FishSense Mobile: A Mobile Device App for On-Deck Fisheries Management Operations

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***Abstract*—Fish are a vital food source for humans and play a crucial role in marine ecosystems around the world. However, overfishing poses a serious threat, prompting efforts to assess and manage fisheries more effectively. Current monitoring programs are resource-intensive, requiring expert involvement and manual data collection to inform fisheries management decisions. Data on fish stocks are often collected through hook-and-line surveys, where fisheries scientists collect information on fish population size, structure, community composition, and individual body condition. This process relies heavily on expert scientists, creating a bottleneck in the data-collection workflow. *FishSense Mobile* uses LiDAR and RGB imaging technologies available on Apple iPhones and iPads to automate fish measurement, thereby reducing the workload of experts. We further demonstrate that these tools can be utilized by independent citizen scientists, facilitating large-scale data collection. We demonstrate that the app achieves an average measurement accuracy of within ±2 cm with respect to length board measurements collected by scientists.**

***Index Terms*—fisheries management, LiDAR, edge-computing, iOS, machine learning, citizen science, fishing, computer vision**

I. Introduction

Fish are a critical source of dietary protein for communities worldwide [10]. Fish heavily influence the biomass and the species composition found in their ecosystem [18]. They also play a vital role in nutrient cycling through excretion and movement between habitats, which supports plant growth and helps maintain ecological balance.[4].

Unfortunately, overfishing poses a serious threat to the sustainability of living marine resources, with many regions already experiencing significant declines [17]. As a result, many efforts are dedicated to understanding and mitigating these impacts. One such program is the California Collaborative Fisheries Research Program (CCFRP), an effort dedicated to evaluating the health and recovery of fish populations off the California coast. In collaboration with local sportfishing fleets and volunteer anglers, CCFRP scientists conduct standardized hook-and-line surveys to generate management-relevant data on nearshore fish stocks.

Citizen scientist-based research programs, such as CCFRP, often rely on volunteer anglers who assist in collecting fish specimens. After an angler catches a fish, it is brought to a scientist on deck, who identifies its species, measures it on a measuring board, evaluates its health, tags it, and then returns it to the ocean [11]. The reliance on trained scientists creates a significant bottleneck for these evaluations. CCFRP excursions couple highly trained scientists with volunteer participants, making them extremely expensive and challenging to replicate in many parts of the world. We need techniques that can scale, especially to resource and data-limited fisheries, which often have inadequate management.

Rather than relying solely on trained scientific field crews, fisheries monitoring can be expanded by engaging recreational anglers as contributors to data collection through independent citizen science. Recreational anglers represent a vast, largely untapped resource for scalable observation with an estimated 118 million participants across North America, Europe, and Oceania—and global figures ranging from 220 to 770 million [3]. If provided with tools that deliver scientifically accurate measurements, anglers could significantly broaden the spatial and temporal coverage of fisheries data.

To effectively engage recreational anglers as independent citizen scientists, the ideal tool should require minimal training to ensure accessibility across a wide range of users. It must also be cost-effective to maximize adoption. The most affordable and practical option is a device that anglers already own—namely, a smartphone.

Modern smartphones are increasingly equipped with advanced sensors that make them well-suited for field-based data collection. Nearly all include RGB cameras capable of capturing high-resolution imagery, which can be used for automated species identification [14] and individual recognition [16]. In addition, some higher-end models incorporate depth-sensing technologies—such as time-of-flight (ToF) LiDAR—that enable the capture of 3D spatial information through depth maps or point clouds. This depth context eliminates the need for a fiducial marker (i.e., a reference object) within the frame, reducing both training requirements and user error. Notably, Apple Pro devices from the iPhone 12 Pro and iPad Pro 4th generation onward include such sensors, making them ideal candidates for implementing a mobile fish measurement system.

These devices also offer substantial processing power, enabling real-time analysis of captured images and measurement quality. Providing immediate feedback allows users to remeasure a fish on the spot if the initial capture is insufficient, reducing data loss and improving reliability. Performing these operations on-device is crucial, as recreational anglers often operate in remote environments—such as offshore locations—where internet connectivity is limited or unavailable. By leveraging edge computing, a system can ensure that key functions remain accessible regardless of network conditions.

Together, these considerations define the key constraints that shape our system design. To ensure the solution is practical, accessible, and scientifically robust, the target device must satisfy a specific set of hardware and usability requirements. These constraints are as follows:

- **Depth Sensor:** Necessary for acquiring accurate depth information, which allows pixel-based measurements to be converted into real-world distances without requiring an external size reference object.
- **High-resolution RGB Imager:** Required to capture detailed imagery of fish, enabling detection of the fish within the image, whether manual or automatic.
- **Onboard compute capabilities:** Essential for running AI-based inference locally, providing real-time feedback on measurement quality and enabling offline operation in remote environments where internet connectivity is unavailable.
- **Commercial availability to end users:** The device should be one that recreational anglers are likely to own or can easily acquire, minimizing barriers to adoption and maximizing scalability.

