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Using location data and image recognition to improve sustainability in fishing

Group J

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Sustainable use of resources below water is a major problem and one of the United Nations' sustainable development goals: 14, life below water. Sustainable fishing means leaving enough fish in the ocean or lakes and protecting habitats and especially the endangered species. It is also important to conserve the diversity of species also then when it comes to life underwater. A lot of countries depend on fishing, so by guarding the oceans we can maintain the industry. In this research we developed a fish recognition system. The system was made to help to identify fish species and to give information about fishing restrictions in Finland. The app we developed was made to help beginner fishers to recognize fish and to browse fishing restrictions and regulations in users' current locations and nearby areas.

Contents

1 Introduction

United Nation Food and Agriculture Organization (FAO) published its latest about the overexploitation of the seas and oceans is leaving without fish and they identified the reasons as proper plans for sustainable fishing. Due to the lacking's of sustainable fishing life underwater seems to be normal, but it is becoming empty day by day. From the beginning, he has extracted almost 6 billion tons of fish which makes a dedicated support to marine wildlife.[1]
More than 3 billion people worldwide have any negative consequences for the loss of marine [1]. These forced journeys in turn create recent problems such as the overexploitation of other fishing grounds and the outbreak of territorial conflicts, especially off the coasts of Africa, Latin America, and south and north-east Asia, the continent with the greatest fishing activity in the world.[1]
Our initiative of this project is sustainable fishing using Map API that will guide the user to find the restricted area and fish availability in the sea which will solve the major problems of becoming empty. Through our project we also can implement ways to protect the marine fauna, as well avoiding waste. The initial approach is to find solutions that have already been made on the subject and look for ways they could be improved or made more available to users. We focused on three main research questions on our project:

1. Are there public APIs on fishing restriction data and datasets on fish species?
2. How can local fishing restrictions be clearly displayed to the user in an easily available format?
3. What type of classifier could be used for classifying different fish species?

With these aspects in mind, we could find many solutions that answer our questions. The downside of these solutions is that they are not easily available or approachable for the average user. Our goal is to make a coherent entirety that is available and easy to use for several types of users by using public data and scientifically approved methods.

2 Related work

Pornpanomchai et al.,2013 have written a report about Shape- and texture-based fish image recognition system. They develop a system known as the “shape- and texture-based fish image recognition system” (FIRS). Their system compared two recognition techniques, a Euclidean distance method and artificial neural networks. Their system’s main goal was to help people who work in the fishing industry to recognize fishes in Thailand. There were 30 fish species and 900 fish images in the FIRS database. Pornpanomchai et al., concluded that FIRS needs access to more fish features and to have a larger database so it would have higher recognition rate. In conclusion the artificial neural network gave better precision rate than the Euclidean distance method. Euclidean distance method used less processing time than the artificial neural network.

Sharmin et al., 2019 have written a paper about Machine vision based local fish recognition. In Bangladesh the new generation people lacks the knowledge of local freshwater fish and for this problem Sharmin et al., have found a solution in vision-based technology. They have used six species of fish and fourteen features. They have used principal component analysis for feature selection.

Report about Underwater drone with panoramic camera for automatic fish recognition based on deep learning, written by Meng et al., 2018 focus on fish recognition using a drone. Their fish recognition is based on deep learning. The 360-degree panoramic image generation and the underwater drone were developed with open-source software; the compute modules were extended on a Raspberry Pi compute module. The 360-degree panoramic images were generated correctly, and fish recognition achieved 87% accuracy by deep learning.

Jonsson has done a report about Real-time fish type recognition in underwater images for sustainable fishing, year 2015. Jonsson has developed a real-time algorithm that could recognize farmed fish from wild fish by searching for presence or absence of the adipose fin. Tests show that it was possible to separate the species by looking at the ratio between the height of the caudal fin and the height of the caudal peduncle. This method used a manual process to do the measurements.

Ulucan et.al., 2020 have done research on classifying fish species with a convolutional neural network. Seafood and fishing are a carrying industry in many parts of the world, especially in countries located near large water systems. According to the Food and Agriculture Organization of the United Nations, the global fish consumption has risen above 20 kilograms a year (FAO, 2016). As a result, avoiding seafood spoilage to prevent economic loss and satisfy expectations of customers has gained more importance (Ulucan et.al., 2020). Using automated methods for classifying fish species, we can analyse food samples with a higher accuracy than with a sense of sight. Developing an objective, fast and robust automated system can solve the problem of detecting spoilage and will lower the economic burden of vendors (Ulucan et.al., 2020). This would also have a great effect on sustainability, since fewer fish would be lost in spoilage.

