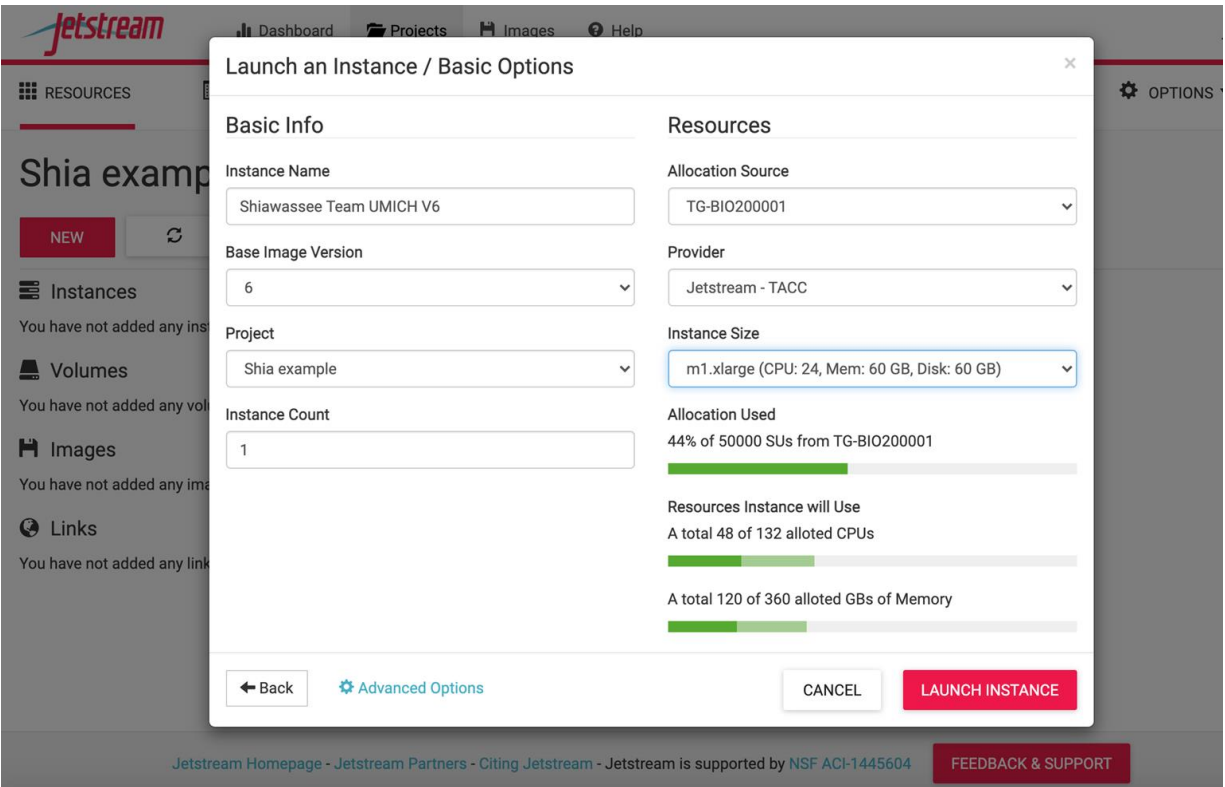
Image 3.1: Screenshot of the Jetstream Instance requirements.

Launching and Linking Volumes

Your "Volume" is the storage center for your Instance. It is like the USB drive that you will "plug into" your Instance to house ARIS files and MLM output files. Volume size is limited and dependent upon the allocation your team receives. Therefore, the Volume is NOT a long-term data storage solution for ARIS footage.

1. If you are not already there, navigate to your Project.
2. Click "New" and "Volume"
3. Name your Volume (example: ARISFiles).
4. Indicate the necessary size of your Volume (example: 100GB).
    a. Remember, ARIS files are ~6.5GB each and you will likely want to store several raw ARIS files at a time, *plus* the converted MP4 files.
    b. Also, remember that the total storage allocation is split amongst all group members. So, if your *total* XSEDE allocation is 500GB, that will be split amongst 5 group members to be 100GB each.
        i. Work with ARC-TS and/or your team to determine how big to make your Volume.
5. Select Jetstream TACC as the Provider.
6. Click "Create Volume".
7. Now you have created the Volume, but you still need to link it to your Instance.
    a. In other words, you have acquired a USB drive (Volume) but you need to plug it into your computer (Instance) to access files.

8. To link the Volume to your Instance:
    a. Unshelve or Unsuspend your Instance if necessary.
    b. Click on the Volume and select "Attach" in the right-side menu.
        i. Select the correct Instance to attach the Volume to.
    c. Click "Attach Volume to Instance".
        i. This will take several minutes.1
    d. NOTE: when attached to your Instance, your Volume will be named /vol_b. This will be very relevant to future steps in this section.
9. In order to "Shelve" or "Suspend" your Instance, you will first need to "Detach" your Volume.
    a. To do this, click on your Volume and select "Detach" from the right-side menu.
    b. Once it is successfully detached, you can "Shelve" or "Suspend" your Instance.

How to Get Started on GCP

Globus is a free file transfer service that efficiently and safely moves files from one directory to another via "cloud" internet. The directories, or "endpoints" can be located on a local computer (saved file to the computer drive or stored on an external hard drive or USB) or can be located on cloud storage servers, e.g., Box, Sharepoint, or Amazon S3. The user can direct Globus to pick up files from their source location and transfer them to an endpoint. This transfer happens "in the background" and "in the cloud", which means the computing capabilities of the machine used for the transfer do not limit this process.

The 2021 UM-Shiawassee Team used a type of Globus connection called Globus Connect Personal (GCP) to pull ARIS footage files from Box (online storage server) and load them into the appropriate Jetstream Volume. The following describes how to link GCP to both Box *and* to a local computer storage system.

PLEASE NOTE: file names, account names, storage platforms, lines of code, etc. listed in this procedure document were used by the 2021 UM-Shiawassee Team. These may change depending on the version of the MLM and on the student team's relationship with ARC-TS. All file names, account names, lines of code, etc. in this procedure document that may change in future years are written in red text.

These steps will only need to be completed once. Please note that steps 1-3 listed below must be completed regardless of the file location (e.g., cloud server or local desktop).

1. Create a Globus account https://globus.org
    a. In the top right, select "Login".
    b. Select the option to "Use your existing organizational login" and search for the "University of Michigan".
        i. NOTE: If you already have your XSEDE/Jetstream account set up, Globus will recognize XSEDE has your default organizational login. Make sure you change this to University of Michigan.
    c. Login with your UMICH credentials.

2. Once your account is created, go to the "Account" tab on the left side menu.
    a. Select the "Globus Plus" menu tab from the top of the "Account" page.
    b. Click "Select a Globus Plus Sponsor" and search for the "University of Michigan".
    c. After doing so, notify someone on the ARC-TS team that you have completed this step. They need to approve your request.

If your files are stored in a cloud server like Box, complete the above 2 instructions and then see "Operating Procedure for MLM in Jetstream." If your files are stored locally on a computer drive, complete the section below before proceeding to "Operating Procedure for MLM in Jetstream."

Link GCP to Local Computer Drive
1. On your Globus account, head to "Endpoints" along the left side menu.
2. Click "Create a personal endpoint" in the top right.
3. You will be prompted to "Download Globus Connect Personal for Windows"
    a. Click this if you are on a Windows device.
    b. If you are not on a Windows device, select "Show me other supported operating systems".
    c. Follow the onscreen instructions to install.
4. Once GCP is successfully installed, you will see an icon at the bottom right of your screen along the toolbar (on a Windows device).
5. Open GCP on your computer
    a. The first time you do this, you'll be prompted to sign in and create an Endpoint.
        i. Make sure to name your Endpoint in a unique and memorable way (example: MyComputerARIS).
        ii. This Endpoint is like your computer's GCP ID.
6. NOTE: if the files are located on an external hard drive, the user will need to configure access to the hard drive. Use this link to do so: https://docs.globus.org/how-to/globus-connect-personal-windows/.

See the following section for how to link GCP to Jetstream and transfer files.

Operating Procedure for MLM in Jetstream
Here we outline two sets of steps and details for successfully running the MLM in Jetstream and trouble-shooting common problems. The first set of steps outlines initial steps that the researcher will only need to complete ONCE, the first time they set up the MLM and GCP in Jetstream. The second set of steps outlines the procedure the researcher will need to complete EVERY TIME they use the MLM in Jetstream.