With these constraints in mind, we develop *FishSense Mobile* – an iOS-based mobile application designed for devices that satisfy all of the outlined requirements, such as the iPhone Pro and iPad Pro. Figure 1 shows a screenshot of *FishSense Mobile* in action. *FishSense Mobile* measures the length of the fish by determining the distance of the fork and snout from the camera using the mobile device's depth camera. The fish need not be on a measuring board; this was done to opportunistically gather and validate fish length during a CCFRP survey.

The remainder of this paper focuses on evaluating the feasibility of implementing *FishSense Mobile* in a practical, real-world data collection setting. We assess the system's ability to provide accurate fish fork length measurements under typical field conditions, including both controlled laboratory environments and active catch-and-release operations. To maintain a focused scope, this study does not explore advanced algorithmic extensions such as snout-fork detection, species identification, pose correction, or individual recognition. Instead, we focus on validating the core measurement functionality and leave these extensions for future work.

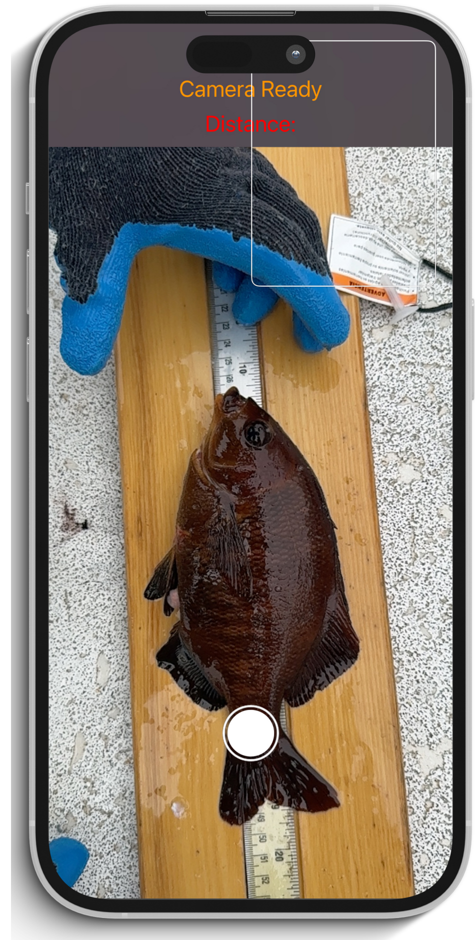


Fig. 1: Example interface of *FishSense Mobile*, measuring a Black Seaperch during a CCFRP field deployment.

II. Related Work

To contextualize our analysis of *FishSense Mobile*, we first review existing systems used in hook-and-line fisheries surveys. We begin by examining the tools and methodologies currently employed by scientists for evaluating fish length, followed by a discussion of technologies developed to improve or augment these workflows.

A. Hook-and-line Surveys

Hook-and-line surveys are a common research tool employed by fisheries scientists to monitor and evaluate fish populations. One simple, yet critically important piece of morphometric information that scientists collect is fish length data, which is generally obtained using traditional measuring boards. The process involves catching a fish, bringing it to a measuring board, and then having an expert evaluate it for species identification and tagging. Reliance on expert knowledge prevents citizens from further contributing to the process and introduces a bottleneck in deployments. This bottleneck, which is amplified when large quantities of fish are caught, can increase the amount of time fish spend out of the water, causing them stress [7]. As such, it is crucial to minimize the amount of time spent measuring the fish.

Several factors further hinder data collection. The need to take handwritten notes introduces additional work and potential for error, as digitization requires additional human labor and can result in clerical mistakes. Another potential source of error is the reliance on a human to capture data from the length board accurately. Humans tend to choose numbers according to patterns when reporting values (referred to as digit preference [5]). As such, they can introduce varying levels of inconsistencies when reporting length data to be recorded [8].

B. Technology

The traditional method of hook-and-line fisheries surveys is often time-consuming, costly, and susceptible to observer bias. Technology has been considered to reduce the handling of animals, lower costs, and minimize observer biases.

Photogrammetry has emerged as a promising tool for enhancing hook-and-line fisheries surveys by enabling non-invasive, image-based measurement of fish. Traditional length measurements in these surveys typically involve bringing fish aboard and measuring them manually—an approach that can be time-consuming, labor-intensive, and stressful for the animals. Photogrammetric techniques offer a scalable alternative by allowing fish to be measured from images or video, reducing handling time and observer bias [2].

Despite their advantages, photogrammetric systems also introduce sources of error. Variability in camera intrinsics and the orientation of the camera relative to the fish can significantly impact measurement accuracy [15]. To address these issues, many systems incorporate fiducial markers—such as paired laser dots [12] or calibrated reference objects placed within the scene—to provide consistent scale and spatial reference [15, 9, 1]. The integration of such tools reflects a growing effort to make image-based measurement more reliable and accessible, particularly in the hands of independent users and citizen scientists operating outside of controlled scientific settings.

Some fiducial marker systems—such as the one proposed by Monkman et al.—improve measurement accuracy by enabling camera calibration and correcting for geometric distortions [15]. However, their method requires a combination of external components, including a laser pair, a size-calibrated background checkerboard, and a foreground checkerboard, which significantly increases system complexity. The use of action cameras further limits accessibility for recreational users who may not own or be familiar with such equipment.