There are numerous studies present in literature in which fish species are classified using different algorithms and various datasets. In feature-based fish classification systems, the feature extraction part is diverse. Most used features are obtained from fish texture, size and shape. Experimental results indicate that the classification accuracy reached up to 75/ when all of the features were combined in the classification process. Along with feature-based methods, classification is also carried out by using distinct techniques in fish classification tasks. Convolutional neural networks (CNN) can be used to classify fish from their body images. While CNNs are selected to extract features from a dataset, in many studies SVMs and K-Nearest Neighbor (KNN) are employed for the classification task. The classification is performed successfully for both SVMs and KNN with accuracy rates of 98.32% and 98.79%, respectively. (Ulucan et.al., 2020).

3 Research design and methods

We started our research by reviewing literature based on our research questions. We found that the National Land Survey of Finland has a solution for displaying fishing restrictions in Finland. However, it has limitations when it comes to accessibility. By using their public API's and open access data we could display ongoing fishing restrictions of the area for the user. Fishing restrictions are very clear and strictly defined by the law in Finland. Using this data, we can map the restrictions so the user can easily verify that he is fishing in an area where it is allowed.

Many of the applications made on the subject of sustainable fishing are old or made for experienced users. According to Wang et.al., (2022), high usability and user experience have a positive effect on improving efficiency and satisfaction of users. By using modern web technology, we could easily improve on this and display the data in a more accessible way. Our plan is to implement a modern and simple user interface that even inexperienced users can use. We also want this user interface to work on different devices, so that the web application is available anywhere and on any device.

To achieve the best user experience, we wanted to choose the best tool for user interface design. Wang et.al., (2022) found that the most frequently used softwares for user interface design were Figma, Adobe XD and Sketch. In the study Figma was found to be the best in terms of efficiency. Also was found that Figma allowed users to adapt to the use of the system fastest. By interpreting these research results, we ended up doing the design using Figma, a collaborative interface designing tool. The initial user interface design can be seen in figure 1.

