

FISHDA: FISH MONITORING AND FORECASTING APPLICATION

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Abstract

Fisheries is a global industry that has a significant impact on the economy of multiple countries, especially the Philippines. However, as demands in the industry continue to increase, mismanagement of resources in the fishing industry poses a danger to its sustainability. This also contributes to the undersupply and oversupply in the country, affecting fish availability and market price. This need motivated the establishment of Fish monitoring systems in various countries. Therefore, this paper aims to create a time-series model that can be used in a fish monitoring system, and to create a prototype that will use the created model. The data came from PSA OpenSTAT data, which included the value and volume of fish from different parts of the Philippines from 2011. Moreover, various time series models were developed using the PyCaret libraries. However, the most appropriate time series model was selected for each fish in each area with the highest MAE values from eight models. The model was integrated into a prototype that gave the capability to forecast both value and volume of the fishes in different areas and different times.

Keywords: Data analytics, Fish monitoring, Forecasting, Philippines, PyCaret.

1. Introduction

Fisheries are regarded as the meeting point of stock, or collection of stocks and their harvesting methods. As such, it consists of fish stocks and the fishing fleets which catch them [1]. Fish stocks pertain to a population of fish that has been caught, hence, only referring to a single species in an area. While fishing fleets catch fish in various ways, each of which defines the fishery and guides management. Fisheries also bear a significant contribution to the global economy, through a range of services enough to support and sustain the fishing industry in general [1, 2].

A big part of the Philippines' economy revolves around this industry, and the need to have enough stock to supply the country is essential to ensure its growth in the economy. In 2015, the fishing industry contributed to the country's gross domestic product (GDP) of 1.7%, employing over 1.6 million people [3]. Fisheries are important to the country as it is a primary source of income to many Filipinos, and the fish stock plays a considerable role in the consumption and diet (about 43% animal protein diet) of every Filipino [3, 4].

Fish trades and prices are projected to increase at a reasonable rate through the years if the industry globally is well-kept and preserved [5]. Currently, global marine fisheries are not performing well on account of overfishing and climate change, and studies show that the fishing industry, in general, will increase from its current condition to a significant state for the following years to come [4]. According to the Fish Price Index (FPI), international fish prices have increased by a reasonable amount since 2016. Despite high prices on various fishes, the consumer's demands were sustained and will continue to do so if the industry performs well in the future [5].

In 2016, the global production of fishes reached its highest peak of 171 million tonnes, wherein approximately 88% of this total was used for direct human consumption, and the rest were utilized for non-food purposes [6]. Based on the study, the rate of production increased significantly over the past decades, and the overall fish production volume is anticipated to grow even more in the upcoming years because of its significant improvement over the past years [7].

Consequently, the Philippines, a country with rich marine biodiversity, was ranked as one of the major fish-producing countries [8]. From the trends of Philippine fisheries in 2015, the bulk of fish catch came from Laguna bay, Lake Lanao, and Taal Lake which covers 74% of the Philippines' total lake area. This indicates that the country's municipal fish catch is majorly sustained by the provinces. In 2016, the Philippine population reached 103 million with a mean per capita fish consumption of 40kg/yr [9]. As the population increases, the demand for fish products also increases over time [10]. This pushes the need to re-examine the current fishing system, in view of its socio-economic importance to the fishing industry of the Philippines [11].

According to related studies, there are various contributing factors for the fluctuating volume of fish production. Fishing activities are among the most significant threats to the production of fish globally. Fishing can change the demography, distribution, and stock structure of many species in the ecosystem. Balanced fishing must be performed in order to sustain the production and population of fishes from all over the world because if not, many species will be

risked and exposed to collapse. In relation to this, seasonal changes primarily account for the volume of fish counts [7, 11].

Considering the foregoing factors, the lack of fish monitoring systems in the Philippines proves to be a major problem, where it could adversely impact various businesses in the fishing industry. Thus, this study is motivated by the difficulties encountered by Philippine fisheries, specifically the lack of fish monitoring systems. A monitoring system makes businesses more aware of the current status and performance of the fishing industry. This addresses the issues concerning the oversupply and undersupply of fish stocks in a certain location, which generally affects its availability and market price. Thereby allowing businesses to control their fish production, effectively manage their resources, and devise strategies to improve their business operations. Moreover, integrating forecasting capabilities to a fish monitoring system would facilitate a data-based decision-making tool for the whole fishing industry and consumers [12, 13]. This would enable businesses to know the perfect time to market a particular type of fish while giving customers insights on where and when to buy this certain fish species. It could also help them anticipate the sudden and unexpected changes in the production of fish, and plan for preventive measures overhead. Hence, filling these gaps would significantly contribute to information availability and efficient decision-making between the mentioned stakeholders [14].

