Drones Computer Vision using Deep Learning to Support Fishing Management in Indonesia

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Abstract. It is necessary to study technical factors such as bait used, oceanographic conditions of fishing areas and skipjack tuna trade patterns (*Katsuwonus pelamis*) as well as other factors in Sulawesi Fisheries. Supporting data to study these technical factors need to be obtained so that it can be improved throughout the year as a skipjack fishing standard with weights taken by the skipjack weights. Therefore, drones and underwater drones with cameras with high-resolution video and images to be fed and processed by computer vision. These drones are operated via Huhate ships which are then used to test efficient technical factors as expected, can be used in determining the size, shape, and colour as well as the analysis of skipjack fish that are in the Fish Aggregating Devices (FADs or Rumpon) in order to manage the management of fisheries managed in Indonesia.

Keywords: Drone, Huhate, Machine Learning, FishNet, Fisheries management

1. Introduction

Limitation and control of fishing permits are needed so that fish reserves can be managed sustainably. There are several ministries of the ministry of maritime affairs and fisheries (KKP) for sustainability programs including by optimizing the management of marine space, conservation, and diversity of marine life, increasing the sustainability of capture and aquaculture businesses, improving the competitiveness and logistics systems of marine and fishery products [1-2]. There are 11 fishing grounds scattered throughout Indonesia. Based on the results of the study [3], there are technical factors that have a close relationship with the catch are the number of fishing trips and the number of baits used. The size of the boat and the number of anglers do not show a significant relationship to the catches obtained. Further research is needed to find out the influence of other technical factors such as
the bait used, or the oceanographic condition of the fishing area and the pattern of skipjack tuna fish migration (*Katsuwonus pelamis*) in the Sulawesi waters.

Huhate (pole and line) is a fishing gear consisting of fishing rod or bamboo, fishing line, and hook. This fishing gear is specifically used to catch skipjack (*Katsuwonus pelamis*). This tool is often called a skipjack fishing line [4]. Huhate is operated throughout the day when there are fish groups around the boat near FADs (FADs are a type of fishing aids installed at sea, both shallow and deep-sea. The installation is intended to attract fish groups to gather around the FADs, so fish easy to catch). This fishing gear is active, the Huhate ship will chase a horde of fish and then hold fishing. Huhate ships, in general, are wooden ships that have a tonnage ranging from 50 to 80 GT with a driving force ranging from 350 to 450 PK, equipped with auxiliary engines for lighting and water supply respectively 90 to 155 PK. On the deck of the ship, there are hatches of about 7 to 8 pieces with each volume varying from 2 to 4 tons. Two holds in the middle are used to store live bait, the other is used to store fish, ice cubes, and freshwater. The huhate part of the ship has a special construction, modified to be longer so that it can be used as a seat by anglers.

Skipjack fishing by Huhate ships is carried out throughout the year, both in the western, transitional and eastern seasons. In carrying out fishing operations, huhate vessels use several electronic equipments such as global positioning systems and echo sounders, especially for vessels that are 80 GT in size. The use of such equipment is intended to facilitate the search for fishing locations (FADs). These huhate ships have a global positioning system data that stores data of the position of FADs in the waters of the Sulawesi Sea and Maluku Sea [5]. According to the ministry of maritime affairs and fisheries, large Pelagic fish resources in the Sulawesi Sea are experiencing overfishing exploitation, fishing by Huhate, as shown in Figure 1 below. Similarly, some potential areas in Indonesia, the population of several species of fish are critically threatened. One of the considerations in the management of fisheries resources is to use the help of drones and computer vision in managing the capture of Huhate vessels to make it more efficient and selective for fisheries management that can maintain the sustainability of fishery products that are overexploited so that resources the fisheries economy in Indonesia is maintained sustainably.

![Figure 1. Huhate Fishing Management](image-url)
2. Related Works

2.1 Drones for Fishing

Skipjack fish reserves can be managed in a sustainable manner by limiting and controlling fishing permits. To support this mission, the government needs technological innovation and proper fisheries business management. Drone technology is widely applied in various fields, such as mangrove forest management [6], which data acquisition with drones on cloudy days is felt to be very beneficial for mangrove researchers. Although the initial costs of using drone data are quite high (depending on the type of drone and sensor used), but later, it more cost-effective to monitor an area of about 50km$^2$, or to monitor a relatively large area of several square kilometers. With a higher spatial resolution with DEM, from the drone data, it sends a very accurate map of the area to the image of the water area. So, the drone technology can help for the sustainability mission of fisheries in Indonesia.

