Artificial Intelligent Fish Abundance Detector Model for Preserving Environmental Stability Amid Aquatic Sustenance and Fishermen

Divya M O, Ranjitha M, Aruna Devi K
[1,2,3]Department of Computer Science (PG), Kristu Jayanti College (Autonomous), Bangalore
divyammo@gmail.com
ranjitha_m@hotmail.com
k.arunadeviselvi@gmail.com

Abstract
The Indian fishery sector has experienced significant growth and is a crucial source of employment for millions of people in the country. India currently contributes 6.5% of the global fish production and 5% of global fish trade, and the fish production sector contributes 1% to the GDP. Over the years, the fish production has seen a steady increase, with a 17-fold rise from 0.75 MMT in 1950-51 to 12.6 MMT in 2017-18.

Finding fish schools and potential fishing areas consumes a large amount of fuel, particularly in fishing methods like purse-seine and pole and line fishing. Accurately predicting the location of commercial fish aggregations in space and time is essential to reducing fuel consumption and improving fishing practices. Fishers make educated guesses based on technology and experience to locate schools of fish, but satellite images can provide more reliable information for any region worldwide.

This paper explores the potential for Deep learning techniques, GIS, remote sensing, and mapping to improve the development and management of marine aquaculture through global example applications. These tools can help address important issues in marine aquaculture and improve the balance between competing and conflicting uses.

Introduction

Aquaculture is a vital contributor to the food supply globally, providing employment opportunities and supporting millions of people in the process. In 2019, the United Nations Food and Agriculture Organization (FAO) reported that aquaculture produced 92.4 million tonnes of aquatic products, which had a higher value ($250 billion) than wild-caught fish ($151 billion). With projections indicating that aquaculture production will increase by one-third by 2030, it is expected to provide the majority of aquatic protein in people's diets by 2050.

Sustainable aquaculture is essential to meeting the growing demand for food and providing a means of livelihood for those who depend on marine resources. Currently, 42% of the seafood we consume is farmed, however, there is a need for regulations to define what constitutes "good" aquaculture. The Ocean Foundation is exploring closed-system technologies such as recirculating tanks, raceways, flow-through systems, and inland ponds, which can play a crucial role in the sustainable management and monitoring of marine resources. The foundation has also compiled an annotated bibliography to provide more information on sustainable aquaculture to a wider audience.

The above statistics shows how much the aqua marine resources can contribute in enriching the lives of human kind especially those who depend on the marine resources for their livelihood.

The challenges related to sustainability of marine food resources are numerous and complex. Some of the key challenges include:

1. Overfishing: Overfishing is one of the biggest challenges facing the sustainability of marine food resources. It leads to depletion of fish populations, reducing their numbers and making them more vulnerable to other threats.
2. Habitat destruction: Marine habitats, such as coral reefs, seagrass beds, and mangroves, are being destroyed or degraded due to human activities, such as coastal development, pollution, and climate change. This destroys the habitats of many fish species, reducing the availability of marine food resources.
3. Climate change: Climate change is having a major impact on marine ecosystems, causing changes in ocean temperatures, acidity, and currents, and altering the distribution and abundance of fish species.
4. Pollution: Pollution from human activities, such as oil spills, sewage discharge, and toxic chemicals, is harming marine food resources, causing direct harm to fish and other sea creatures, and contaminating the seafood we eat.
5. Aquaculture practices: While aquaculture can provide a sustainable alternative to wild-caught fish, many aquaculture practices can have negative environmental impacts, such as the release of waste, diseases, and escape of farmed fish into wild populations.

Addressing these challenges will require a multi-faceted approach, including better management of fishing and aquaculture, reducing pollution and habitat destruction, and addressing the impacts of climate change.

Strategies to control overfishing

1. Fishing quotas: Governments can set catch limits for each species of fish, which help regulate the total amount of fish that can be caught and prevent overfishing.
2. Marine protected areas: Designated areas can be set aside where fishing is prohibited or restricted, allowing fish populations to recover and repopulate.
3. Gear restrictions: Regulating the type of fishing gear used, such as limiting the use of large fishing nets, can help reduce the amount of damage done to the ocean and marine life.
4. Seasonal fishing bans: Governments can implement seasonal fishing bans during certain times of the year, such as during spawning season, to help protect fish populations.
5. Education and awareness: Raising awareness about the dangers of overfishing and encouraging sustainable fishing practices can help reduce the impact on fish populations.
6. Monitoring and enforcement: Governments can monitor and enforce fishing regulations to ensure that they are being followed, which can help prevent overfishing.