To address the aforementioned problem, the researchers' main objective is to create a prototype for a fish monitoring and forecasting application. The application will contain accurate and consistent information regarding fisheries, including the type, location, value, and volume of their fish stocks, and its projected price. The following are supplemental activities to the main objective:

- To determine the time series forecasting model that is most appropriate for every data set based on their performance metrics;
- To integrate the developed time series forecasting model in a prototype and create a design that will display essential information.

Fishda provides a platform where users can conveniently compare fish volumes and values from different locations in just a single source. It can also provide greater transparency for users wherein they can monitor and check the availability, value, and stock levels of fishes that are accessible from different locations. Fishda can also tell forecasts which increases the awareness of its users regarding the flow of fish production, thus allowing its users to anticipate future changes and act on them and make earlier and better decisions [15, 16].

2. Methodology

This section of the paper discusses the framework of the creation of the application at its prototype level. As presented in Fig. 1, the entire process was composed of three phases which were preparation, data analysis, and prototype. The first phase involved data collection, sampling, data preprocessing, and processing. Moving on to the second phase, this also included the identification and enumeration of models, evaluation of these models, and selecting which would be the appropriate choice for the application. Finally, the prototype phase included the creation of the prototype.

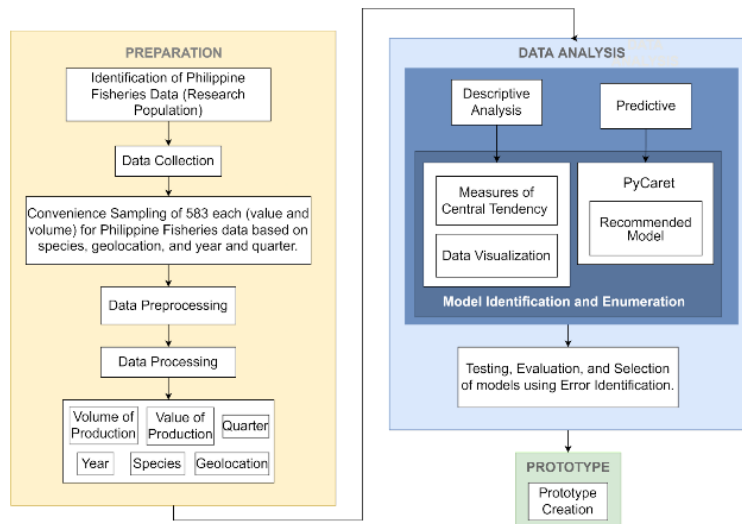


Fig. 1. Project framework.

2.1. Determining the time series forecasting models

2.1.1. Research population or community

A research population is defined as a large group of individuals, organizations, and objects that have common characteristics which are of interest to the researcher [17].

The Philippines fisheries industry comprises marine fisheries (municipal and commercial), inland fisheries, and aquaculture [6]. These fisheries were decided on by the researchers to be the population since their data is readily available online and conforms to the objectives of the research.

2.1.2. Data collection

The researchers collected data concerning Fisheries in the Philippines along with its related components such as price projection and volume of fish species per municipality from related websites, journals, articles, and similar studies. The researchers decided to use data available to the public provided by the Philippine Government through the Philippine Statistics Authority (PSA) for the materials. The researchers used the datasets entitled “Fisheries: Volume of Production by Species, Geolocation, Year and Quarter,” which used metric tons as the unit through this website. The table was created on February 16, 2011 and was still updated quarterly up to the creation of this paper. The table has column headers of year and quarter and rows that include a total of 66 species and 101 geolocations which include regions and provinces [18]. The researchers also used datasets from the table entitled “Fisheries: Value of Production by Species, Geolocation, Year and Quarter,” which was also created on February 15, 2011, and updated last April 12, 2021. Units used in the data set are in thousand pesos, and also have the same rows and headers present in the previous [19]. The independent variables, fish species, and location, were derived from these data sets. These variables were then used to determine the dependent variables which are fish volume and value.