Fig. 2: Proof ball used as a fiducial marker by the *Fishtechy* mobile app.

This reliance on external markers and post-capture processing reduces the practicality of the system in field settings and hinders real-time operation, making it less suitable for rapid or independent citizen science workflows.

MrRuler is another example of a system that leverages fiducial markers to estimate fish length [6]. Rather than relying on multiple checkerboards and lasers, *MrRuler* uses a simpler reference object—two perpendicular lines forming a “cross scale.” While this design reduces physical setup complexity, it still requires the cross scale to be correctly placed within the frame and the fish to be without distortion. Although this approach may not demand extensive user training, acquiring or preparing an accurately scaled cross can still pose a barrier for independent citizen scientists. Moreover, the system’s reliance on post-processing continues to limit its applicability in real-time data collection workflows.

Ocean Ruler also relies on fiducial markers—specifically, reference objects with known dimensions—to estimate fish lengths [9]. Unlike systems requiring custom markers, *Ocean Ruler* allows users to employ any object of known size as a reference, lowering the barrier to entry. For example, a US quarter—commonly available to many users—can serve as the reference. However, incorporating a reference object still introduces practical challenges: it must be placed within the frame during image capture. Additionally, the authors report that *Ocean Ruler* consistently overestimates fish lengths, a systematic error that requires further investigation. Any distortions in the fish or the reference object can further degrade measurement accuracy.

Another example is *Fishtechy*, which uses a proprietary size reference object—referred to as the “proof ball”—along with edge detection techniques to estimate fish length (see Figure 2) [1]. While the method is generalizable across fish species, the proof ball must be positioned at the same depth as the fish relative to the camera to ensure accurate scaling. This requirement adds complexity to the measurement process, as users must keep both the fish and the reference object within the frame and on the same imaging plane. Although the proof ball is commercially available, it lacks the accessibility of *Ocean Ruler*’s use of everyday objects like coins.

However, it offers the advantage of being more controlled and rotationally invariant. Like other fiducial-based systems, it also relies heavily on off-device post-processing, which limits its usability in remote or real-time field environments. Given its shared goal of enabling independent citizen science through image-based fish measurement, *Fishtechy* serves as a primary point of comparison for *FishSense Mobile*.

III. FishSense Mobile System Design

As introduced in Section I, our goal is to support accurate and accessible in-field fish measurement through a system that minimizes complexity while maximizing usability. To achieve this, we identified four essential hardware requirements: a depth sensor to enable real-world distance estimation without fiducial markers, a high-resolution RGB camera to support fish measurement, onboard computing for real-time and offline processing, and commercial availability to ensure accessibility for recreational anglers. These criteria led us to target consumer devices that already meet these requirements—specifically, Apple's iPhone Pro and iPad Pro models—which provide a robust foundation for our system.

In addition to meeting current measurement requirements, we designed the system with future extensibility in mind. For example, the inclusion of an RGB camera enables potential expansion to species identification and virtual tagging. Similarly, selecting a device with sufficient processing power lays the groundwork for future support of real-time feedback, even though this functionality is not yet implemented in the current version.

FishSense Mobile fulfills these design goals by providing a streamlined, accessible solution for in-field fish measurement that requires minimal training or additional equipment. The system captures RGB imagery and LiDAR-based depth data using the built-in sensors on supported Apple devices, enabling accurate, scale-aware length estimation without the need for fiducial markers or size reference objects. By targeting widely available consumer hardware, *FishSense Mobile* lowers the barrier to entry for recreational anglers and independent citizen scientists.

Figure 3 shows a flowchart illustrating the *FishSense Mobile* processing pipeline. The remainder of this section provides a step-by-step overview of how the *FishSense Mobile* system converts an RGB image and corresponding LiDAR depth data into an estimated fork length measurement of the fish.

A. Image, Depth Map, and Confidence Map Collection

First, an RGB image (Figure 4a), a LiDAR-based metric depth map (Figure 4b), and a confidence map (Figure 4c) are collected using Apple's ARKit framework. The confidence map, as defined by Apple [13], encodes the reliability of each depth estimate using three discrete values: 0 (low), 1 (medium), and 2 (high) confidence.

In many systems, performing sensor fusion between RGB and depth data requires manual calibration, which can be a significant barrier for widespread use in citizen science. A key advantage of using Apple's iPhone and iPad Pro devices is