Steps you only need to complete ONCE:
1. Login to your Jetstream account.
2. Launch the correct instance.

a. Make sure that the Activity status reads "N/A" - this indicates that the instance is fully launched.
3. Attach the correct volume to that instance.
4. Open the Web Desktop via your instance (right-hand side of the instance details page).
    a. When you open the Web Desktop, a pink banner will appear at the bottom of the window. You can close this.
5. Open the terminal in the Web Desktop ("Terminal Emulator"). This should be located along the bottom icon menu on the Web Desktop, desktop.
    a. You will see your Jetstream username and some other code in the first line before the cursor. This means your terminal is successfully connected.
6. Input sudo chown -R USERNAME /vol_b and replace USERNAME with YOUR Jetstream username.
    a. Click "enter"
    b. NOTE: the easiest way to paste code into the terminal is to right click and select "Paste"
7. Input chmod +x /vol_b and click "enter".
    a. Steps 6 and 7 here are making your Jetstream volume (vol_b) available for transferring data.
8. Input /opt/arcts/globus/globusconnectpersonal & and click "enter".
    a. This code launches GCP (via Jetstream).
        i. A box will pop up and prompt you to "Connect to GCP". Select "Connect".
        ii. You should get a notice that you have connected successfully.
    b. Since this is your first time completing this step, you will be prompted to sign in.
        i. NOTE: if you are NOT prompted to sign in, check your terminal for an error message stating that you need to install "tcllib".
            1. If this occurs, input the following code: sudo yum install -y tcllib
            2. After installing "tcllib", input /opt/arcts/globus/globusconnectpersonal & again.
        ii. Sign into your GCP account.
    c. You will be prompted to create a name for your Personal Endpoint. This will be the "directory" for your Jetstream Instance.
        i. Make sure to name this Personal Endpoint in a unique and memorable way (example: ARIS20).
        ii. NOTE: if you are using GCP to connect to your desktop or local hard drive, you still need to create another Endpoint. The Endpoint you create in this step is like your Jetstream's GCP ID.
    d. Go to your Globus account (on your personal browser, outside the virtual desktop) and open the "File Manager" tab along the left side menu.
        i. NOTE: make sure that you are signed in via UMICH and not XSEDE (check this by navigating to the "Account" tab on the left side menu). If you are logged in with XSEDE, log out and log back in via UMICH.

    ii. Search for your Personal Endpoint in the "Collection" search bar.
     1. The "search" function can be tricky and you may need to search only part of your Endpoint name and scroll until you find it.
     2. All you are doing in this step is verifying that you can *find* your Personal Endpoint.
    iii. Navigate to the"Endpoints" tab on the left side menu and confirm your Personal Endpoint is listed under "Administered By You".

9. Once you're logged in, a new window will pop up that displays the status of your GCP and Jetstream connection. If it does not say "Connected", click "Connect" and make sure the "Globus Online" status changes to "Connected".

10. In the same pop up window, click "File" and "Preferences"
  a. Click "+"
  b. Text reading "Path" will appear. Click on this and replace "Path" with the name of your volume (include the "/"): /vol_b
  c. Make sure the check box under "Write" is checked and click "Save".

Steps you need to complete EVERY TIME you use the MLM in Jetstream:

If you *just* completed the above section ("Steps you only need to complete ONCE"), complete ONLY Step 6 below and check if Step 9 applies to your user status before proceeding.

1. Login to your Jetstream account.
2. Launch the correct instance.
  a. Make sure that the "Activity" status reads "N/A" - this indicates that the instance is fully launched.
3. Attach the correct volume to that instance.
4. Open the Web Desktop via your instance (right-hand side of the instance details page).
  a. When you open the Web Desktop, a pink banner will appear at the bottom of the window. You can close this.
5. Open the terminal in the Web Desktop.
  a. You will see your Jetstream username and some other code in the first line before the cursor. This means your terminal is successfully connected.
6. Input xrandr -s '1920x1080'
  a. NOTE: If you copy and paste this, the quotation marks turn into question marks.
    i. Make sure to change these back to quotations for the command to work.
  b. This command improves desktop screen resolution and makes it easier to work in the Web Desktop.
7. Input /opt/arcts/globus/globusconnectpersonal & and click "enter"
  a. This code launches GCP (via Jetstream).
  b. NOTE: the easiest way to paste code into the terminal is to right click and select "Paste"

8. A window will pop up that displays the status of your GCP and Jetstream connection.
    a. Click "Connect" and make sure the "Globus Online" status changes to "Connected".
9. If you are transferring files to Jetstream from a local machine drive, you also need to open the installed GCP program on your machine and click "Connect".

Loading Files into Jetstream via GCP
Follow these steps regardless of where files are stored (Box or local drive). Note that some steps may have different instructions depending on where files are stored.

You can load files into Jetstream in advance of running the MLM. You may choose to load several files using the steps below on Monday and run the model on Tuesday. This is okay to do as long as you do not exceed the memory and storage capacities of your Jetstream allocation.

1. Complete the steps listed above in "Steps you need to complete EVERY TIME you use the MLM in Jetstream" if you have not yet done so.
2. If you are not logged in already, login to your Globus account (https://globus.org)
    a. Make sure you are signed in via UMICH and NOT XSEDE.
        i. You can check this by navigating to "Accounts" and examining the "Identity" column. It should say USERNAME@umich.edu.
    b. If your files are located on a local hard drive, make sure to open and sign into GCP on your machine as well.
3. In your online Globus account, navigate to the File Manager tab (along the menu on the left side).
    a. In the File Manager window, make sure your screen view is set to side-by-side panels (options in the upper right corner of the File Manager window).
4. In the left "Collections" search bar, search for your GCP endpoint.
    a. Click on the endpoint (the endpoint name should populate the "Collections" bar).
    b. Fill in the "Path" bar with the name of your volume (/vol_b).
5. In the right "Collections" search panel, search for the location of your files
    a. If files are in Box, search "UMich Box Collection"
        i. NOTE: if this does not work, make sure you are successfully logged into your Box (or file storage) account.
    b. If files are stored locally on your machine's drive, search for your computer's GCP ID (that you created when you first signed into the GCP program on your machine).
6. Navigate within the right-hand panel to the Box or local drive data folder with the files you plan to work with in the MLM.
    a. NOTE: here, you are essentially viewing your Box account via GCP. So the folder organization you see in the GCP right-hand panel will reflect the organization in your Box account.
    b. Select the appropriate file.

c. You can transfer entire folders, just select the folder instead of an individual file.

7. Navigate in the left-hand panel to /vol_b.
    a. To keep files organized, you can create folders within your /vol_b. Do this by right-clicking in the left-panel and selecting "New Folder".
        i. NOTE: if you need to create a new folder in /vol_b, do NOT include any spaces. Add dashes or underscores.
    b. Select the appropriate folder.

8. Once you have the correct files (or folders) selected in each panel, click "Start".
    a. After a few seconds, a notification window will pop up telling you that your transfer request was successfully submitted.
    b. Here, you are transferring files from Box or your local drive into your Jetstream storage volume (/vol_b) using GCP as the conduit.

9. You can track the progress of the file transfer in the "Activity" tab in the left-side menu of your Globus account.
    a. You will also receive an email when the transfer is complete.

Converting .aris Files to MP4

The ARIS camera produces footage files as *.aris* files. The MLM cannot read these files, and they must be converted to MP4, which is a readable file format for the MLM. For more information on this, please see Part 2 of this report, Machine Learning Model Development and Performance.

10. Complete the steps listed above in "Steps you need to complete EVERY TIME you use the MLM in Jetstream" if you have not yet done so.

11. Open your Web Desktop and terminal.

12. If you have not done so already, make sure to connect to GCP (input /opt/arcts/globus/globusconnectpersonal &)
    a. Remember, you may have files sitting in your Jetstream waiting to be run through the MLM if you chose to upload files separately from running them.

13. If you have already connected to GCP, check that the code that includes your Jetstream username remains before the cursor in your terminal.
    a. If it is NOT there anymore, open a new terminal (but do NOT close the first one).

NOTE: you are able to convert multiple files at one time. Converting files in bulk is more efficient than converting each file one at a time. The following steps are split depending on if you wish to convert just one file or if you want to convert a group of files in bulk.

CONVERTING ONE FILE

14. Input python3 /opt/arcts/desktop_app/desktopApp.py to launch the MLM window.
    a. This will take several seconds.

15. IF THERE IS AN UPDATE TO THE MLM AVAILABLE, input /opt/arcts/model-update into the Web Desktop terminal.
    a. ARC-TS will notify you if there is an update to the MLM.
16. Click "Load File"
    a. Make sure the directory is set to "/" in the drop-down menu and that you select /vol_b.
    b. Select the file you want and click "Open".
17. In the window that opens, set the CPU to 12.
    a. Set the Directory, which tells the program where to save the converted MP4 output.
    b. Click "Convert"
18. Typically, one hour of footage (~6.5GB) takes 30 minutes to convert to MP4.
19. You will know that files have successfully converted when the progress bar pane says "Done processing". Click "Close".
    a. To confirm it is complete, you'll also see a still frame of footage in the application window with the file name and ".*mp4*" at the top.

CONVERTING MULTIPLE FILES IN BULK
20. In your Web Desktop terminal.
21. IF THERE IS AN UPDATE TO THE MLM AVAILABLE, input /opt/arcts/model-update into the Web Desktop terminal.
22. Input python3 /opt/arcts/desktop_app/arisConvert.py --input /FOLDER LOCATION/ --output /FOLDER DIRECTORY
    a. Input the path to the folder where the *.aris* files are located in place of "FOLDER LOCATION".
    b. Input the path to the folder for where converted MP4 outputs should be saved in "FOLDER DIRECTORY".
23. If you want to ensure that no files are overwritten in the output folder, add a space and then --no-overwrite to the end of the line of code above.