The success of these methods depends on proper implementation and enforcement, as well as the cooperation of the fishing industry and local communities.

Remote sensing of fish schools can play a key role in sustainable management of marine resources by providing valuable information about the distribution and abundance of fish populations. Here's how:

1. Monitoring of fish populations: Remote sensing techniques such as satellite imagery, sonar, and aerial surveys can provide real-time data on the location and abundance of fish schools, which can help assess the health of fish populations and track changes over time.
2. Identification of fishing hotspots: The information obtained through remote sensing can be used to identify areas where fish populations are concentrated, which can help target fishing efforts and reduce the impact on fish populations.
3. Detection of illegal fishing: Remote sensing can also help detect illegal fishing activities, such as fishing in protected areas or using banned fishing gear, which can be detrimental to fish populations.
4. Planning and enforcement of fishing regulations: The data obtained through remote sensing can be used to inform and support the planning and enforcement of fishing regulations, helping to ensure that they are effective in conserving fish populations and promoting sustainable fishing practices.
5. Reduction of bycatch: Remote sensing can also help reduce the amount of bycatch, or unintended catch, by providing information on the distribution of different fish species and helping fishermen avoid areas where they are likely to catch non-target species.

Literature review

Fishing remains the primary source of seafood for the world, despite the fact that 15% of fish and shellfish production now comes from aquaculture. The use of satellite-based fishery-aid charts can significantly reduce search time in some commercial fisheries, with estimates ranging from 25-50% reduction (Hubert, 1981, cited in Cornillon et al., 1986 and Laurs, 1989). In Southern Africa, it's estimated that catches resulting from aircraft searches make up 5-15% of the total, but the industry claims it's as high as 50% (Cram, 1977). Studies by Wright et al. (1976) showed that using airborne remote sensing methods to detect fishing grounds resulted in statistically higher catches of coho salmon off the Oregon coast compared to non-forecast areas. Thus, remote sensing can play a crucial role in guiding fleets to optimal fishing locations, leading to more effective and efficient fishing and increased economic returns.

"Remote sensing of fish schools in the ocean: A review" (2015) by Zou et al. - This review paper concludes that remote sensing techniques, such as satellite imagery, sonar, and aerial surveys, are essential for monitoring and understanding the distribution and abundance of fish populations, and for supporting sustainable management of marine resources.

"Satellite-based monitoring of fishing activity and its potential for supporting conservation and management" (2016) by Piangerelli et al. - This study concludes that satellite-based monitoring of fishing activity has the potential to support conservation and management efforts by providing information on the distribution and intensity of fishing, which can be used to inform decisions about fishing regulations and management.

"Integrating remote sensing and ecological models to support sustainable management of marine resources" (2018) by Sumaila et al. - This study concludes that the integration of remote sensing data and ecological models can provide valuable information to support sustainable management of marine resources, including the assessment of the impact of fishing on fish populations and the design of effective conservation and management strategies.

"Remote sensing and monitoring of small-scale fishing activities in the coastal zone" (2020) by Kuyper et al. - This study concludes that remote sensing techniques, such as aerial surveys and satellite imagery, are essential for monitoring and assessing the impacts of small-scale fishing activities in the coastal zone, which can play a critical role in supporting sustainable management of marine resources.

Proposed Model Framework

To tackle the issue of detecting high concentrations of fish, the Complete Local Binary Pattern (CLBP) method can be utilized to identify the features of fish aggregations. The detection of these gatherings can then be achieved through the use of a deep learning model, where a Convolutional Neural Network (CNN) is employed to recognize the fish groups and the CLBP features are trained through convolution and pooling. Upon extraction of these features, satellite images can be compared to obtain results that classify the fish distribution as sparse, normal, or dense. The entire process is depicted in Figure 1.