2.1.3. Sampling

Sampling is the process of selecting an accurate representation of a population [20]. It is a necessary procedure to perform since it would be impractical and inefficient to fully analyze a large number of data. In this way, it would be easier to control the quality of the data [21].

In this research, the researchers used a convenience sampling technique to reduce the data set from the population. Convenience sampling is a nonprobability sampling technique wherein the selected samples from the population are chosen because they are “convenient”, from the term itself [22]. Using this technique allows for easier and faster data collection, a short time investment, and only a few rules to follow [23].

The convenience sampling technique was appropriate since the researchers’ devices did not have the computing power needed to process large amounts of data. One example of this situation was when said devices took almost 3 hours to output one graph of a model using the whole data set. Through this technique, the dataset was reduced by choosing the rows within the data set that are most suitable and would cause minimal errors for the models to be used. As such, the data was split into a 70:30 ratio where 70% of data were set for training and validation, and 30% of data was used in testing through the PyCaret setup, which is further discussed in the data preprocessing and processing.

2.1.4. Data preprocessing and processing

After the researchers collected the needed data, the researchers sifted through for usable data that would be used in the models. The usable data were preprocessed where duplicate or null values were replaced or removed. Using the default Pycaret set-up, null values for numeric features in the dataset were replaced with the mean values [5, 24]. Furthermore, the raw data set was composed of multiple columns of various quarters, which were formatted as year-quarter. The data was melted according to species and geolocation. The resulting column, the compressed quarters, is then separated into year, and quarter columns. Furthermore, from these columns, date values for each row were also generated.

After processing, the data set was split into train and test data using the default PyCaret setup function. This uses a 70:30 ratio, wherein 70% of the data was allocated for training and validation, while 30% was used for testing [5, 24]. In this function, data type interference was also conducted. The date and year were used as numerical features, while the month and day of the week were categorical features. Furthermore, the data split shuffle feature was also disabled as time series was employed in forecasting.

The data was then processed to fit the models identified which were scaled to fit the model or arranged or grouped for a certain parameter. This was also where values needed for the models were calculated such as the volume/value of the fish species and others.

2.1.5. Data analysis

Data analysis is hierarchical wherein some analyses focus on estimation of simple summary statistics such as mean and variance. Other analyses rely on inferential

statistical tests or modeling. In fisheries, data can be summarized using a variety of approaches such as the analyses used by the researchers which are discussed in this section.

Descriptive Analysis, also known as Descriptive Statistics, generates accessible insights from uninterpreted data [25]. The results gathered using this analysis were used to have a general idea regarding certain information related to the application such as location, prices, and volume of fish. These insights were then used to further support both predictive analyses. In this analysis, the central event or response was measured using a ranking sort where the highest and lowest value and volume were used to define the highest and lowest species and location. These were used to suggest where to buy such species of fish as these will be used to calculate the prices of that species.

Predictive Analysis, by the term itself - helps predict what will happen in the future. In Predictive Analysis, machine learning and historical data are used to find trends and patterns that will help the prediction process in the present data [26]. The results produced by this analysis contained the forecasted data of the prices and volume of fish species using the fish species, and region as input variables; and time as a modifier for the range of the prediction. The resulting analysis aided in predicting both the value of specific fish species and the volume of these species in certain regions which in turn helps the identification of regions that are likely to have sufficient, oversupply, or undersupply of certain fishes. In this regard, forecasting was done through machine learning using the pool of regression models in PyCaret's library. The time or date was considered as a feature or predictor in order to use regression for time-series forecasting of the PyCaret Library [27]. This was done as the volume and value were considered as continuous values that will be predicted by the models [5]. The regression models are chosen by the library's functions as they perform with more accuracy and lesser errors.

2.1.6. Model identification and enumeration

The researchers identified the possible models to meet the required requirements and assigned the models that were used in the identified features. The models that were addressed are Descriptive and Predictive where the type of each model was then enumerated and explained in order for the researchers to understand where they can be used.

In order to identify which models would be appropriate for every time series, the researchers used PyCaret. Moreover, among the list of models available in the PyCaret module, it evaluates and cross validates them to calculate their forecasting errors. Through this process, PyCaret was able to identify the best models to use for each of the time series, which was further explained in the next section.