Running the MLM

24. You will know that files have successfully converted when the progress bar pane says "Done processing". Click "Close".
    a. To confirm it is complete, you'll also see a still frame of footage in the application window with the file name and ".*mp4*" at the top.
25. If you do not already have it open, input python3 /opt/arcts/desktop_app/desktopApp.py to launch the MLM window.
    a. This will take several seconds.
26. If necessary, click "Load File" to select the MP4 file you want to run in the MLM.
    a. Make sure the directory is set to "/" in the drop-down menu and that you select /vol_b.
    b. If you have *just converted* a single file, it will already be loaded into the MLM application
        i. You can tell which file is already loaded by looking at the file name at the top of the still frame of ARIS footage on the right.

c. If you converted files in bulk, you will need to select the individual MP4 file you wish to run.

d. NOTE: the MLM can only analyze one file at a time.

27. Select your "CSV Output Settings".

    a. The 2021 UM-Shiawassee Team recommends selecting all 3 output options.

28. Click "Start Algorithm"

    a. A progress bar will appear.

    b. A standard file of one hour of ARIS footage (~ 6.5GB) takes ~ 6-7 hours to run through the MLM at 12CPU.

        i. As long as you leave your Web Desktop open and your computer remains on, you do not need to monitor the MLM's progress and you can use your computer as normal.

29. When the model is complete, click "Save Results" and select the option for "CSV File".

    a. A directory window will appear.

    b. Choose your volume directory (/vol_b) and input an appropriate file name (with no spaces) and manually add ".*csv*" at the end of the file name.

        i. Example: "March20Output.*csv*"

30. You can also save the labeled output video by clicking "Save Video".

    a. Choose your volume directory (/vol_b) and input an appropriate file name (with no spaces) and manually add ".*avi*" at the end of the file name

        i. Example: "March20Video.*avi*"

31. IF YOU CAN'T SAVE YOUR OUTPUT:

    a. If you are unable to save your output after the MLM finishes running, you can still access the output CSV and video file the next time you log into your Web Desktop terminal.

        i. The next time you login to your Web Desktop terminal:

            1. Connect to your GCP.

            2. Input cp ~/.seasAppData/modelOutput /vol_b/modelOutput.*csv* to save the last CSV output the MLM generated to your /vol_b.

            3. Input cp ~/.seasAppData/labeled.*avi* /vol_b to save the last labeled video file the MLM generated to your /vol_b.

Exporting MLM Outputs via GCP

32. Navigate to your Globus account and the File Manager page.

    a. Make sure the File Manager screen view is set to side-by-side panels (see page view settings in upper right corner).

33. Populate the left panel with your Jetstream endpoint name in the "Collections" bar and /vol_b in the "Path" bar.

    a. For instructions on how to do this, see "Loading Files into Jetstream via GC."

    b. Select the folder and/or file in /vol_b that contains your MLM CSV output, AVI output, and/or converted MP4 file.

      c. NOTE: The 2021 UM-Shiawassee Team strongly recommends you save the output CSV and MP4 file for every ARIS footage file you run through the MLM.

          i. The CSV contains the data you need for footage analysis.

          ii. The MP4 is valuable to have backed up in case you need to run that footage through the MLM again.

          iii. Your *.aris* file still lives in Box, and you don't need to retransfer it back.

34. Populate the right panel with the location of your files (Box, Sharepoint, local computer drive)

      a. For instructions on how to do this, see "Loading Files into Jetstream via GCP."

      b. Select the folder in Box or your local drive where you would like to store MLM output files.

35. Click "Start".

      a. This will transfer files *from* your /vol_b to your storage folder.

Deleting Files from Jetstream

Remember that your Jetstream allocation has limited storage and memory, so it is best that you frequently delete all unnecessary files from your volume.

After successfully running the MLM and transferring the outputs into your storage directory (either online or local), you will be able to delete the original *.aris* file, the MP4 file, the CSV output, and the AVI output from /vol_b.

36. In the Jetstream Web Desktop, navigate to the desktop window.

37. You will see a desktop icon for your volume drive (/vol_b).

      a. Click on this icon to open your volume drive.

38. Select and delete all unnecessary files.

Data Workflow Options for Method 1

There are serveral ways to make camera footage available to run through the MLM in Jetstream. The following outlines several options for this data workflow.

Camera → external hard drive → shared Box account → Jetstream via GCP

Camera → external hard drive → shared Sharepoint account → Jetstream via GCP

Camera → external hard drive → local desktop computer → Jestream via GCP

Camera → external hard drive → Amazon S3 server → Jestream via GCP

Transferring files from an external hard drive to an online storage platform (Box, Sharepoint, S3, etc.) is time-intensive and internet-dependent. If the student team plans on running substantial amounts of data using Method 1, they need to allocate time for uploading files (see Part 4 of this report, Recommendations for Future ARIS and MLM Use, for recommendations regarding workflow). Additionally, if COVID-19 prevents the 2021 student team from having access to the external hard drives, they will need to adjust their workflow plan regarding Method 1 so as to avoid placing the upload burden on USFWS refuge staff.

METHOD 2 DESCRIPTION: LOCAL DESKTOP

The MLM can be installed on a computer and run locally, which eliminates the need for an internet connection and for a GCP account. The MLM will run on the computer's hardware, meaning the device's CPU and RAM need to be adequate in order to run the model efficiently. This method must be used on a Windows computer.

When selecting a computer for local MLM operation, users should consider:
- CPU of the computer
  - CPU will influence how long it takes for the MLM to process footage.
  - 1 hour of footage takes 6-7 hours to process through the MLM at 12CPU. The processing time and CPU are directly proportional (so a 4CPU computer will take 18-21 hours to process).
  - All computers have two "threads" in each of its "cores" (components of CPU).
    - This means that a 4 core computer has 8 threads.
    - The computer may thus be advertised as having 12 cores (4 cores + 8 threads). However, this is NOT the same as having 12 physical cores.
    - It is best to select a computer with 12 physical cores.
- RAM of the computer
  - RAM will influence how long it takes for the MLM application to convert files from *.aris* to MP4.
  - The conversion tool uses, at most, 14RAM.
    - It is best to select a computer that has at least 14RAM.

See Part 4 of this report, Recommendations for Future ARIS and MLM Use, for recommendations on selecting an adequate computer for MLM Method 2.

Setting up MLM on Local Desktop

ARC-TS put together a software package that contains the file conversion tool and MLM for easy download. This software package was developed for a Windows machine. Consult ARC-TS for a software package designed for use on a Mac/Linux machine. The following steps for downloading the package are based on the Windows software package.

NOTE: The following steps only need to be completed once upon installation and set up.

NOTE: You may need administrative access to run the two installation programs on your computer.

NOTE: File names, account names, storage platforms, lines of code, etc. listed in this procedure document are pulled from the 2021 UM-Shiawassee Team. These may change depending on the version of the MLM and on the student masters project team's relationship with ARC-TS. All file names, account names, lines of code, etc. in this procedure document that may change in future years are written in red text.

ONLY COMPLETE THESE STEPS ONCE:
1. Install XMing by following the instructions at this link:
   https://sourceforge.net/projects/xming/
2. Install Docker for Windows (assuming you are on a Windows device) by following the instructions at this link: https://docs.docker.com/docker-for-windows/install/
3. After both programs are successfully installed, open up a command terminal on your computer.
   a. On a Windows computer, this can be done by searching "CMD" in your program search bar (typically bottom left or located in the Start menu).
   b. Open the program called "Command Prompt" or "Command Terminal".
4. Input the following line of code: docker pull richeymumich/seas-desktop-app
   a. This command pulls in the MLM program in Docker (which is called the Docker "image").
5. When the program opens, set the environment variable "DISPLAY" to be the Ethernet adapter IPv4 Address
   a. To find this address, input the code ipconfig into the terminal and the Ethernet adapter IPv4 Address will come up.
6. NOTE: if there is an update to the MLM, you will need to complete steps 3-5 again, as the Docker "image" will be updated and will need to be re-installed.