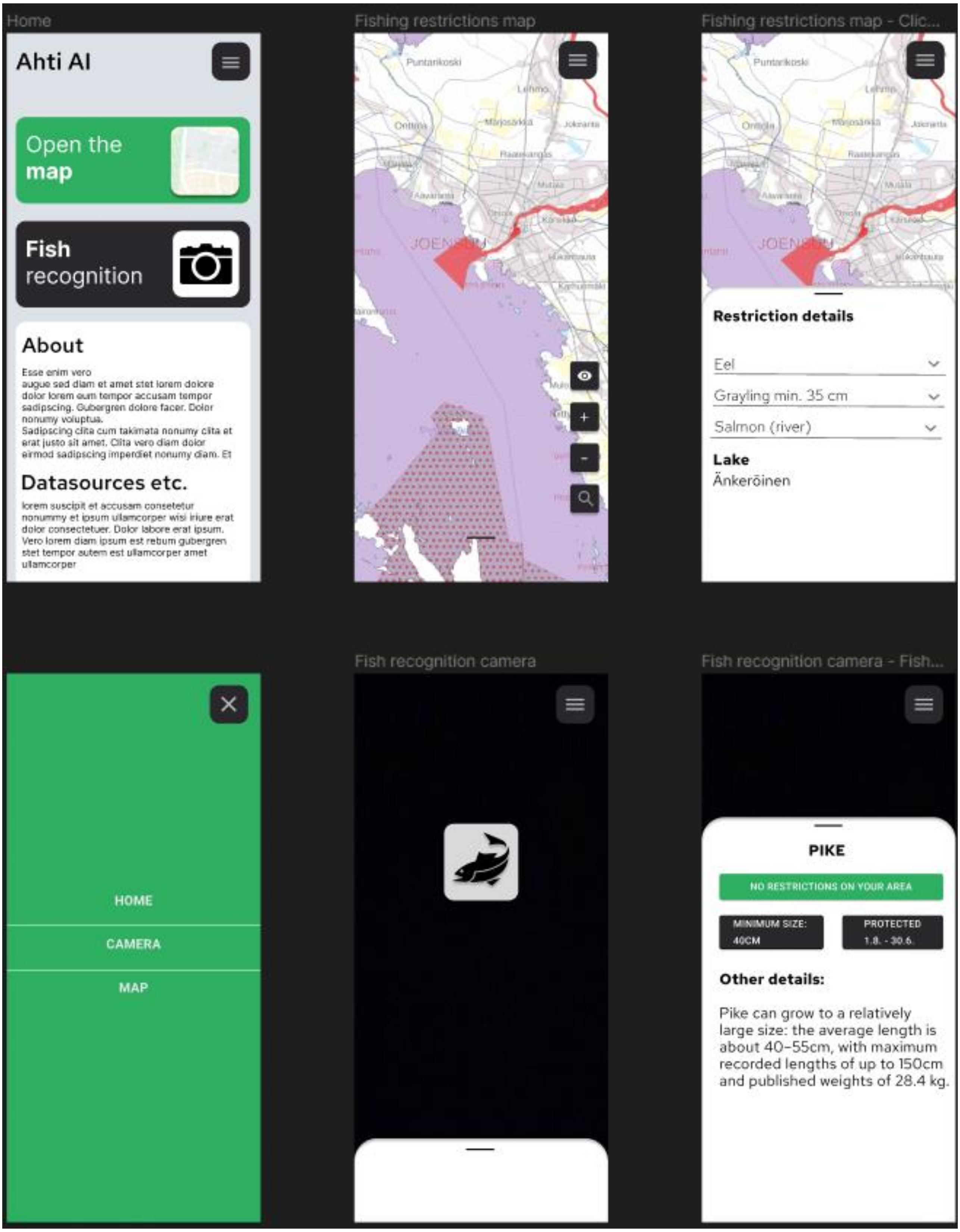

Figure 1: The initial user interface design.

After designing the mockup, it was easier to develop the web-based application by using React, the JavaScript library, and Material UI, which is a React library that has a large collection of accessible and reactive components.

When doing research on fish classification and public datasets containing images of fish, we came across Lucan et.al.'s (2020) article on a large fishing dataset and a classifier to classify species of different fish. We found a few optional datasets, however, most of the publicly available datasets are not fit for the mentioned purpose, as they mainly contain images taken underwater or consist of seafood, which is generally not widely consumed (Lucan et.al., 2020).

Figure 2: Example images from the collected dataset (Ulucan et.al., 2020).

4 User testing

4.1 Plan for the testing of the application for the group 1

The group 1 is supposed to consist of two people. Plan is to allow the group of users to test the application through a Discord call by sharing the screen and showing them the application through Google's Chrome browser in a mobile testing view. The navigating of the application will be done by following their requests. This way it is possible to avoid the trouble of users having to setup the environment needed for testing the application on their end or setting up a different way to access the application. Before starting the testing, the group will be informed about the name of the application, about what the application is about as well as given a short background story for the testing. As for the background story the users are told that they are located in Joensuu, they are planning on going fishing and wonder at what locations they'd be able to fish at. During the testing the group is given three different tasks to try to complete. After the testing the group will be asked three questions.
The tasks to try to complete are following:

1. Take a look at information about restrictions on your current location, which is Joensuu
2. Look up information about restrictions from two different areas of your choice
3. Try to recognize a fish with the camera

After the testing is done the users will be asked following questions:

1. Were there any parts of the application which you found difficult to understand?
2. What are your opinions about the usefulness of this application?
3. Which parts of the app could be in your opinion improved and how?

4.1.1 Results of the user testing for the group 1

Group members for user testing changed a bit but there were still two people testing the application at the same time through Discord. The group members were briefed about what the application is meant for before the actual testing. During the test at the map view, the users were focused on the bottom drawer when it comes to finding the information about the restrictions instead of the colours/pattern on areas show on the actual map. They didn't end up looking up the information available under the info button about the meanings of different colours as well as pattern on the map. When looking up the restrictions in the drawer the group was informed that the restriction information (in the drawer) is a mock up.