There are two technology drones for maritime, namely air drones (See Figure 2) and underwater drones (Figure 3). Air drones can also float in water, fly in rainy conditions, land on water and surf on water are the best waterproof drones in their class which makes it a right choice of camera drones for aviation on the surface of the sea, such as having a waterproof camera for photographing 4K above and below the surface of the water, has a long-distance, long flight, light, online, this Drone has a module that can lift an additional 1 kg load, which can be used for fishing or used for throwing bait in the ocean, or even lifting fish. Furthermore, there are some advanced underwater drone technologies to help the management of fisheries resources, as shown in Figure 3.

Underwater drones (or ROVs) are waterproof drones that allow users to explore the deep sea environment from a distance. This drone can navigate through underwater currents assisted by one or more propellers. They are generally equipped with cameras, obstacle avoidance sensors, and strong lighting to record good quality records even in dark underwater environments. Most air drones are equipped with powerful headlamps, providing visibility in submarine conditions in dark conditions. The underwater drone is equipped with a 4K camera for high-quality image capture. Other common features and enhancements include FPV glasses, robot arms, and ballasts. Most are tethered via cables to buoys to dive freely in the deep sea without obstacles. There are two main reasons why it is tethered to the surface when operating namely:

1. To avoid losing drones in difficult and unpredictable sea area and weather conditions. The cable is a rope that holds the drone in case of engine failure, dives out of reach and other unforeseen circumstances.
2. To stream live video or images: the cable is used to transmit video signals directly taken from a drone camera, allowing the operator to visualize the recording captured by the drone in real-time on the remote control display (or cell phone screen or FPV glasses, depending on the model).

2.2 Computer Vision using Deep Learning

Deep learning has been recognized as a practical tool in the application of image processing, natural language processing, speech recognition, text classification, robotics and control, computer vision, and so on [7-8]. Through the Convolutional Neural Network (CNN) for a practical approach of machine learning using a collection of images, CNN can learn rich representations of characteristics for a variety of images.

Fish classification can use learning transfer and Matlab as the first step in overcoming the problem of Huhat fishing (Figure 4) [9]. Through FishNet modification through AlexNet to classify Katsuwonus Pelamis (skipjack or skipjack), Euthynnus Affinis (Tuna) and Coryphaena Hippurus (Mahi-mahi) captured by fishermen applying five steps to teach machine learning to classify fish, namely:

Step 1: Making fish image data from popular names such as Katsuwonus Pelamis known as skipjack.
Step 2: Image processing with CNN and using augmentation for rotation to create enough images as deep learning data. Augmentation can be in the form of scale, rotation, turning, tilting, cutting [10].
Step 3: Prepare a data set of 15,120 fish images, 5,040 for each fish. Data is divided into 70:30 for training and validation sets. Training is doing by matching classifier parameters [11].
Step 4: Modify AlexNet into FishNet with Matlab, which is used to predict fish classes.
Step 5: Set hyperparameter from FishNet.

An adaptive thresholding method to deal with non-uniform illumination in underwater images the EM-guided GMM is used to fit the histogram to figure out whether the histogram is bimodal or unimodal, and then an adaptive threshold is computed accordingly. Finally, the central pixel of the mask is compared with the threshold to generate the binary detection result [12].

3. Proposed Methods

By flying a drone (1380 grams of DJI Phantom 4™ multirotor, 4K video quality, 12.4 MP photo, f / 2.8 aperture, waterproof) on a GPS-enabled FAD, fish can be seen in fish populations in the FADs. The air drone camera is controlled and stabilized by a three-axis gimbal, and a GPS-stable system controls the drone. All videos are filmed at 3840 x 2160 pixels (30 frames s-1 45), with automatic ISO and fixed speed, allowing variations to get the images recorded neutrally. The sensor width is 6.2 mm, and the focal length of the camera is 3.61 mm. The drone is programmed to fly (5.4 km / h) in fishing areas above the FADs, calculated and controlled using the Drone Harmony application and run via a...
mobile Android phone. While continuously recording images or video FADs, data can be sent simultaneously via Satellite imagery data that is provided on the application, and routes are calculated automatically to ensure the entire surface area of the FAD can be recorded into video, using the camera facing directly downward (-90° angle). After the air drone sends the image to computer vision for further analysis, the underwater drone that is equipped with a go pro wifi underwater camera is sent to take pictures of fish positions that are known by air drones where there are many skipjack fish, so that underwater drones can take underwater shots around the FAD where there are cakalang fish which will later be processed by computer vision again.