Operating Procedure for MLM on Local Desktop
COMPLETE THESE STEPS EVERY TIME YOU USE THE MLM ON A LOCAL MACHINE:
1. Open and run XMing on your computer.
   a. XMing is a program that runs "in the background" and allows the MLM to operate on your computer.
2. Open your command terminal
   a. On a Windows computer, this can be done by searching "CMD" in your program search bar (typically bottom left or located in the Start menu).
   b. Open the program called "Command Prompt" or "Command Terminal".
3. In your command terminal, input: docker run -ti --rm -e DISPLAY=$DISPLAY richeymumich/seas-desktop-app:latest
   a. NOTE: if this does not work successfully or the display is not adequate, input the following code instead: docker run -ti --rm -e DISPLAY=YOUR ETHERNET ADAPTER IPv4 ADDRESS richeymumich/seas-desktop-app:latest
      i. Make sure to input your Ethernet Adapter IPv4 Address in place of "YOUR ETHERNET ADAPTER IPv4 ADDRESS" in the code above.
      ii. See the previous section on how to find this Address.
4. The MLM application window will open.
5. You will need to load ARIS footage files and convert them from .aris to MP4
   a. NOTE: you are able to convert multiple files at one time. Converting files in bulk is more efficient than converting each file one at a time. The following steps are split depending on if you wish to convert just one file or if you want to convert a group of files in bulk.

   b. CONVERTING ONE FILE:
      i. Click "Load File"

1. Navigate to the Directory where the file is stored.
2. Select the file you wish to convert and click "Open"

ii. In the window that opens, set the CPU to **12**
1. Set the Directory, which tells the program where to save the MP4 output.
2. Click "Convert"

iii. Typically, one hour of footage (~6.5GB) takes 30 minutes to convert to MP4 on a computer with a RAM of at least 14.

iv. You will know that files have successfully converted when the progress bar pane says "Done processing". Click "Close".
1. To confirm it is complete, you'll also see a still frame of footage in the application window with the file name and ".*mp4*" at the top.

c. CONVERTING MULTIPLE FILES IN BULK

i. Open your computer's command terminal.

ii. Input python3 /opt/arcts/desktop_app/arisConvert.py --input /FOLDER LOCATION/ --output /FOLDER DIRECTORY.
1. NOTE: this command may not work on a local desktop, as it is specific to Jetstream. Consult ARC-TS for an alternative command if this does not work.
2. Input the path to the folder where the *.aris* files are located in place of "FOLDER LOCATION".
3. Input the path to the folder for where MP4 outputs should be saved in "FOLDER DIRECTORY".

iii. Since you are running the conversions from the command terminal, there will not be a progress bar as there is when converting via the MLM application.

6. Once you have converted your file(s), if necessary, click "Load File" to select the MP4 file you want to run in the MLM.
   a. If you have *just converted* a single file, it will already be loaded into the MLM application
      i. You can tell which file is already loaded by looking at the file name at the top of the still frame of ARIS footage on the right.
   b. If you converted files in bulk, you will need to select the individual MP4 file you wish to run.
   c. NOTE: the MLM can only analyze one file at a time.
7. Select your "CSV Output Settings"
   a. The 2021 UM-Shiawassee Team recommends selecting all 3 output options.
8. Click "Start Algorithm"
   a. A progress bar will appear.
   b. A standard file of one hour of ARIS footage takes approximately 6-7 hours to run through the MLM at 12CPU.
      i. As long as your computer stays "Awake", you can leave the MLM running unattended.
9. When the model is complete, click "Save CSV Output".

a. A directory window will appear.
b. Choose where to save the output files on your machine.
c. A file name will auto-populate. Use this to save.
   i. If you want to change the file name later, do so via the file directory (navigate to the folder where the file is saved and change the name there).
   ii. This feature was added to ensure there are no saving errors that could result in loss of data.
10. You can also save the labeled output video by clicking "Save Video"
   a. Choose where to save the output files on your machine and input an appropriate file name (with no spaces) that includes ".*avi*" at the end of the file name
      i. Example: "March20Video.*avi*"
11. IF YOU CAN'T SAVE YOUR OUTPUT:
   a. If you are unable to save your output after the MLM finishes running (if your computer crashes *after* the MLM runs or you accidentally close the application before you can click save), you can still access the output CSV and video files.
      i. Navigate to your computer home directory (on a Windows computer, this is usually C:\Users\<YOUR_USERNAME>).
      ii. There will be a "hidden folder" called .seasAppData containing your output files.
         1. To view a "hidden folder", see https://support.microsoft.com/en-us/windows/view-hidden-files-and-folders-in-windows-10-97fbc472-c603-9d90-91d0-1166d1d9f4b5

Data Workflow Options for Method 2

Since Method 2 does not require an internet connection or GCP account, external hard drives from ARIS footage files can be uploaded directly into the MLM application. The user can simply open the MLM application on the local computer on which it is installed, plug in an external hard drive, and upload footage directly from the hard drive and into the model for conversion and processing.

Please see Part 4 of this report (Recommendations for Future ARIS and MLM Use) for recommendations on workflow for future Master's Project teams using Method 2.

CAPABILITIES OF METHODS 1 AND 2 TOGETHER

Methods 1 and 2 can be used together. Committing to Method 1 does not mean you cannot use Method 2. Indeed, utilizing both Methods to run separate footage files is likely the most effective and efficient way to process higher volumes of data.

Method 1 is best suited for University of Michigan students with limited or no access to footage external hard drives or USFWS facilities (due to COVID-19, for example). Method 2 is best suited for University of Michigan students, USFWS staff, and/or USGS staff with access to external hard drives and USFWS facilities.

Please see Part 4 of this report, Recommendations for Future ARIS and MLM Use, for more details regarding workflow recommendations.

PART 4: RECOMMENDATIONS FOR FUTURE ARIS AND MACHINE LEARNING MODEL USE

INTRODUCTION

After one field season of experimental ARIS camera usage at a single location within SNWR, the first iteration of a functional machine learning model (MLM) was developed to assist in the analysis of camera data output. The current MLM provides an accurate estimate of the number of fish passing through the camera frame and assigns directionality to each passing fish. While the current MLM's abilities are impressive, a great deal of work will need to be done in the coming years so that the MLM can meet the analysis goals of USFWS and USGS. Ultimately, USFWS and USGS hope to be able to utilize the ARIS camera at various locations throughout the refuge, increase the analysis capabilities of the current MLM, and create a more efficient and manageable plan to continue data collection. Here we provide recommendations to ensure that the future MLM is a fully functional processing tool for future ARIS use. The objectives for this section of the report are as follows:

1. Make recommendations for future setup of the ARIS camera.
2. Make recommendations for expansion of current MLM abilities.
3. Make recommendations for more efficient data collection and analysis.

RECOMMENDATIONS FOR FUTURE ARIS CAMERA SETUP

In an effort to capture fish movements in and out of floodplain units, the ARIS camera was mounted in P1A, directly next to a culvert leading to a channel of the Shiawassee River, where it remained for the duration of the 2020 field season (Figure 4.1). The ARIS was mounted at a downward angle to face a rocky substrate. The camera and all accessory equipment were powered by a gas generator and housed in an enclosed trailer.

Transition to Solar Power

Per discussions with clients about 2020 field experiences, we recommend a complete transition from gas generator to solar power to run ARIS and its accessory equipment.

Not only would this greatly improve the efficiency of running the camera, but it would also reduce the consumption of fossil fuels by the refuge. Use of a gas-powered generator requires an intensive time commitment by refuge staff to ensure continuous operation of the ARIS. This requires a trip to refill the gas tank every other day, and even with consistent maintenance, data were lost due to generator issues. The generator sometimes burned gas at more rapid and unpredictable rates, resulting in the camera shutting down for many hours. Additionally, the generator seemed to cause occasional power surges, resulting in loss of data for long periods of time until staff could troubleshoot the issue and get equipment back up and running.

The transition to solar power would reduce staff oversight to one trip per week to ensure that the camera is operating properly and that the hard drive is not full. Additionally, solar power should prove ideal for the operation of ARIS, as any location that the camera could be placed at the refuge would be in full sun (6 or more hours of sunlight daily), or very nearly so.

Figure 4.1: An aerial photo of the Shiawassee National Wildlife Refuge. The red circle indicates the location of the ARIS camera placement at a culvert connecting the Shiawassee River to P1A. (Image source: Google Maps).

If a transition to solar power is not achievable for the coming 2021 season, we recommend that future Master's Project teams incorporate ARIS maintenance into their summer monitoring and work plan. Master's Project teams would be responsible for refilling gas in the generator and ensuring that all accessory equipment is functional. This will assist refuge staff during the busier summer months.

Installation of a Neutral Background

We recommend the installation of a neutral background along the rocky substrate beneath the camera that would constitute the backdrop of the camera footage frame. We suggest that this background be a smooth, substrate-colored, rectangular, steel panel large enough to cover up rocks and debris that may be lying on the channel bed within the camera frame.

The ARIS camera was positioned to face the rocky substrate that lies at the bottom of P1A. These rocks are captured by the camera and create a very busy and cluttered background and can also create turbulence on the video output, which can confuse and limit interpretation by the MLM. This is because the rocks are often similar in shape and appearance to fish in the ARIS video footage. This was particularly problematic when creating a training set for the MLM, as it was sometimes difficult to distinguish between the shape of a milling fish and a rock when looking at a still image. If a trainer marks a rock as a fish or vice versa, this will result in lower

accuracy of the overall model, leading to incorrectly labeled fish. In addition, a rocky substrate makes it more difficult to distinguish between turbulence in the water column and schools of small fish, a group that is already difficult to accurately identify or estimate the biomass of using hydroacoustic technologies (Martignac et al. 2014).

To eliminate this issue, we recommend the installation of a substrate-colored board or similar flat surface along the rocky substrate beneath the camera. This will remove all background "noise" from the frame of the camera and make it much easier for the MLM to identify and label any fish that pass through the frame. Additionally, the presence of large rocks in streams and pools encourage milling behavior and also can provide fish with spaces where they are hidden from the hydroacoustic beam (Pipal et al. 2010). Covering up such desirable habitats could encourage fish to continue moving through the frame, thus avoiding issues of milling or hiding. This includes smaller fish and minnows which were not yet distinguishable by the current MLM against the rocky background.