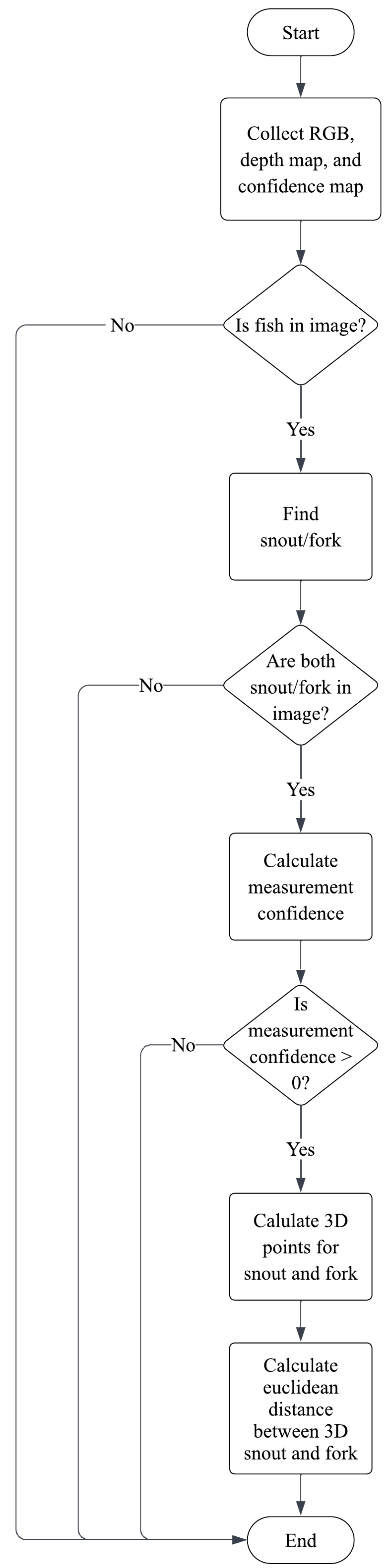
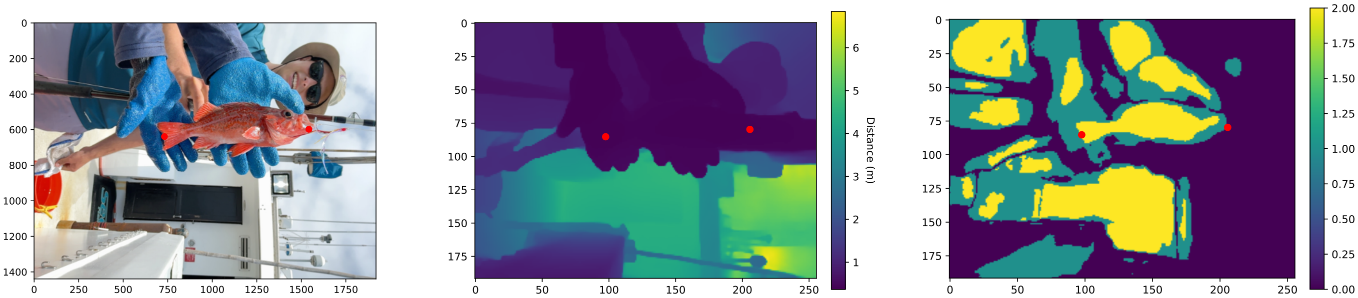


Fig. 3: The *FishSense Mobile* System Flowchart describes the relationship between processing tasks to ensure high-quality fish measurements.



(a) RGB Image (b) Depth Map (c) Confidence Map

Fig. 4: Associated confidence map (right) and LiDar depth map (middle) for an iPhone photo taken of a fish (left). Each image has the head and tail position labeled for reference.

that they are factory-calibrated, ensuring consistent alignment between the RGB camera and LiDAR sensor. This built-in calibration provides the spatial correspondence necessary for accurate fish length estimation without requiring user intervention.

B. Finding the Snout and Fork

Next, the system must determine whether a fish is present in the image. We focus this paper on evaluating *FishSense Mobile*'s length measurement capabilities and use fish detection performed by a human labeler. If a fish is present, the head (snout) and fork are also manually annotated. In future versions, this process could be automated using computer vision models. Once these key points are identified, their corresponding depth confidence values are extracted from the confidence map. An example of these labeled points is shown in Figure 4. If either the snout or fork is occluded or poorly visible in the image, the image can be flagged as invalid and prompt the user to capture a new one.

C. Determining the Quality of the Measurement

The confidence score assigned to an image is determined by evaluating the confidence levels at the labeled snout and fork positions within the ARKit confidence map. Each of these labels is associated with a confidence value—low (0), medium (1), or high (2)—and the overall image confidence is defined by the lower of the two. For example, in Figure 4c, the fork label is assigned a high-confidence value. In contrast, the snout is labeled with medium confidence, resulting in an overall measurement confidence score of medium (1). Apple's ARKit computes these confidence values based on the LiDAR sensor's ability to reliably measure depth at each pixel, which can be degraded by highly reflective or light-absorbing surfaces. The accuracy of each depth measurement is quantified using ARKit's raw `ARConfidenceLevel` values [13].

The resulting confidence score can be used to reject images with low-confidence depth measurements, preventing unreliable data from being processed. In such cases, the measurement workflow is terminated early, and users are prompted to retake the image to ensure better data quality.