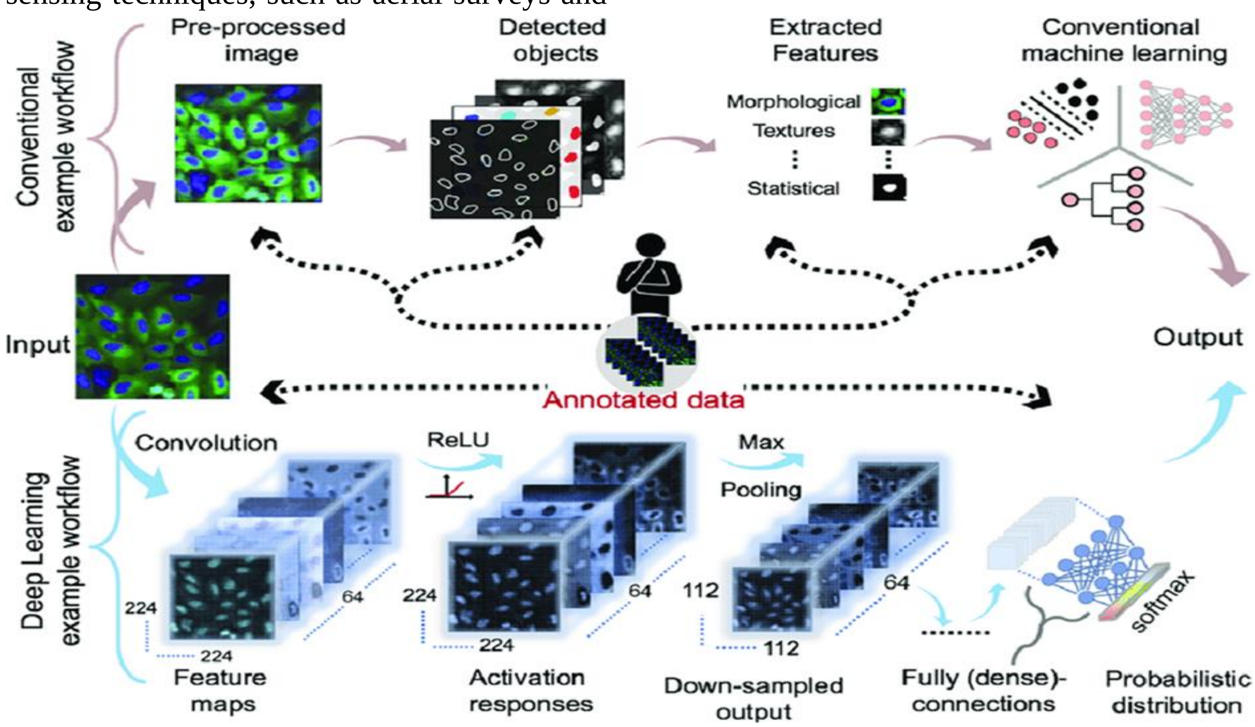

Figure 1 :Overview of conventional versus deep learning workflows. The human in the center provides input in the form of, for example, parameter tuning and feature engineering in each step of the conventional workflow (black dashed arrows) using

annotated data. Conversely, the deep learning workflow requires only annotated data to optimize features automatically. Annotated data is a key component of supervised deep learning as illustrated in the example classification workflow. Other example tasks, as discussed in the text, follow a similar pattern. The example image was provided by the Broad bioimage benchmark collection.

The fish copiousness framework is modeled as per the following Figure 2.