Additionally, the use of a moveable neutral background would make it much easier to move the camera and mount to new locations in the refuge. This year, due mainly to COVID-19 restrictions, the camera was kept in only one location for the duration of the field season. Consequently, the existing MLM was trained using images with only this background. Moving the camera to a location with a new background could confuse the model, lead to reduced accuracy, and require model re-training per the new background. The installation of a mobile neutral background would eliminate this problem entirely.

A neutral background will also increase the likelihood of effectively expanding the MLM's analysis capabilities in the future; see "Expansion of MLM Abilities" below.

Ground Truthing Data
We recommend periodic ground truthing of fish species composition in waters near the camera throughout the field season. As more data is collected and analyzed throughout this monitoring process, we suggest that a more seasonal and stratified approach be taken to ground truthing.

Strategic sampling of fish in waters near the camera will help to improve understanding of the types of fish utilizing the restoration units and rivers, and likely passing by the camera. Ground truth samples can inform fish species identification in the ARIS footage; a requirement for improving MLM capabilities in future iterations.

RECOMMENDATIONS FOR EXPANDING MLM ABILITIES
The MLM is currently capable of counting the total number of fish that pass through the camera view in any given video file. It can also determine the directionality of fish movements. This is achieved through the MLM viewing a chronological sequence of still frames and identifying any objects that move between images. The MLM then counts the number of fish that cross the centerline of the frame and records which side of the frame (left or right) each fish exits from view. Knowledge of the total number of fish passing through the camera frame allows for a deeper understanding of the abundance of fish that are using the floodplain units over time. Likewise, knowledge of fish directionality can showcase differences in unit usage over time, particularly across different seasons.

The advantage of our MLM is that it can be expanded to accurately and efficiently achieve more complex analysis goals than existing technologies. We have created a list of recommendations for future expansion of MLM abilities, in consultation with our clients, various aquatic ecologists, and ARC-TS (Table 4.1).

Desired Ability	Level of Difficulty	Timeline	Requires Retraining of MLM?
Increase model accuracy	Low	2021	Possibly
Determine fish length	Low	2021	No
Refined directionality analysis	Medium	2021-2022	Yes
Count small fish and minnows	Medium	Potentially within two years	Yes
Identify fish species	High	Several years into the future	Yes

Table 4.1: Desired future abilities of the current MLM ordered by priority, including overall feasibility of the ability, timeline for achieving the ability, and whether or not the ability will require a retraining of the current model.

Increase Model Accuracy

Based upon statistical analyses of MLM outputs, the model currently has a precision rate of 64.94%. This relatively low rate of precision is likely due in large part to the rocky substrate that the camera is facing, creating substantial "visual noise." When accounting for images with zero or one mismatched fish label, the precision jumps to above 89%. This suggests that the overall precision of the model could be improved with relative ease by reducing "visual noise". The installation of a neutral background will likely make it much easier for the MLM to accurately detect nearly all fish swimming through the frame. Assuming that this is the only contributing factor to low precision, it should be very feasible to improve precision in the coming field season. Likewise, this step should not require retraining of the model, provided fish can be accurately detected on a neutral background based on its current training set.

True levels of precision and errors in MLM fish detection could also be investigated by visually cross-checking several video files that have been run through the model. We recommend that next year's student team perform a review of video output from the model and then compare their manual fish counts to that of the MLM. Because the video output includes boxes drawn around fish, the team should easily be able to determine when the model is inaccurate. This could help to identify areas of weakness in the model which could be remedied through additional training.

Through these efforts, overall precision of the MLM could be improved in a very short time frame. This would likely give the refuge a better idea of floodplain unit use by fish in 2020 and would also likely improve the chances of eventually being able to use the ARIS camera to identify types of fish that are utilizing the refuge.

Determine Fish Length

The MLM could be programmed to determine the approximate length of fish passing through the frame of the camera. According to the ARC-TS, this would be a relatively simple addition to the current model. This analysis capability would be a post-processing addition and would not require any additional training of the MLM. Since the model already draws boxes around fish as they move through the frame, the only modification required would be the addition of a frame of reference for the model (adding a reference point for the model to scale the boxes it already draws around fish in the frame).

This can be achieved in two ways. The first is to define the size of the frame and approximate the distance of a fish from the camera. The second is to incorporate the neutral background recommended above and to add a reference scale to that surface so it is visible in the camera footage. This scale could also take the form of measuring instruments placed in frame at various distances from the camera. This will help to estimate the distance of fish from the camera.

Identify and Count Small Fish

The MLM capabilities could be expanded to include identification of minnows and other small fish. It was challenging for our team to pick out and label images of small fish during the image training process due to the busy background of the footage. Since the model was not trained to recognize and label small fish, these individuals are unaccounted for in the fish total outputs from the current MLM. Juvenile fishes and minnows are vital parts of the ecology of wetland systems and help tell the story of seasonal fish migrations in and out of the floodplain units, and thus cannot be ignored (Mueller et al. 2006).

This problem could likely be addressed to some degree by the installation of a neutral background to cover the substrate in frame. This should make it much easier for a person to discern what is a fish swimming through the frame versus turbulence in the water column or debris at the bottom of the river. If the researchers training images are able to discern these small fish, they will be able to properly label all fish in a given frame. This more intensive and complete training set will teach the MLM to recognize fish of all sizes, thus producing a superior version of the model.

If the installation of a neutral background does not dramatically improve the ability to discern individual small fishes, we recommend that a new training set of images be created to retrain the model. This second training set should include two different label types for fish: one type for individual fish and another for schools of fish. This will allow individuals to draw one training box around a school of fish, which the MLM will understand as a separate entity from other larger fishes. With enough training images, the MLM should begin to identify schools as separate from other fish. This will not allow for an understanding of how many individual fish may be in a school but would capture behavior of schools and also could allow for post-processing estimates of overall school biomass based on the size of box drawn around the school.

While the installation of the neutral background will likely make it more feasible to detect fish of smaller sizes swimming through the frame in schools, the quality of hydroacoustic footage produced by the ARIS may be too poor to accurately detect individual small fishes, as studies suggest that hydroacoustic technologies not be used to monitor fish that are less than 5cm in length (Mueller et al. 2006). A study using a DIDSON camera (the predecessor to ARIS) suggests that fish of less than 8cm are difficult to individually identify, though schools of fish are readily visible using this technology (Eggleston et al. 2020).

Refined Directionality Detection

We also suggest that the directionality analysis of the MLM be refined. Currently, the model records if a fish exits the frame on the left or the right. This is used as a proxy for the direction that a fish is swimming and, based on the camera's placement at the time of footage acquisition, if the fish is moving into the floodplain unit or into the river. The model does not take into account the direction that a fish is facing when this occurs. A fish can therefore be facing to the right but drift out of frame on the left due to the current.

This is a minor problem, as fish are not helpless to the direction of the current. They can swim both forward and backward and utilize currents to travel in the direction that they wish to go, regardless of the direction that they are facing. Our team feels, however, that the knowledge of which way a fish is facing, as well as the side of the frame that it exits, may provide valuable information on swimming patterns on fish in wetlands that have not previously been studied.

The addition of this ability into the model would require the MLM to be fully retrained to recognize if a fish is facing right or left. These images would then be used to train the model and create a new version of the MLM. This complete retraining would be time intensive for the student team and would also require new coding by ARC-TS but would likely be a simple modification provided camera resolution is high enough to distinguish morphological features of passing fish.

Identify Fish Species

Per discussions with our clients and project advisors, we understand that the ultimate goal of the model is to identify the species composition of fishes swimming through the video frame. While challenging, through discussions with ARC-TS, our team believes it is possible to incorporate this capability into the MLM. It is possible for a researcher to identify large defining features of fish in the camera footage, such as the placement and number of dorsal fins, general body shape and size, and tail shape. Since these features can be visually identified, it is likely that the MLM could be trained to characterize them.

The MLM would need to be retrained on a new set of training images to achieve this objective. In order for researchers to accurately label new training images, ground truth fish sampling in waters near the camera will be essential. Determining what types of fish are around the camera at any given time will help researchers make informed, but still estimated, identifications of fish in training camera footage. There is currently no tool that allows for the analysis of hydroacoustic footage at such a fine scale. Though this MLM capability would require high inputs of time and

effort, if successful, the MLM would be a novel and highly valuable tool for use at SNWR and in other aquatic environments.