D. Calculating the Fork Length

To accurately estimate fish length from image and depth data, the system performs a multi-step pipeline that maps 2D annotations to 3D space, corrects for alignment discrepancies, and projects the points using camera intrinsics. LiDAR provides an accurate depth map that enables reconstruction of the scene's 3D geometry, allowing pixel measurements in the RGB image to be converted into real-world distances. To achieve this, annotated 2D points on the RGB image (e.g., the fish's snout and fork) must first be mapped onto the corresponding depth map. The RGB and depth images differ in resolution. Thus, we convert between coordinate spaces by expressing the labeled points as percentages of the RGB image's height and width, then scaling these percentages to the dimensions of the depth map.

After this mapping, the projected points may not lie precisely on the fish due to slight misalignments between the RGB and LiDAR data. To correct this, we calculate the midpoint of the line connecting the snout and fork, segment the surface surrounding this midpoint, and snap the snout and fork points to their nearest neighbors on the segmented surface. This step ensures that both points lie on the fish—or a connected surface—with minimal error introduced.

Finally, the corrected 2D points are projected into 3D camera space using an inverse pinhole camera model. This process leverages the per-pixel depth values from the LiDAR map and the factory-calibrated intrinsic parameters of the RGB camera. The tight alignment between the RGB and LiDAR sensors on supported devices eliminates the need for physical reference objects, enabling precise and scalable length estimation directly from image and depth data.

IV. Methods

To evaluate the scientific accuracy of *FishSense Mobile*, we curated a dataset designed to assess its ability to estimate fish length under realistic conditions. This study focuses on validating the system's length measurement performance as a foundation for its potential use in field-based fisheries research. Data were collected in collaboration with the California Collaborative Fisheries Research Program (CCFRP) and include samples from two distinct settings: (1) on-deck during routine hook-and-line surveys and (2) in a laboratory prior to specimen dissection. These environments allow us to examine the system under both operational and controlled conditions.

To quantify measurement error, we compared software-derived length estimates to traditional hand measurements obtained using a length board. While these manual measurements are widely used as reference values in fisheries science, they are not free from error. Elstner et al. [9] reported a hand measurement error (σ_{hand}) of 11.1 mm in their dataset. Consequently, while we treat hand measurements as reference values in this study, we acknowledge that they are subject to their own sources of uncertainty. Comparing software-based errors to known rates of manual error could be a valuable avenue for future work.

For the software length measurements analyzed in this study, we rely on manually annotated data rather than automatically detected keypoints. Specifically, human annotators labeled the snout and fork positions in fish images collected during both laboratory and field testing. This approach was chosen to minimize confounding variables and isolate measurement performance, thereby avoiding additional sources of error introduced by automated detection algorithms. This area is left for future development beyond the scope of this work.

A. Lab Testing

During their scientific data collection, CCFRP retained samples of deceased fish for later analysis. We leveraged this collection to obtain high-quality measurement data under controlled conditions. Photos were taken outdoors in bright sunlight to approximate on-deck lighting environments. The dataset comprises 266 *FishSense Mobile* images and 75 *Fishtechy* images.

We took multiple photos of each individual to assess measurement consistency. Each fish was placed on a flat surface, and at least 14 images were captured from varying angles with an iPhone 15 Pro and a 7th-generation iPad Pro. Photos were taken at distances ranging from 40 to 80 cm, with the device positioned as parallel to the fish as possible.

To benchmark our system, we also evaluated the current state-of-the-art citizen science tool for automatic fish length detection, *Fishtechy*. To ensure a fair comparison, each photo used for testing *Fishtechy* was captured on the same devices. As *Fishtechy* requires a fiducial marker for scale—specifically, its proprietary proof ball was included in each image (see Figure 2). *Fishtechy* results were obtained via cloud-based inference after uploading each image. Only successful length outputs were included in the comparison.

B. Field Testing

This study addresses the critical question of whether *FishSense Mobile* is feasible for use in real-world field scenarios. In collaboration with the California Collaborative Fisheries Research Program (CCFRP), we participated in live fishing deployments to evaluate the system under operational conditions. These trips encompassed a variety of challenges, including fish movement, inconsistent lighting, and complex backgrounds. During each survey, volunteer anglers used standardized tackle to target local groundfish species. We tested the system on a diverse range of species, including various rockfish, Scorpionfish, California Sheephead, and Ocean Whitefish. This dataset consists of 125 *FishSense Mobile* images, as well as corresponding lengthboard measurements of fish fork length.

Once caught, fish were transferred to a measuring board for evaluation by the onboard scientific team. While the fish were being assessed, we captured images using *FishSense Mobile* by positioning the device approximately 40 to 80 cm above the fish, aligned as parallel as possible to the plane in which the fish was resting. Care was taken to ensure the fish lay flat before capturing the image. The measurements and species identifications provided by the scientists served as reference values for evaluating system accuracy. All fieldwork associated with this project was conducted in full compliance with appropriate research permits and approved animal care and use protocols. Fish specimens were handled only by trained CCFRP staff.