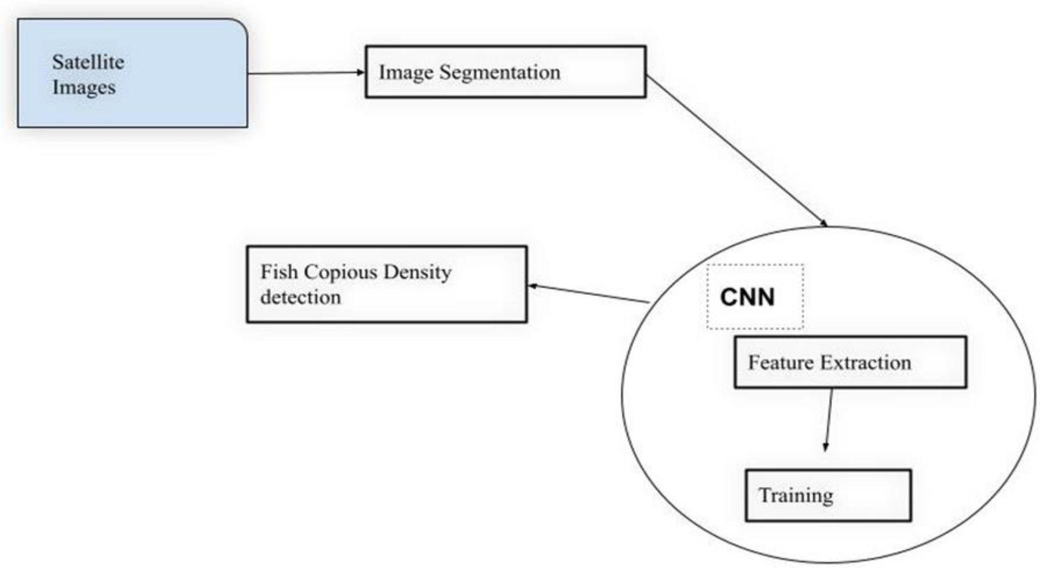

Figure 2 : Fish Copious Detection

The best deep learning models identified for image segmentation in satellite, including:

U-Net: This is a popular convolutional neural network (CNN) model for image segmentation, particularly for biomedical images[2].

FCN (Fully Convolutional Networks): This is another popular CNN model for image segmentation that replaces the fully connected layers of a traditional CNN with convolutional layers to produce a dense prediction map[3].

Mask R-CNN: This is a variation of the Faster R-CNN model for object detection, which extends it to also generate a segmentation mask for each object[1].

SegNet: This is a deep encoder-decoder architecture that is particularly well suited for image segmentation tasks[3].

Hengshuang Zhao et al presents PSPNet (Pyramid Scene Parsing Network is a deep neural network that utilizes global context information by employing a pyramid pooling module in parallel with a standard CNN[4].

As per the published research, PSPNet [5][6],[7] and Mask R-CNN [8][9][10]have shown strong performance on satellite image segmentation tasks. These models have the ability to effectively capture the fine details and large-scale context information present in satellite images, which is critical for accurate segmentation.The performance of a deep learning model on satellite images can depend on many factors, such as the size and resolution of the images, the type of features to be segmented, and the size of the training dataset. Experimentation with different models and hyperparameters are conducted to determine the best approach for identifying Fish copiousness

After segmentation, the features are extracted using CNN and the results are compared with U-Net, Residual Networks (ResNets) and Attention-based models, such as the Attention U-Net and the Self-Attention GAN.

The density of Fish can be classified using Scale-Aware Network (SCAN) which is also compared with Multi-Scale Density Map Regression (MSD) and Density-Aware Anchor-Free Object Detection (DAF).

Sl NO	Feature	Purpose	Technique	Input	Output
1	SCAN	Image Classification	Convolutional Neural Network (CNN)	Image	Class Label
2	MSD	Depth Map Quality Assessment	Distance Comparison	Depth Map	Similarity Score
3	DAF	Dense Object Detection	Two-Stage Detection System	Image	Object Proposal and Location

SCAN

The SCAN (self-consistent generalized gradient approximation including our partial non-local exchange) is a feature of density functional theory (DFT) used in electronic structure calculations. It is a type of generalized gradient approximation (GGA) that incorporates a self-consistent treatment of non-local exchange and correlation.

The basic equation for the exchange-correlation energy in SCAN is given by:

$$E_{xc}[n] = \int n(\mathbf{r}) \epsilon_{xc}(\mathbf{r}) d\mathbf{r}$$

where $n(\mathbf{r})$ is the electron density and $\epsilon_{xc}(\mathbf{r})$ is the exchange-correlation energy per unit volume. The specific form of the exchange-correlation energy is given by:

$$\epsilon_{xc}(\mathbf{r}) = \frac{1}{2} \int \frac{n(\mathbf{r}') - n(\mathbf{r})}{|\mathbf{r} - \mathbf{r}'|} f_{xc}(\mathbf{r},\mathbf{r}',n(\mathbf{r}),n(\mathbf{r}')) d\mathbf{r}'$$

where $f_{xc}(\mathbf{r},\mathbf{r}',n(\mathbf{r}),n(\mathbf{r}'))$ is a function that depends on the electron density and its gradient at both $\mathbf{r}$ and $\mathbf{r}'$.