Previous research has shown that acoustic shadow analysis can be useful in visualizing features important in fish identification. Shadows can be more easily studied through the placement of a stainless-steel plate facing the hydroacoustic beam at a 45° angle from the ground (Langkau et al. 2012). This allows for realistic and proportional lateral views of fish morphology (Figure 4.2). A post-processing addition could be made to the model to analyze these shadow images for key morphological identification characteristics of different species of interest. While this has never been attempted in a field study, if successful, this could allow for accurate estimations of species composition in refuge units (Langkau et al. 2012).
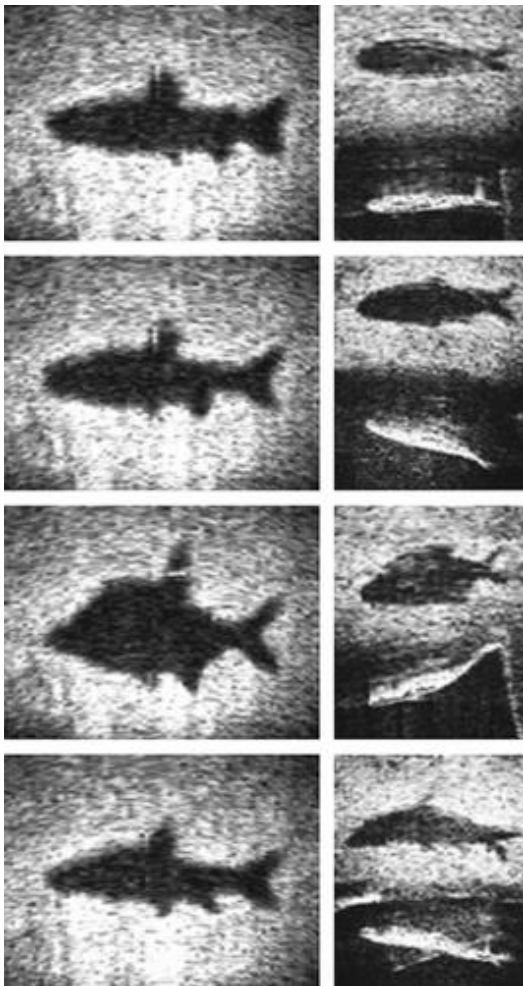
Figure 4.2: Acoustic shadows of fish from DIDSON on steel plate background. From top to bottom: Trout *Salmo trutta*, Chub *Leuciscus cephalus*, Bream *Abramis brama*, and Barbell *Barbus barbus* (Langkau et al. 2012).

RECOMMENDATIONS FOR DATA SAMPLING AND ANALYSIS

The ARIS camera produces a great deal of data in a relatively short time frame, so researchers must subsample the footage for data analyses. For every one week of nonstop ARIS footage collection, approximately one terabyte (1TB) of data is produced. Nearly 20TB of data were collected throughout the course of this past field season (5/18/2020 - 11/18/2020).

The ultimate objective of USFWS and USGS are to use the MLM to attempt to answer biological questions, complement the field-based ecological monitoring work, and inform management decisions. To help achieve these objectives, we present two options for data collection, subsampling, and analyses. Both options are feasible but would occur under different time frames. Whichever option the refuge and USGS choose will strongly influence the direction of ARIS work for future master's project teams. Regardless of time frame, however, next year's Shiawassee Project team should work with clients and advisors to develop a new footage collection plan for the ARIS camera. As we learned this year, collecting footage 24 hours a day indefinitely is inefficient for maintenance and makes data storage and analysis challenging. For this reason, the ultimate goal for next year should be to collect only as much footage as is necessary to answer biological questions.

PLEASE NOTE: ARIS data can be processed in the MLM using two Methods (see Part 3 of this report, Operating Procedures for the ARIS 2021 Machine Learning Model). As the next ARIS project team determines which subsampling option to pursue, they should consider which processing method or combination of the two methods will be most effective. Assuming the 2021 field season can proceed as the 2019 season did, without COVID-19 restrictions, we recommend clients consider putting a desktop computer with adequate CPU for MLM processing in the living quarters at the refuge. This will be useful to the Shiawassee Project team members to process footage in the MLM using Method 2 (see Part 3 of this report, Operating Procedures for the ARIS 2021 Machine Learning Model) regardless of the subsampling and data processing option they choose to pursue.

Option 1: Develop Analysis Subsampling Plan

Option 1 would allow researchers to answer biological questions about the restoration units at SNWR in a dramatically shorter time frame. Currently, it takes approximately 7 hours to process a 6GB file through the MLM. Researchers could process a strategically sub-sampled set of footage (from the existing 20TB) in the MLM to capture differences in fish movements based on season. We recommend that if this option is implemented, the next Shiawassee Project team work closely with CSCAR, a University of Michigan group that specializes in advising students on statistical projects, to develop a statistically sound data subsampling plan.

After processing a subsample of the existing 20TB of data, the team can use this initial subset analysis as a guide to adjust the recording patterns of the ARIS camera by the 2021 field season. The ARIS camera comes with a variety of pre-programmed options for timing, duration, and frequency of footage collection. Examples of pre-programmed options and customizations are outlined below. Creating a plan to adjust how the ARIS collects footage is the ultimate subsampling strategy for Option 1. This strategy will lead to a more manageable volume of data being produced by the camera that can later be run through the MLM and analyzed to answer biological questions.

Examples of how the camera can be programmed to subset footage data for collection are listed below:
- Gather one hour of footage every three hours.
- Gather two hours of footage at 12 AM, 6 AM, 12 PM, and 6 PM every day.
- Gather one and a half hours of footage five times each day at random intervals.

With a pre-subsampled dataset, the next Shiawassee Project Team could spend the post-field-season semester processing these data to answer more biological questions to be published in their final report in 2022.

Option 2: Run All 2020 Data Through Model

The second option, as stated above, is to run all 20TB footage collected in 2020 through the MLM. This will inform a footage subsampling plan (detailed in Option 1) that is as accurate and comprehensive as possible. This option will ensure that future ARIS collections are guided by the most thorough and scientifically sound analyses.

However, this option necessitates MLM processing of the full 20TB footage data archive. As previously stated, each 6GB file (roughly one hour of footage) takes approximately 7 hours to process in the MLM. Given the quantity of existing data, it would take approximately one and a half years for one person to process all 20TBs if the model is run nonstop. With each member of the next Shiawassee Project team consistently processing footage, the timeline will look different.

The 7-hour processing time noted above is based on a 12-core processor (CPU) virtual machine, which is four times the CPU of a standard laptop (please see Part 3 of this report, Operating Procedures for the ARIS 2021 Machine Learning Model, for more information). The processing time of the MLM is directly proportional to the CPU of the machine on which it is housed. For example, if the MLM is housed on a 4CPU machine, the complete processing time would take approximately 21 hours for one 6GB file. For this reason, next year's Shiawassee Project team should prioritize applying for a Jetstream virtual machine computing allocation (see Part 3 of this report, Operating Procedures for the ARIS 2021 Machine Learning Model, for more information). We also recommend that the next Shiawassee Master's Project team applies for a larger allocation than our team did so that they are able to process larger quantities of data (see Part 3 of this report, Operating Procedures for the ARIS 2021 Machine Learning Model, and/or contact ARC-TS for more information).

For this option, we suggest that USFWS and USGS consider hiring interns whose sole responsibility will be to process files through the MLM. We recognize that this would be an added expense to our clients and therefore might not be feasible. Additionally, existing USFWS and USGS refuge staff should consider processing files in the MLM during working hours whenever possible, as the MLM can run in the background.

We also recommend that our clients and the future Shiawassee Master's Project team look into two potential avenues for even faster data analysis.

1. Use of a supercomputer to run files with extreme speed. This would likely be costly.
2. Use of USGS Cloud Hosting (CHS). This may involve some cost and would not be nearly as fast as the use of a supercomputer but is a more likely option given USGS involvement in this project.

Ultimately, while Option 2 is more time consuming than Option 1, the results produced would inform a more scientifically and statistically robust ARIS footage subsampling plan. In turn, it will potentially make for more accurate answers to biological questions, though at the cost of having to wait at least one more year to begin answering these questions.

RECOMMENDATIONS SUMMARY

We recommend that the ARIS Team (includes the Shiawassee Project team, USFWS, USGS, project advisors, and ARC-TS):

- Consider incorporating a neutral surface beneath the camera and at the back of its image frame.
- Consider incorporating ground truthing into the Shiawassee Project team's 2021 field monitoring plan.
- Determine and execute a data subsampling plan based on the two options outlined above.
  - If subsampling Option 2 is selected, consider incorporating one of the three avenues for faster data analysis presented above.
- Consider which MLM processing method or combination of methods will be utilized in the selected subsampling plan (see Part 3 of this report, Operating Procedures for the ARIS 2021 Machine Learning Model, for details on each method).

We recommend that the clients (USFWS and USGS):
- Install solar panels to power the ARIS camera and its associated technological infrastructure.
- Consider installing a desktop computer with adequate CPU in the "swamp house" so the next Shiawassee Project team can process footage through the MLM using processing Method 2 (see Part 3 of this report, Operating Procedures for the ARIS 2021 Machine Learning Model) during their field season residency there.
- Consider hiring interns to process existing footage data if the ARIS Team decides to pursue subsampling Option 2.
- Consider using MLM processing Method 2 to process existing footage data if the ARIS Team decides to pursue subsampling Option 2.

We recommend that the next Shiawassee Project team:
- Consider incorporating an ARIS camera maintenance plan into the summer sampling work plan. This should be considered regardless of the camera's power source (generator or solar).
- Apply for a larger Jetstream computing allocation than our team did (see Part 3 of this report, Operating Procedures for the ARIS 2021 Machine Learning Model, and/or contact ARC-TS for more information).
- Prioritize the development of a subsampling plan for the 20TB of existing footage data if the ARIS Team as a whole decides to pursue subsampling Option 1.