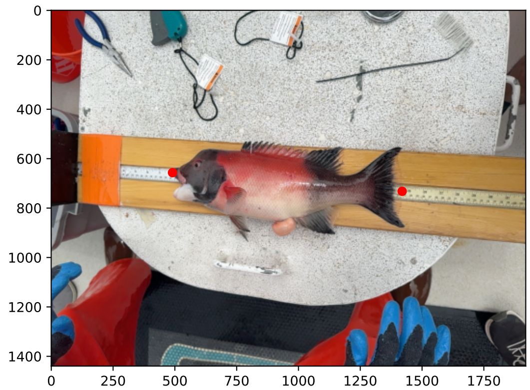
Ideally, images would be captured without any hands on the fish; however, with live specimens, this is often impractical. As discussed in Section II, removing fish from water frequently induces erratic movement, making it necessary for anglers to stabilize the fish by hand. As a result, many images in our field dataset include hands in the frame.

To isolate the accuracy of LiDAR-based fish length estimation, we used hand-labeled annotations for the snout and fork, which were projected onto the corresponding ARKit confidence map (see Figure 4b). A confidence score was then computed based on the depth quality at these two key points.

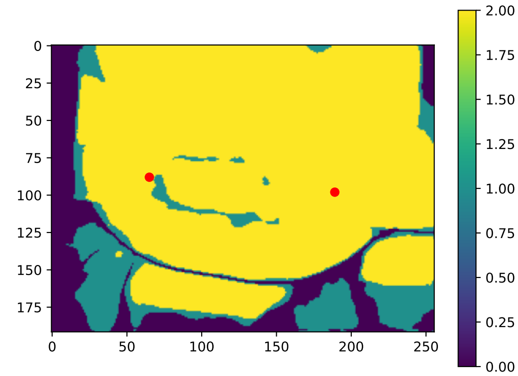
The confidence map quantifies the reliability of depth data at each pixel, with the snout and fork labels serving as reference points for evaluating measurement quality. We used a confidence score of 1—indicating a minimum of medium confidence at both of the labeled points—as the threshold for including an image in the analysis. For example, in Figure 5b, both the snout and fork fall within high-confidence regions, resulting in a score of 2. In contrast, Figure 5d shows a case where the snout falls in a moderate-confidence region, yielding a total score of 1. This threshold ensures that only images with accurate 3D depth information at both endpoints are used in length calculations.

V. Results

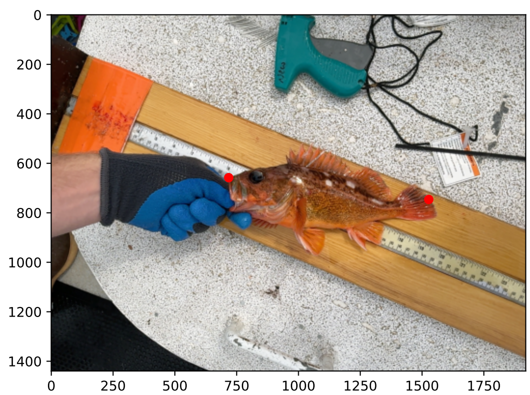
This section presents our evaluation of *FishSense Mobile*, focusing on its ability to provide accurate fork-length measurements under realistic conditions. We report results from two settings described in Section IV: field deployments and laboratory testing. In both cases, measurements are compared against reference values obtained by CCFRP scientists using length boards. For the lab dataset, we also benchmark *FishSense Mobile* against *Fishtechy*, the state-of-the-art citizen science tool. Our analysis emphasizes the practical performance of *FishSense Mobile* in field-relevant scenarios.



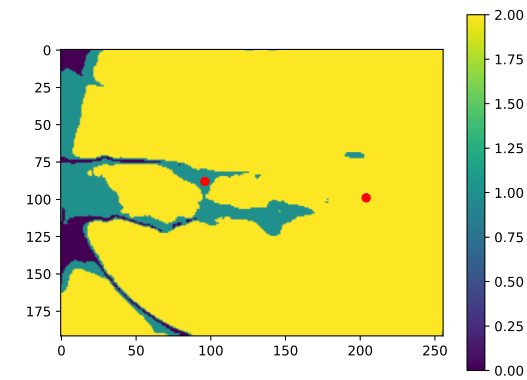
(a) RGB Image 1



(b) Confidence Map 1



(c) RGB Image 2



(d) Confidence Map 2

Fig. 5: RGB images (left column) and corresponding confidence maps (right column).

A. Field Testing

During field testing, we evaluated the performance of *FishSense Mobile* by comparing its fork-length estimates to those collected by onboard scientists using traditional fork-length measuring boards. While these manual board length measurements serve as a standard reference in fisheries science, they are subject to known biases and should not be considered exact ground truth [5, 8]. Therefore, we treat them as reference values and evaluate *FishSense Mobile* using percent difference.

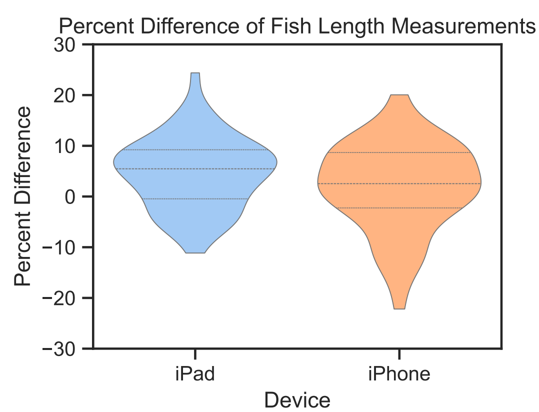


Fig. 6: Distribution of percent error between *FishSense Mobile*–measured lengths and onboard measuring board lengths, separated by device (iPhone 15 Pro vs. iPad Pro M4). Positive values indicate overestimation.