When it comes to the feedback after testing for the first question, the difficulties were about understanding if you need to click on the area or zoom in to the area to get the restrictions. For the second question when it comes to the usefulness of the app, the application was found useful in a case where you actually want to go to fishing and wonder if you can keep the fish or if the fish is endangered. For the feedback about the third question which is about improvements for the app, the idea of options for different languages as well as a share button were brought up.

5 Results, summary, and conclusions

In this paper, we researched the use of image classification and location data in improving the sustainability of fishing. We decided to use Ulucan et.al.'s (2020) dataset and classifier, because they were publicly available and the classifier was found to be relatively accurate (Ulucan et.al., 2020). By using an already existing dataset, we didn't have to create our own.

The neural network classifier was trained with A Large-Scale Fish Dataset (Lucan et al., 2020). The dataset contains a thousand pictures for each of the nine fish species (red mullet, gilt head bream, horse mackerel, sea bass, red sea bream, black sea sprat and striped red mullet) collected from a fish counter of a supermarket. All fish in the image acquisition process are fresh, and they are positioned in various displacements and angles, but lighting conditions do not change significantly (Ulucan et.al., 2020). Lastly, instead of a clean white background, a blue and noisy background is preferred in order to make the dataset usable in studies with real-life problems (Ulucan et.al., 2020). The images in the dataset are coherent, of good quality and labelled according to the species. Although the dataset is relatively large and made with high quality, the similarity between the pictures may affect the results so that they might not reflect reality.

The classifier achieved good results, 98.01% training accuracy and 88.69% testing accuracy which reflect those on Ulucan et.al.'s paper. For the experiments, eight independent support vector machines (SVMs) are trained. The lowest average training and set accuracy were obtained by using the bag of features (BoF) algorithm. This was explained by the BoF algorithm sometimes failing to select suitable features for a given task when the images contain very similar texture and color. The best training and test results were acquired when a gray-level co-occurrence matrix (GLCM) contract feature was adopted to the SVMs classifier. This led to a mean accuracy of 98.74%, which is almost 1% higher than the result obtained through CNNs-based features. Lastly, the adoption of CNNs features in the SVMs algorithm leads to significantly higher accuracy rates than BoF, and it follows the success rates of the GLCM contrast and energy features in the training process. (Ulucan et.al., 2020).

	Train Accuracy	Test Accuracy
Gilt Head Bream	97.12	96.82
Red Sea Bream	98.21	91.84
Sea Bass	95.69	82.98
Red Mullet	99.02	90.32
Horse Mackerel	98.90	86.97
Black Sea Sprat	97.52	89.66
Striped Red Mullet	99.24	89.60
Trout	97.32	80.45
Shrimp	99.06	89.59
Average	98.01	88.69

Table 1: SegNet segmentation results in percentages (Ulucan et.al., 2020).

	Contrast	Energy	Contrast+Energy	2^{nd} Order Moment	3^{rd} Order Moment	2^{nd}+ 3^{rd} Order Moment	BoF	CNNsF
Gilt Head Bream	98.00	97.26	96.41	87.93	90.11	89.04	81.67	93.07
Red Sea Bream	97.41	98.67	98.81	95.04	86.15	88.48	64.58	96.17
Sea Bass	95.56	96.37	95.24	91.93	91.30	89.19	75.00	92.08
Red Mullet	98.89	98.44	98.06	86.85	92.93	90.46	87.25	89.90
Horse Mackerel	97.41	98.15	96.74	96.89	92.85	90.81	80.33	92.74
Black Sea Sprat	97.85	96.41	95.83	89.37	92.37	90.70	93.33	96.07
Striped Red Mullet	97.33	97.85	97.11	87.67	86.93	86.72	65.00	86.66
Trout	99.19	97.15	97.28	98.15	91.78	91.07	95.83	95.00
Shrimp	97.15	96.96	95.57	89.00	90.52	89.67	90.95	97.56
Average	97.64	97.47	96.78	91.43	90.55	89.57	81.55	93.25

Table 2. Feature-based classification results for testing of SVMs (Ulucan et.al., 2020).