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APPENDIX 1.1

The unsigned version of the Service Level Agreement between our team and ARC-TS for work on the MLM.

Service Level Agreement Between Information Technology Service and the 2021 Shiawassee Restoration Master Project Team

Completed on: 6/9/20

Table of Contents

1.0 INTRODUCTION

This Service Level Agreement (SLA) describes the relationship between the University of Michigan School for Environment and Sustainability (SEAS) 2021 Shiawassee National Wildlife Refuge Masters Project Team (Shiawassee Team) and the University of Michigan Information Technology Services. The Shiawassee Team has been contracted by their clients, the US Fish and Wildlife Service and US Geological Survey (the Client Organizations), to develop an analysis process for hydroacoustic, ARIS camera footage of fish movements at the Shiawassee National Wildlife Refuge (SNWR).

The Shiawassee Team has identified the development of a machine learning model, designed primarily to count total and directional fish movements, to be the most appropriate means to achieve this goal. Due to their lack of programming experience, the Shiawassee Team sought to collaborate with the University of Michigan Information Technology Services division of Advanced Research Computing Technology Services Group (the ARC-TS Team) to lead the programming portion of this project. This agreement details the scope of this relationship, deliverables from the collaboration, and expectations from each party.

The ARC-TS Team has classified the counting task as an object detection problem. Since the ARC-TS Team is working with a known training set and classifying objects into known categories, the Team have identified several supervised learning algorithms that will help accomplish this task. The ARC-TS Team will implement a convolutional neural network, trained on proprietary, labeled training data, and evaluated with a holdout set of test data.

2.0 PURPOSE OF THIS DOCUMENT

The purpose of this SLA is to clarify roles, responsibilities, and deliverables between the two parties. In particular, this document describes the time and effort commitment on the part of both parties and the financial agreement between them.

3.0 AGENCIES INCLUDED

The Shiawassee Team:

> This team consists of five members:
>
> > 1. Julie Dellick
> > 2. Jonathan Gorter
> > 3. Anna Greenberg
> > 4. Xinmiao Liu
> > 5. Maria Salem
>
> The five members are all masters students at the University of Michigan SEAS.
>
> These students are advised by two faculty members at SEAS:
>
> > 1. Paul Seelbach (primary advisor)
> > 2. Karen Alofs

The Shiawassee Team is working closely with their clients, the US Fish and Wildlife Service (USFWS) and US Geological Survey (USGS) (the Client Organizations). This SLA applies only to the Shiawassee Team unless the Client Organizations are explicitly mentioned.

The ARC-TS Team:

ARC-TS is a division of the University of Michigan Information Technology Services. This document is signed by the following representative of The ARC-TS Team:

> 1. Brock Palen: ARC-TS Executive Director

The following three individuals will assume responsibility for advancing the goals and deliverables described in this agreement on behalf of ARC-TS:

> 1. Armand R. Burks, Ph. D.: Research Data Scientist
> 2. Todd Raeker, Ph.D.: Research Experience Manager
> 3. Meghan Richey: Machine Learning Specialist

4.0 TERMS OF COLLABORATION

4.1 DELIVERABLES

At the end of this collaboration between the Shiawassee Team and the ARC-TS Team, the following will have been completed:

> 1. A fully functional machine learning algorithm and model that counts total fish passage, total count of directional fish passage moving left, and total count of directional fish passage moving right.
>   a. Should time allow, the Shiawassee Team will pursue adding fish movement calculations and fish classifications to the machine learning model capabilities.

2. A fully functional self-contained website application that houses the complete machine learning model that is available to and managed by the Client Organizations for long-term use and further development.
3. An automated file conversion system that converts video footage files from the original *.aris* file format to *.mp4* or other formats readable by the machine learning model.
   a. This automated system will also be provided and available to the Client Organizations for long-term use and further development.

4.2 COOPERATION

The Shiawassee Team agrees to the following:

- A minimum weekly commitment of 12 hours per team member to work on the machine learning model.
    - This includes footage training, learning about programming, Python, and the model algorithm, and meeting regularly with the ARC-TS Team to discuss progress and questions.
- The provision of all machine learning model training clips (with the use of the automated file conversion system to be built by the ARC-TS Team).
- Consistent and open communication with the ARC-TS Team and the Client Organizations regarding the process.
- Collaboration with the Tech for the Social Good organization for mounting the machine learning model to a website application for use by the Client Organizations.
    - NOTE: this relationship has not yet been determined. Should it fail to occur, the ARC-TS Team will take on the website application hosting work. ARC-TS will not be responsible for providing the hosting environment but can make recommendations.
- Accrediting the ARC-TS Team for their role in this portion of the SNWR 2021 Masters Project in any and all publications, presentations, or other project deliverables.

The ARC-TS Team agrees to the following:

- Programming and troubleshooting an automated file conversion system into which *.aris* files can be input to create *.mp4* file format outputs.
- Limiting access, use, and analysis of all ARIS footage, data files, and analysis results to ARC-TS Team members only. These data will not be shared outside the ARC-TS Team and the ARC-TS Team agrees to deny and prevent access and use of these data by anyone outside the ARC-TS Team.
- Returning and subsequently deleting all ARIS footage, data files, and analysis results from ARC-TS Team professional and/or personal computers and devices after completion of the collaboration detailed in this SLA.
- Confirming with the Shiawassee Team and/or Client Organizations if a new and/or previously undiscussed use of the ARIS footage, data files, and analysis results is permissible.
- Designing an entirely new machine learning model should predesigned models be insufficient and/or inadequate.
    - Forfeiting ownership of any newly developed model to the Shiawassee Team.
- Developing a website application for machine learning model housing should the collaboration with Tech for the Social Good fail.
    - Incorporating object detection visualization and video visualization to this website application if time allows. The specifics of these will be agreed upon later and added to this SLA as an Addendum.
- User-training for the Shiawassee Team for the following programs:
    - Matlab and the Video Labeler App

- Note: Matlab will only used for initial evaluation of video quality, project follows license terms with MathWorks
    - ○ Gaussian Mixture Model
    - ○ LabelImg
    - ○ SSD Inception v2 neural network

Both the Shiawassee Team and the ARC-TS Team accept the following considerations:
- Video footage may not be of high enough quality to use a pre-trained machine learning model. If this is the case, the ARC-TS team accepts that they will need to build a new object detection model. The Shiawassee Team accepts that, in this case, the project will take more time.
- Video footage may not be feasible for use in a neural network.
    - ○ In order to mitigate this consideration, the two teams will try a small sample of data through the Matlab classifier program before expanding to developing a Python system.

4.3 RESOURCES

The Shiawassee Team agrees to the following:

- The Shiawassee Team and the Client Organizations agree to cover up to $6,500 worth of work by the ARC-TS Team on this project.
    - ○ The Client Organizations agree to provide a total of $5,000 ($2,500 from USFWS, $2,500 from USGS) to the Shiawassee Team's University of Michigan shortcode account (belonging to Paul Seelbach) to cover work by the ARC-TS Team.
    - ○ Should each member of the Shiawassee Team be awarded the Rackham Graduate Student Research Grant, the Shiawassee Team agrees to provide up to $2,000 to cover work by the ARC-TS Team.
    - ○ Should the Shiawassee Team not be awarded adequate funds from the Rackham Graduate Student Research Grant, Paul Seelbach agrees to provide up to $1,500 to cover work by the ARC-TS Team.
    - ○ Should the Shiawassee Team be able to cover more than $6,500, an Addendum to this SLA will be added.

The ARC-TS Team agrees to the following:

- To provide up to 20 additional hours of support that exceed those covered by the $6,500 agreed upon without additional cost to the Shiawassee Team.
- To assist with access to the following programs:
    - ○ Matlab and the Video Labeler App
    - ○ Gaussian Mixture Model
    - ○ LabelImg
    - ○ SSD Inception v2 neural network

5.0 DISCLAIMER

All activities described in this SLA will take place in compliance with University of Michigan, SEAS, USFWS, USGS, state, and federal regulations.

6.0 CONDITIONS OF ALTERATION OR TERMINATION

ARIS Final Report:
Appendix 1.1

This SLA agreement is subject to alteration should any of the terms described above become infeasible. The Shiawassee Team agrees to communicate consistently with the ARC-TS Team should the needs and deliverables of this project change.

This SLA agreement is subject to termination should the deliverables described above become infeasible. The ARC-TS Team agrees to communicate consistently with the Shiawassee Team regarding feasibility of achieving the described deliverables. The Shiawassee Team will cease all payments to the ARC-TS Team should this SLA agreement be terminated.

7.0 SIGNATURES

The Shiawassee Team:

Julie Dellick   _____   _____

                       Signature   Date

Jonathan Gorter   _____   _____

                       Signature   Date

Anna Greenberg   _____   _____

                       Signature   Date

Xinmiao Liu   _____   _____

                       Signature   Date

Maria Salem   _____   _____

                       Signature   Date

Paul Seelbach   _____   _____

                       Signature   Date

Karen Alofs   _____   _____

                       Signature   Date

Representative of the ARC-TS Team:

Brock Palen
ARC-TS Executive Director

      _____   _____

                       Signature   Date

APPENDIX 3.1

Below is the application for an XSEDE - Jetstream account (including resource request details), from the 2021 UM-Shiawassee Team (with help from ARC-TS) for reference.