Figure 6 presents the percent difference distributions for the iPhone 15 Pro and iPad Pro M4. Both devices exhibit comparable error profiles, with similar means and standard deviations summarized in Table I. While both tend to overestimate fish length slightly, there is no statistically significant difference in measurement bias between the iPad and iPhone (two-sided t-test, $p = 0.08$). In total, this analysis considers 125 *FishSense Mobile* photos—54 from the iPad and 71 from the iPhone.

Figure 8 breaks down the percent difference by species. Although our dataset does not support detailed statistical analysis of inter-species variance, some species appear to

TABLE I: Summary of *FishSense Mobile* (FSM) performance in the field (percent difference)

Statistic	iPad	iPhone
Mean (%)	4.64	1.90
Standard Deviation (%)	7.09	8.63

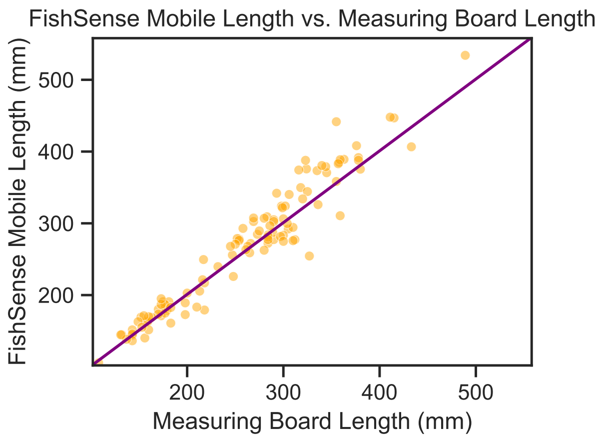


Fig. 7: *FishSense Mobile* length vs. measuring board length from field deployment data.

show a greater spread of bias than others. This consideration suggests that future work could explore species-specific effects in more detail.

When evaluated across the whole field deployment dataset, *FishSense Mobile* exhibits a strong correlation ($R^2 = 0.994$) with measuring board lengths, as shown in Figure 7. *FishSense Mobile*'s measured fork-length is within ± 1.92 cm with respect to the measurements collected by the expert scientists, on average. This result suggests that *FishSense Mobile* can reliably approximate traditional fork-length measurements under field conditions, although it exhibits a slight overestimate.

Overall, these results demonstrate the potential for LiDAR-derived scaling to replace physical fiducial markers in field-based fish length measurements. In both Figures 6 and 8, a mean percent difference that is close to zero is suggested, implying that *FishSense Mobile* is accurate on average. This may provide a way to improve accuracy on single fish through a simple multi-shot strategy, which may help improve accuracy in future deployments. We will further explore this in the next section.

B. Laboratory Testing

During laboratory testing, we focused on evaluating the variance of *FishSense Mobile* by taking repeated measurements of the same fish. Because the fish were deceased and immobile, this setting allowed for controlled, consistent data collection. The stable internet connection also enabled us to benchmark against *Fishtechy*, which relies on cloud-based processing. For *FishSense Mobile*, we collected 133 photos each from the iPad and iPhone. In comparison, we obtained 36 iPad photos and 39 iPhone photos for *Fishtechy*, with the discrepancy in sample

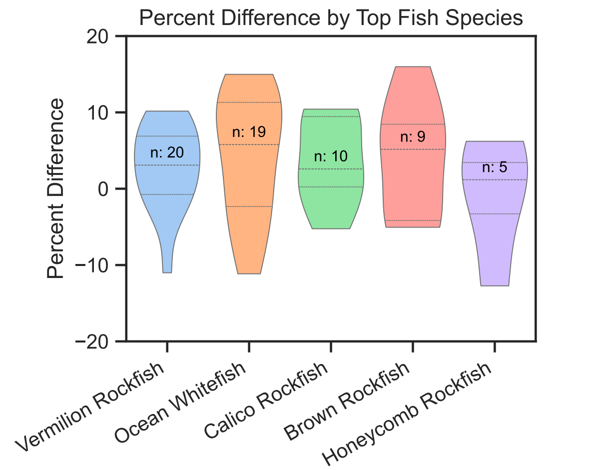


Fig. 8: Distribution of the percent difference in measurement between *FishSense Mobile* and measuring boards for common fish species.