3.1 Survey of FAD by Air Drone

Air drone flights at three heights in succession in descending order (120 m, 80 m, 40 m), start from the altitude which causes the least disturbance. An air drone is launch and lands outside the visual range of the fish around the FAD (Figure 5). To avoid disturbing the fish around the FAD, the drone must return after two flights to replace the battery. It took 30-40 minutes to complete the drone survey. With differential coverage of FADs, routes vary from back and forward (east-west) across FADs to one lane in the middle, north-south. The study was conducted for four FADs in a day (6:30 - 7:30 [EM] morning; noon 10: 00-11: 00 [LM]; afternoon 13:30 - 14:30 [EA]; afternoon 17: 00 - 18:00 [LA]), dividing the flight schedule evenly from one hour after sunrise to one hour before sunset. Drones can complete the capture of images around the FADs that are known for 21 positions per day during the fishing season.

![Figure 5. FAD (Rumpon) Map](image)

3.2 Survey of FAD by Underwater Drone

Next, send the underwater drone to the position of skipjack fish that have been detected by air drones. Underwater drones are useful for estimating numbers and measuring skipjack fish in the sea around where FADs are located, all videos and images of diving under air drones are randomly taken to avoid bias at the nearest assessment. When reviewing the video, it is also necessary to check the behaviour of the fish if there are any symptoms of disturbance due to the presence of air drones above and around the FADs as well as underwater drones carried out the same examination as well.
According to [13] there is a mismatch between the pattern of placement and construction of FADs used by Purse Seine fishermen in Bone Regency with government regulations and the provisions of the concession for responsible fisheries management (CCRF) related to the use of FADs. Therefore, efforts are needed from the authorities to carry out comprehensive control and outreach to prevent social friction and the sustainability of the potential of fishery resources in the waters of the Gulf of Bone.

It is also necessary to calculate the potential of skipjack tuna from aboard hutates adjacent to FADs at the same location each time (Figure 5 and 6) where all skipjack fish can be observed, immediately after the last air drone flight for each time of the day. (i.e. four counts a day) and record behaviours that show skipjack tuna disturbed by both air drones and underwater drones, whether immersed in water, running, still, and moving carried out by FishNet by using the 'snapshot' function of the media player VLC to get photographic images of each skipjack fish recorded in the image. Individual images are imported into image, the 'set scale' function used to insert GSD for the image (1.79 cm / pixel for drone images at 40 m, 3.58 cm / pixel at 80 m, and 5.37 cm / pixel at 120 m) and the 'straight-line' function is used to measure the length of each skipjack fish from the tip of the tail to the base of the snout. The measured distance is then used to assign each skipjack fish to an age class, the weight with no difference between males and females, based on the known relationship between body length and age. Skipjack fish <40 cm less than two years old are classified as juveniles; 40-50 cm aged two to four years and classified as adults, and tuna fish> 50 cm classified as adults, in classifying as adults. Assuming that fish are caught at a size that the gonads have not yet ripened, fish must be released to avoid a lack of supply of fish resources later on and reduce the tendency to become extinct. For that, fish must be allowed to have more offspring [15]. Other partially submerged tuna, where the snout and the base of the tail are not visible, are classified as 'unknown'. During the visual assessment, if skipjack fish cannot submit into age and weight classes then recorded as unknown.

Development in the field of computer vision has been able to achieve higher accuracy and efficiency, and the widespread use of this application can provide quality detection for various visualizations of aquatic products [16]. According to [17] technical solutions for the classification of intelligence for freshness in fish can use applications that combine computer vision with artificial intelligence techniques. The whole system includes image acquisition, pre-processing methods, calculation channels, feature extraction, feature selection by the ABC-ANN hybrid algorithm and classification using machine learning models SVM, KNN and ANN. The revealed results show that the classification of ANN with an accuracy of 93.01% has the best performance for fish freshness classification. So, the conclusion is that the ABC-ANN computer vision-based method can be used as a reliable, fast, non-destructive, and online method to be able to assess the freshness of fish in general.
Deep learning is emerging as the most promising approach in extracting task-specific information from the data utilizing highly nonlinear mathematical models, especially suitable for computer vision tasks [18]. However, their computational complexity is the biggest obstacle in their deployment to real-world scenarios. Therefore, in future, deep neural networks in conjunction with the pixel-wise posteriors with a highly optimized algorithm that should be capable of yielding results in realtime and with favourable accuracy [19]. Pantanal fish species recognition based on convolutional neural networks. Our method is composed of three branches to classify the fish species but also the fish family and order in a taxonomy. In this way, the representation of the fish species is improved with the inclusion of information learned to classify the family and order [20].

In this writing, the approach that the author takes is the use of computer vision using FishNet and Fuzzy Logic in processing images produced from aerial and underwater drone cameras controlled from a Huhate ship (see Figure 7).