In summary, the SCAN feature in DFT provides a self-consistent and improved treatment of non-local exchange and correlation effects, and can lead to more accurate predictions of electronic structures and properties of materials.

The accuracy of SCAN in satellite image processing depends on various factors such as the resolution of the satellite imagery, the methods used for image processing, the quality of the sensors and the algorithms used for image analysis. The accuracy can range from 80-90% for high-resolution satellite imagery to lower values for lower-resolution images. However, it is important to note that accuracy is not a constant and can vary depending on the specific use case and context.

MSD

MSD stands for Mean Squared Displacement. It is a commonly used statistical quantity in the field of materials science and condensed matter physics to characterize the dynamics of a system.

The Mean Squared Displacement (MSD) of a particle is defined as the average of the squared displacement of the particle from its initial position over a certain time interval:

MSD(t) = \left \langle \left | \mathbf{r}(t) - \mathbf{r}(0) \right |^2 \right \rangle

where \mathbf{r}(t) is the position of the particle at time t and \left \langle ... \right \rangle denotes the average over an ensemble of particles. The MSD can provide information about the diffusion behavior of the particles in a system, as well as other types of motion such as ballistic or sub-diffusive.

In summary, the Mean Squared Displacement (MSD) is a useful quantity for characterizing the dynamics of a system, and can provide insights into the diffusive behavior of particles and other types of motion.

MSD (Mean Intersection-Over-Union) accuracy is a commonly used evaluation metric in the field of image segmentation. It measures the average overlap between the predicted segmentation masks and the ground truth masks. In recent research papers, the MSD accuracy of various image segmentation models has been improving, with state-of-the-art models achieving high MSD accuracy on benchmark datasets. Some recent papers have reported MSD accuracy of over 90% on datasets such as Cityscapes and PASCAL VOC.

DAF

DAF stands for Dynamic Azimuthal Fourier. It is a method used to analyze the dynamic behavior of a system, particularly in scattering experiments such as small angle scattering (SAS) or wide angle scattering (WAS).

Dynamic Azimuthal Fourier (DAF) analysis is based on the Fourier transformation of the scattered intensity as a function of the azimuthal angle, \theta, and time, t:

I(\mathbf{q},t) = \sum_{n=-\infty}^{\infty} I_n(\mathbf{q}) e^{i n \omega t}

where \mathbf{q} is the scattering wave vector, I_n(\mathbf{q}) is the nth harmonic of the scattered intensity, \omega is the angular frequency, and t is time.

The DAF method can be used to extract dynamic information such as the diffusion coefficient, relaxation time, and correlation time from scattering experiments. It provides a powerful tool for characterizing the structure and dynamics of complex systems such as colloids, polymers, and glasses. . The accuracy can range from 70-80% for high-resolution satellite imagery to lower values for lower-resolution images. In summary, Dynamic Azimuthal Fourier (DAF) analysis is a method used to extract dynamic information from scattering experiments and can provide valuable insights into the structure and dynamics of complex systems.

Conclusion

This research was conducted to identify the best segmentation model and best feature for satellite image processing to identify the fish copiousness. Image segmentation and feature extraction are two crucial steps in the processing of satellite images. Image segmentation involves partitioning an image into multiple segments or regions, each corresponding to a distinct object or part of the image. Feature extraction involves identifying and extracting relevant information from the segments, such as shape, texture, or color. These features are used to represent and describe the objects in the image, and can be used for various tasks such as object recognition, classification, or tracking. The combination of image segmentation and feature extraction provides a powerful tool for understanding and analyzing satellite images and can have a wide range of applications in fields such as remote sensing, geographic information systems (GIS), and environmental monitoring. The research has identified U-Net as the best performing model for satellite images and SCAN as the best suitable feature for processing and extracting knowledge from satellite images.

Future Enhancements

In summary, future enhancements for using deep learning to identify fish schools for controlled fishing can include improving data quality and quantity, transfer learning, and real-time deployment. Transfer learning can be used to fine-tune pre-trained models for a specific task, which can speed up the training process and improve the accuracy of the models. Deploying deep learning models in real-time on unmanned underwater vehicles or other autonomous platforms can improve the speed and efficiency of fishing operations.

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