Project: Reconnecting People and Floodplains: The Social and Ecological Restoration of Shiawassee National Wildlife Refuge

Abstract: *Describe the science that will be enabled by XSEDE resources.*

The 2021 University of Michigan-SNWR Team through the University of Michigan's School for Environment and Sustainability is working to maintain and enhance the ecological restoration mission of the Shiawassee National Wildlife Refuge (SNWR). SNWR consists of wetland and floodplain ecosystems where four tributaries merge to form the Saginaw River. The Refuge is a coastal wetland influenced by Lake Huron and a feature of the Saginaw Bay watershed, which drains 15% of Michigan's land area. This spectacular resource provides numerous ecosystem functions; including flood attenuation, water purification, and habitat for a wide variety of waterfowl, fish, and reptile species. SNWR is a crucial stopover point for migratory birds during both the spring and fall migration seasons and is globally recognized as an Important Bird Area by the National Audubon Society. In addition, SNWR provides spawning habitat and nursery for a wide array of fish, including yellow perch, northern pike, and several forage species such as banded killifish and gizzard shad.

Primarily championed as a haven for migratory waterfowl and invaluable fish spawning territory, SNWR was established in 1953 in order to recover ecosystem processes historically lost to the agriculture and timber industries. Since its establishment nearly 70 years ago by the United States Fish and Wildlife Service (USFWS), SNWR still focuses heavily on ecosystem restoration and management for the benefit of waterfowl and fish through management and subsequent creation of high-quality habitat. Within the last decade, SNWR has received millions of dollars in federal grant funding through the Great Lakes Restoration Initiative (GLRI) to support its ongoing hydrologic restoration work that aims to reconnect the floodplain wetlands to the intersecting river channels through strategically placed and monitored gates. This post-restoration monitoring began in 2019 and its continuation is of the utmost importance to the goals of USFWS. By carrying out monitoring efforts before and after reconnection to the floodplain, USFWS will be able to determine the ecological impacts of wetland restoration and reconnection.

To address SNWR needs for monitoring and communicating their major restoration initiatives, our 2021 University of Michigan-SNWR Team was hired to perform ecological monitoring in the field beginning in May 2020, but in light of the COVID-19 pandemic, this portion of project had to be halted and reevaluated so as to meet the health and safety requirements of both the University of Michigan and USFWS. Field work was initially predicted to occupy the vast majority of our masters project time, but after it was halted due to COVID, we were forced to quickly adapt and shift the focus of our research. Now, our focus is exploring the management potential of an ARIS hydroacoustic submarine camera for monitoring fish movements and migrations.

This camera, which captures underwater video using sound rather than light, was placed at the entrance of one of the Refuge's controlled monitoring wetland units. This device can be used to track the movements and migration of fish in and out of the restoration units. Originally, our group planned to lightly analyze the video data produced by ARIS and make recommendations to our client on how best to utilize it in the future. This was likely to have included recommendations for future camera placement and a rough estimation of the type of data that may be able to be collected by ARIS.

Once the stay at home order took effect, however, the main focus of our research shifted to ARIS. We aimed to do a much deeper analysis of data from ARIS and ideally generate information on the number and types of fish utilizing the Refuge, including a total count of fish, directionality, and seasonality of use. Our team quickly identified an option to reach these new goals: machine learning. With this allocation the 2021 University of Michigan-SNWR Team will be able to achieve our goal of producing a machine learning model to track fish movement within the SNWR wetland system.

Disclose Access to Other Compute Resources:
Resources are broken into three areas, Advanced Services, Compute, and Storage. Advanced Services are for consulting/collaboration with XSEDE staff to improve the productivity of the XSEDE user community through successful, meaningful collaborations which optimize applications, improve work and data flows, increase effective use of the XSEDE digital infrastructure and broadly expand the XSEDE user base by engaging members of underrepresented communities, domain areas and gateways. Compute resources are available from many cores/nodes, GPUs, large memory, visualization and VMs. Lastly, Storage resources are available and most compute resources have a complementing storage resource. More details on XSEDE Allocated resources can be found here. It is assumed that code performance/scaling testing has been done on the resources being requested, either through a Startup award, Campus Champion award or a prior Research award.
Because of the high demand for XSEDE-allocated resources, XSEDE and the XRAC closely consider whether the PI has access to other, less constrained resources on which the proposed work could be conducted. All PIs must describe their local resources and other non-XSEDE resources available to them. Please also include details of collaboration on other XSEDE Research allocations. For more information, please refer to our documentation.

Compute

Bridges PSC Regular Memory	
Bridges GPU PSC GPU	
Bridges GPU Artificial Intelligence PSC GPU-AI	
Bridges Large PSC Large Memory	
Comet SDSC Dell Cluster with Intel Haswell Processors	
Comet GPU SDSC Comet GPU Nodes	
Jetstream IU/TACC	
OSG Open Science Grid	
Stampede2 TACC Dell/Intel Knights Landing, Skylake System	

Storage

Bridges Pylon PSC Storage
Data Oasis SDSC Medium-term disk storage
Jetstream Storage IU/TACC Storage
Ranch TACC Long-term tape Archival Storage

Other

SGCI The Science Gateways Community Institute
XSEDE Public Data Collections
XSEDE Extended Collaborative Support

Advanced Services

SGCI The Science Gateways Community Institute
XSEDE Extended Collaborative Support

Supporting Documents:
- CV for PI and all co-PI(s) *XSEDE portal ids are needed for each PI, co-PI and Allocations Manager
- Main document

The Main Document is the primary and most critical component of a successful request. Research requests must include a well-documented resource-use plan that describes how the requested allocations are necessary and sufficient to accomplish the project's research objectives. An effective resource-use plan must address the XSEDE allocation Review Criteria and, in particular, must include the following elements, with the bulk of the document focused on the Research Objectives and the Resource Usage Plan:

1. Scientific Background-with more detail required of requests that do not have a merit-reviewed funding award
2. Research Objectives and specific questions to be pursued
3. Resource Usage Plan to achieve the research objectives
4. Justification of the allocation amounts for all resources and resource types
5. Resource Appropriateness
6. Access to other CI resources and why those resources are not available or sufficient for the work proposed in this request

Page limits: 10 pages for less than 10 million SUs total; 15 pages for 10 million SUs or more

- Code Performance and Scaling document *performance/scaling should be from resource(s) being requested

This REQUIRED document should contain code performance timings, resource usage details, and scaling information (for HPC resources) to support the calculation of the resource request. For highly competitive HPC resources, the code performance data should be provided from benchmark runs on the resource requested, using the model configuration(s) needed for the computational plan proposed and demonstrating the scaling efficiency to the job size(s) planned. For smaller size requests, the panel may accept well-justified performance data from architecturally equivalent systems.

For less competitive systems or for non-traditional resources, this document should contain sufficient justification to convince the panel that you have a solid basis for calculating your allocation request.

Page limit: 5 pages.

In order to accurately estimate the necessary computational resources for converting the raw ARIS data into MP4 video for our analysis phase, we conducted a series of executions of our ARIS file conversion code. We executed the code on ARIS files of size 6.3GB using varying levels of parallelism (different number of cores) in order to compare the amount of time taken for each setting. Table 1 below lists the timings for the different settings that we used.

Cores Used	Input File Size (GB)	Time to Convert (hours)
6	6.3	0.981
9	6.3	0.648
10	6.3	0.563
11	6.3	0.534
12	6.3	0.448

We can see from Table 1 that the 12-core setup achieved the best performance (0.448 hours to convert a 6.3GB file). Given the total data set size of 7TB, we must utilize the 12-core setup in order to minimize the total time taken to convert the raw ARIS data into MP4 so that the data can be analyzed by our machine learning model in the next phase. Using the 12-core setup, we are able to convert ARIS data at a rate of 0.014TB per hour. Therefore, at this rate, we estimate that it will take 498.128 hours (e.g. 5977.56 SUs at 12 cores per hour) in order to convert the full data set of 7TB.

Resources Request Information:

- What percentage of the work you expect to do in the allocation will be the following types:
    - Production: 90%
    - Exploration/porting: 10%
    - Education: 0%
- What percentage of the jobs to run this allocation will be the following types:
    - Submitted through command line/script:100%
    - Submitted using Grid tools: 0%
    - Submitted through a meta-scheduler: 0%
- Please estimate what percentage of the science runs you expect to perform in the allocations will be the following types:
    - Independent: 100%
    - Independent but related: 0%
    - Tightly-coupled: 0%
    - Dependent: 0%

Resource Requested: JetStream - multiple 12-core instances with 500 GB storage. Numerous members of the project will be running jobs simultaneously.

Resource Requested Amount: 50,000 SUs

Resources
- JetStream: multiple 12-core instances with 500GB storage. Numerous members of the project will be running jobs simultaneously. Resource Requested Amount: 50,000 SUs
- 5 Virtual Machines (or however many people will be working on this portion of the project)
- 5 public IP addresses (or however many people will be working on this portion of the project)