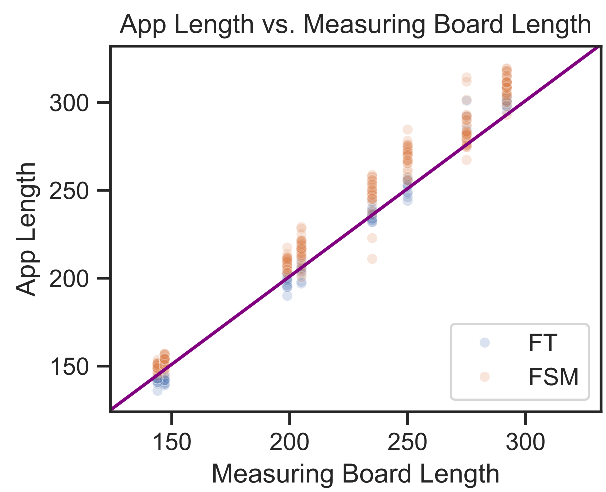


Fig. 9: App Length vs. measuring board length for *Fishsense Mobile* (FSM) and *Fishtechy* (FT) from lab data.

counts due to differences in the timing and duration of image collection for each system.

TABLE II: Summary of *FishSense Mobile* (FSM) and *Fishtechy* (FT) performance in the lab, measured in percent difference.

Statistic	iPad		iPhone	
	FSM	FT	FSM	FT
Mean	4.62	0.183	5.46	-0.155
Standard Deviation	2.89	1.95	3.02	3.38

Table II lists the statistics for the laboratory testing. These results are not significantly different than the CCFRP field data ($p = 0.14$), suggesting that the conclusions drawn from the field data will continue to hold in the laboratory setting.

FishSense Mobile demonstrates a correlation with length

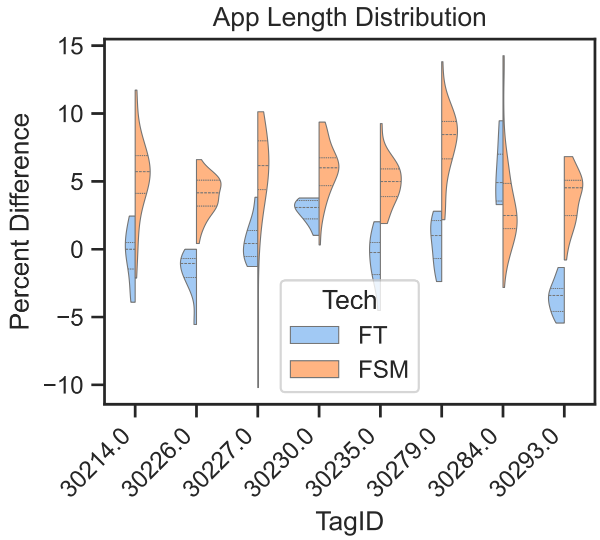


Fig. 10: Distributions of percent difference between app length *Fishsense Mobile* (FSM) and *Fishtechy* (FT) from lab data.

board measurements in the lab environment, as shown in Figure 9. The lab data also has a difference of ± 1.03 cm compared to the expert scientists' measurements, on average. This indicates that *FishSense Mobile* achieves similar performance to the state-of-the-art citizen science fish measurement tool without requiring a fiducial marker. Each vertical group of points in Figure 9 represents repeated measurements of an individual fish, showing more variance with *FishSense Mobile* than *Fishtechy*. Figure 10 further illustrates that *FishSense Mobile* exhibits greater variance across repeated measurements of the same fish compared to *Fishtechy*, suggesting that multi-shot sampling could mitigate this variance.

C. Practical Considerations

The measurements produced by *FishSense Mobile* across the field and laboratory datasets demonstrate promising accuracy. As shown in the results above, the system's estimates exhibit a strong correlation with length measurements obtained by scientists using traditional measuring boards. These findings suggest that *FishSense Mobile* has the potential to support independent citizen science efforts by enabling reliable, in-field fish length measurements without requiring specialized equipment.

VI. Conclusion

FishSense Mobile provides key advantages over traditional human-based measurement, including usability by non-experts, reduced handling time for fish, and decreased reliance on manual data entry. *FishSense Mobile* maintained an accuracy of less than ±2 cm with respect to the length board measurement collected by the expert scientists. The system runs on commercially available hardware, uniquely positioning it to scale without additional infrastructure costs.

The success of *FishSense Mobile* in the field highlights the potential of integrating consumer-grade sensing to support scalable and efficient fisheries monitoring. As we expand validation with live fish and integrate species identification capabilities, this system empowers scientists and independent citizen scientists to contribute to more sustainable participatory marine resource management. To evolve from a measurement tool into a comprehensive fisheries management platform, several core functionalities must be developed, and support for additional devices must be expanded. We are currently working on adding Android support, automatic fish species recognition, pose correction, and snout and fork detection of fish in images.

To test additional features, more field expeditions are needed, as well as broader adoption by fisheries research programs outside California. Ease of use, efficacy, and accessibility to a wider variety of devices will ensure that programs external to the University of California research network can successfully contribute to the growing number of *FishSense Mobile* measurements. With the implementation of a central database, recreational anglers, researchers, and policymakers alike could contribute to and learn from *FishSense* statistics. With the advancements mentioned above and expanded usage, *FishSense Mobile* holds promise to increase the amount of data available to fisheries managers and enhance engagement with local fishing communities, especially in understudied regions. With *FishSense Mobile*, citizens around the world can contribute to efforts to understand our oceans.

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