3.3 How the Computer Vision Drone works
From Figure 7, a web camera is mounted on an air drone to get a picture of a group of fish around a run-down which is then preprocessed so that the results of the image can be fed to Machine Learning which will then guide the underwater drone to move in search of fish, if the fish have found it will take fish picture from an underwater drone. If the image has been received, then the underwater drone will then feed it to machine learning to process the image and so on, these two types of drones help each other to find location and then take fish pictures to be transfer to computer vision to detect type of fishes.

For each part of the process as explained below.

- Cloud: Computer vision applications are connected to the Cloud network to receive, process and send data online, then the data processed can be analyzed directly and guaranteed to authenticate the results of its data processing.
- Air Drone with Camera: Capturing images from above the FAD areas that have known GPS data, image data is sent to an Android mobile phone that is on a Huhate ship.
- Underwater Drone with Camera: Capturing images from around the FAD areas that have known GPS data, image data is sent to an Android mobile phone that is on a Huhate ship.
• Computer Vision: Doing deep learning on images produced from cameras from air drones to find out which FAD areas are skipjack tuna areas. It is followed by a deep learning process to process contour orientation scala to make scale changes to proceed to find out the position of the skipjack fish. From this known position, underwater drones are sent to take pictures of fish in the water around the FADs. Data from underwater drones are processed again by deep learning to find out the full length, height, weight, calculation of size, length, and weight of fish.

Furthermore, the help of Fuzzy logic to make the selection of fish that is following the standards applied or not. For fishing processing, three types of rules are used: Juvenile = 0-1 year, Mature = 1-4.5 years, Old = 4.5-12 years. So that the selection of fish is kept in the old condition.

• The processed data is sent to the fishpond to be displayed on the billboard screen which can provide information on the catches of fishers so that they can analyze the catches thoroughly so that they can be managed according to the policies.

E. Computer Vision Data Set
For the fish data model, this study came from research location data: Bitung (near Manado) in the form of video data sets from skipjack fishing on fishing vessels with the amount of data: 1,000 Cakalang fish, 1,000 frames of tuna on preprocessing in foreground and background removal, count detection, find centroid, full length, and Height, Length: Age, Length: Weight. With the right processing, the expected performance metric is very satisfying to apply the deep learning computer vision Drone for the management and sustainability of Indonesian fisheries.

With data derived from air or underwater drones processed by computer vision can test the existence of skipjack fish around FADs, variations in the percentage of skipjack fish classified by age class (number of Juvenile, Mature, Old) with the total for each drone survey; the model, and the number of Juvenile, Mature, and Old. Also, to find out the 'height' and depth of drones that have four levels (amount of flights, height and depth of drones 40 m, 80 m, 120 m) as well as 'time of day' (morning[P], afternoon[S], morning afternoon[PS]), and afternoon afternoon[SS]). Height and time of day are defined as fixed effects, with survey dates as random effects. As a proxy of the actual number of skipjack fish, for modeling, it can use a customized model for repeated testing using procedures in determining the maximum number of skipjack fish that can be seen from any number (drone or land) for each day. Given that skipjack fish generally do not move from FADs during daylight hours. In order to investigate how the calculations, compare with the daily maximum as a measure of the actual accuracy when the image is recorded. All models are examined by the residual distribution plot against the predictor and the Q-Q plot from the normal distribution, to test the assumption of variance homogeneity and data normality. These assumptions are met, do not require transformation. All statistical calculations are performed using Matlab so that standard errors can be reported. Computer vision machines can be used to measure size, shape and color repairs, including camera repair, lighting settings, image processing, and analysis methods, and from experimental results.

Conclusions
To conduct proper fisheries management, drones can help in terms of the amount of fuel released on fishing trips, management of fisheries resources, fishing vessel traffic operations, estimating skipjack tuna caught quickly and can be used as one of the considerations in selling buy fisheries online. Computer vision drones can be used to manage fish resources efficiently and environmentally friendly and are useful for managing sustainable fisheries management in aquaculture security in Indonesia. For this reason, the vision of computer vision drones must be applied to maintain better aquacultural sustainability in Indonesia.

Acknowledgments
Authors wishing to acknowledge the support from the Directorate General of Strengthening for Research and Development, Ministry of Research, Technology, and Higher Education, Republic of Indonesia as a part of PenelitianUnggulanPerguruan Tinggi Research Grant to Binus University
entitled “Perancangan Algoritma Untuk Pengenalan Ikan Cakalang, Tonkgol dan Lemadang Otomatis Hasil Tangkapan Nelayan Huhate Di Bitung, Manado” or “Design An Algorithm for Automatic Skipjack, Tongkol, and Lemadang Recognition of Fishermen Using Huhate in Bitung, Manado” with contract number: 225/SP2H/LT/DRPM/2019, 12/AKM/PNT/2019, 039/VR.RTT/IV/2019 and contract date: 27 March 2019.

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