2.1.7. Model testing, evaluation, and selection

With the datasets processed, testing was done for each model enumerated in the previous phase. Testing was performed by subjecting the models through error identification, which was used to identify the accuracy of the forecast models. Through error identification, mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), coefficient of determination (R2), root mean squared log error (RMSLE), mean absolute percentage error (MAPE), was computed for each model.

R² shows the correlation between the dependent variable and independent variables [28]. This score ranges from 0 to 100% wherein higher scores denote higher correlation.

Both the MAE and RMSE are used for measuring the accuracy for continuous variables. They both express average model prediction errors in a set of forecasts. Both metrics can range from 0 to ∞ and do not consider the direction of errors. Their difference is that MAE is a linear scoring, while RMSE is a quadratic scoring, meaning that RMSE is only favored when dealing with larger errors. Lower values denote better accuracy [28].

MSE is defined as the average of the squared difference between the observed and predicted values [28]. Lower MSE values denote a more refined and accurate model.

The RMSLE is similar to the RMSE and MSE wherein both are used to determine the difference between predicted and actual values. However, RMSLE uses the log of the actual and prediction values which changes the variance that is used [28]. This is commonly used to avoid penalization due to the huge difference between actual and predicted values.

The MAPE aims to measure the accuracy of forecasts and presents the results in a form of percentages. Lower values in MAPE represent better accuracy.

In computing for the different metrics, the researchers used a function in the PyCaret module that is able to compare error identification scores with the use of time series cross-validation to derive which models are the best for each time series [24].

2.2. Integrating the time series forecasting models and designing the prototype

2.2.1. Time series forecasting models integration

From the model that was selected, Voila is used to integrate the model into a low-fidelity prototype that will allow the user to choose the geolocation and species, and eventually show the graph containing the actual and predictive values of the model.

2.2.2. Designing the prototype

In order to have a proper visualization, a prototype was created to showcase a possible user interface for FISHDA. The researchers used Adobe XD for the prototype creation. Moreover, the prototype focused on emulating features that used previously discussed data analysis techniques. Specifically, these features are price forecasting, news, and predictions. The information and elements shown on the prototype are based on data that can be captured and generated using PSA OpenSTAT's Fisheries Database.

3. Results and Discussion

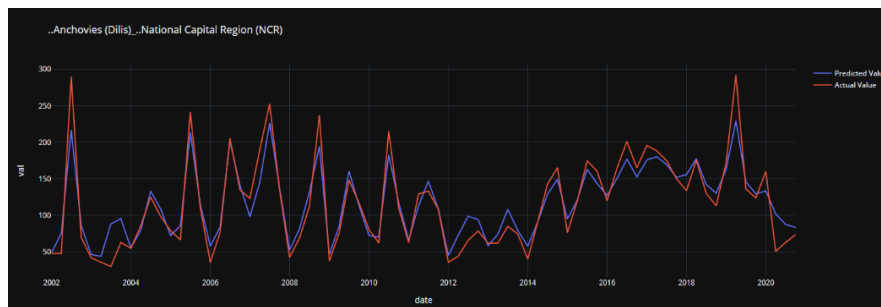
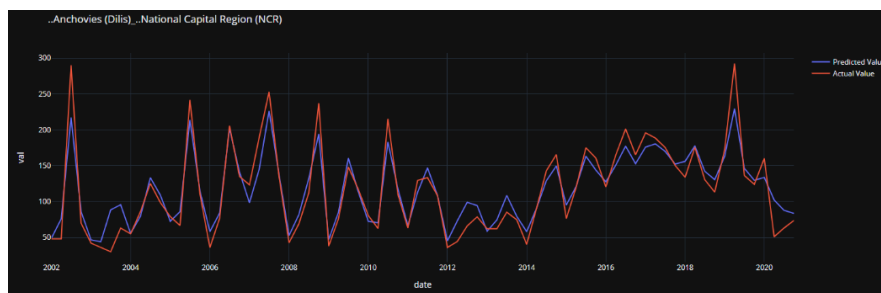
3.1. Determination of the time series forecasting models

As seen in Table 1, the value time series forecast of the Anchovies-NCR uses a model suggested by the PyCaret Library that is the most suitable for that time series.