An important challenge in fish classification studies is the lack of publicly available datasets containing commonly consumed fish image samples. Already present datasets contain fish images taken underwater and consist of fish species that are not usually consumed (Ulucan et.al., 2020). Ulucan et.al.'s dataset is an improvement to other solutions, but unfortunately their dataset does not contain any of the common Finnish fish species and therefore the classifier can't recognize most of the traditional Finnish fish species. Though, for this project it is not a problem, because it was designed to be proof of concept work. For further research it could be possible to gather dataset with all kinds of fish by web-scraping or by gathering a comprehensive image collection manually.

According to the Fisheries Act (Finlex, 2015), undersized and protected fish must always be released. This is highly valuable to the fish stock. By displaying the user, the fishing restrictions and offering a solution for confirming if the fish is suitable for keeping, we can lower the amount of overfishing and prevent the fish stocks from falling.

Together with the image recognition software we used a map to present currently active fishing restrictions in a certain area. In accordance with our goal, we managed to create a user interface that is responsive regardless of the size of the device. Due to the responsiveness of the web application, it doesn't matter on which device our web application is used. Identifying fish and keeping up to date with restrictions is therefore easily possible with our web app. We ended up using Material UI as component library which helped us to create a accessible user interface. The complete user interface programmed with React can be seen in figure 3. Also, the complete user interface in desktop view can be seen in figure 4.

The data was consumed from the Finnish Food authority's WMS geo server, which is publicly available. Unfortunately, the spatial data was only available in lakes and seas in Finland, which means that we are not able to show fishing restrictions outside of Finland. For future research it would be possible to search or implement a global interface, which could make it possible to show fishing restrictions all over the world. The idea of measuring the sizes of the fishes could be possible to try to be implemented as when it comes to things that could be improved. Also, in the case of a real-world implementation we could ask or explore the option if it would be possible for us to get a hold of the copy of a fishing restriction data for setting up our own WMS service as well as offer translations for other languages. The map tiles shown are from Open Street Maps servers, but as it can't be used for real implementations as their tile policy forbids heavy usage, we'd need to implement our own server or explore the possibilities of tile providers for the map (Open Street Maps, 2022).

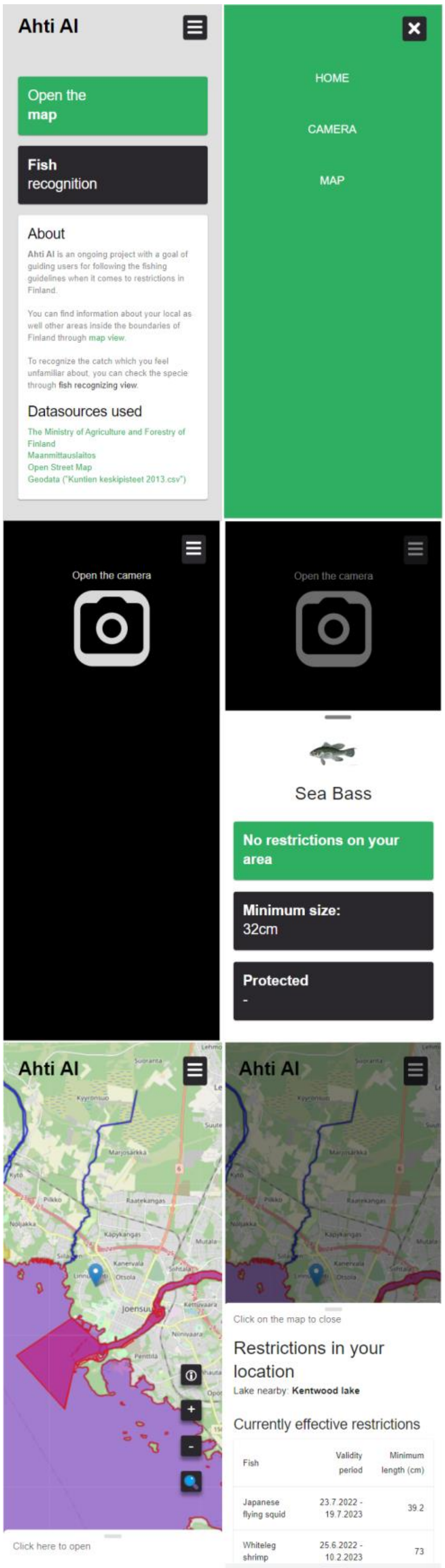

Figure 3. A finished web

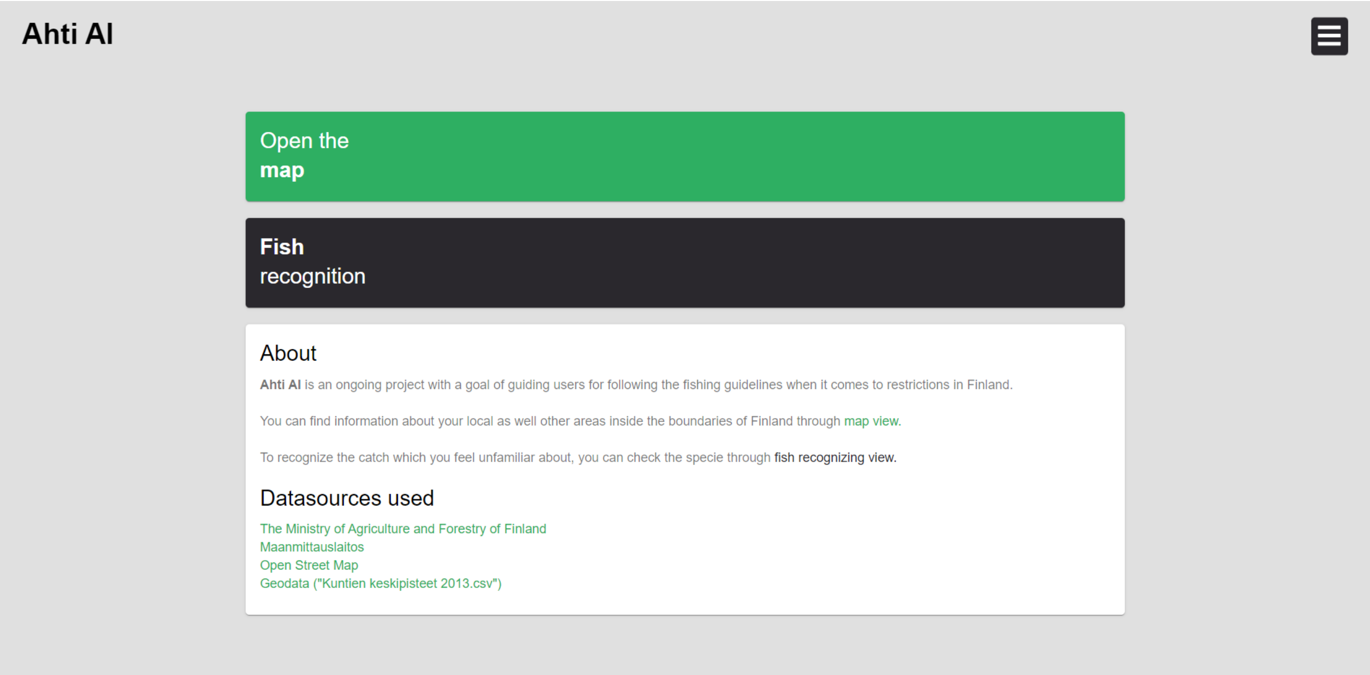

Figure 4. The web app in desktop view.

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Appendices

		Assignee					
Name of the task	**Progress**	**Teemu**	**Juuso**	**Arifa**	**Minni**	**Eetu**	**Juho**
Presentation							
Slides	100.00%	40.00%		15.00%	25.00%		20.00%
Presentation (who is holding)	0.00%	x	x	x	x	x	x
Application							
UI design	100.00%		33.34%			33.33%	33.33%
User inteface (frontend)	100.00%	20.00%	25.00%	20.00%		35.00%	
Map	100.00%	50.00%					50.00%
Research if we need a Backend (not needed) and mock implementations	100.00%		10.00%			35.00%	55.00%
Fish classifier	100.00%		90.00%			10.00%	
Academic paper							
(topic)	100.00%				100.00%		
introduction	100.00%	0.00%	40.00%	60.00%			
abstract	100.00%			10.00%	50.00%		40.00%
Research design and methods	100.00%		70.00%	10.00%		20.00%	
Related work	100.00%		25.00%		75.00%		
User testing	100.00%	100.00%					
Results (when solution is ready)	100.00%		40.00%		20.00%	20.00%	20.00%
Conclusions (when solution is ready)	100.00%	50%	50%				