Table 1. Value dataset evaluation results.

Model	MAE	MSE	RMSE	R2	RMSLE	MA PE	TT (s)	Time series
gbr	3104.83	1.67e+07	4051.86	-1.30	0.58	0.41	0.04	Anchovies (Dilis) National Capital Region (NCR)
dt	52065.97	4.01e+09	63124.75	-1.60	0.38	0.30	0.02	Anchovies (Dilis) Region V (Bicol Region)
xgboost	15728.24	3.93e+08	19436.54	-0.83	0.98	0.99	0.28	Anchovies (Dilis) Region XI (Davao Region)
knn	50228.10	3.31e+10	113546.87	0.14	1.42	17.16	0.08	Milkfish.. National Capital Region (NCR)
xgboost	24320.45	1.25e+09	34112.14	0.42	0.44	0.28	0.30	Milkfish.. Region V (Bicol Region)
xgboost	168528.87	5.32e+10	225758.22	-0.25	0.53	0.38	0.34	Milkfish.. Region XI (Davao Region)
xgboost	368.21	2.05e+05	409.79	-3.55	1.13	10.98	0.25	Snail (Suso).. Region V (Bicol Region)
lgbm	40.69	1.31e+04	86.04	-0.39	1.36	3.22	0.02	Snail (Suso).. Region XI (Davao Region)

It can be seen from Figs. 2 and 3 that the resulting graphs for both value and volume are identical. This can be attributed to the direct relationship between the two, wherein if the volume increases it is expected that the value will also increase. Furthermore, both graphs displayed that the predicted value follows the downward and upward trends of the actual values which may denote accuracy and relationships of the actual and predicted data of the models used. The predicted value is shown where the value of both value and volume of the time series is plotted until 2050 where it shows the trend within that time frame. The accuracy of these predictions was further discussed in the next section.

**Fig. 2. Value time series forecast (anchovies-NCR).****Fig. 3 Volume time series forecast (anchovies-NCR).**

3.1.1. Testing and evaluation results

In order to select a model that would be more appropriate for a monitoring and forecasting prototype, the models underwent error identification by the use of the PyCaret. The testing of the models is divided into two, which are forecasting for value and volume of products.

3.1.2. Value data

The models provided by PyCaret for the time series of the value data are only desirable to some of the time series as seen in Table 1. This was because most of the scores of the models are not within an acceptable range from 0. However, given this situation, the most accurate model would be the Light Gradient Boosting Machine for the Snail Region XI Series as the MAE value is 40.6852 which was the closest value to 0 compared to the rest of the MAE. It was also the most accurate in terms of the RMSE as it has the closest value to zero of 86.0367. In terms of the MSE and RMSLE, the Light Gradient Boosting Machine still performs the best out of the rest but for some RMSE such as the Decision Tree Regressor for the Anchovies Region V time series, it has the best value of 0.3792. As for the MAPE, the performance, in general, is in the acceptable range excluding the K neighbors Regressor and Extreme Gradient Boosting for Milkfish NCR and Snail (Suso) Region V which has a value greater than 10. Overall, PyCaret provided models of accurate performance to some time-series in the sample.

3.1.3. Volume data

Overall, PyCaret was able to provide suitable accurate models for the volume data due to the results seen in Table 2. MAE for some time series such as the Snail Region XI provided a value close to 0 that would signify that the model would have an accurate forecast or indicate no error. It was also seen in the MSE of the same time series where it would produce fewer errors as the value is 1.58. The same goes for the other metrics such as the RMSE and MAPE having a low or close to zero value which signifies reduced differences in the observed actual and predicted accuracy.

Table 2. Volume dataset evaluation results.

Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (s)	Time series
rf	47.11	4.12e+03	63.62	-1.28	0.51	0.40	0.53	Anchovies (Dilis)... National Capital Region (NCR) ...
dt	1017.43	1.70e+06	1207.35	-0.85	0.30	0.28	0.02	Anchovies (Dilis)... Region V (Bicol Region)
xgboost	282.54	1.44e+06	375.90	-0.88	0.91	1.12	0.26	Anchovies (Dilis)... Region XI (Davao Region)
catboost	851.09	1.94e+05	1885.19	-0.20	1.44	15.07	0.26	Milkfish.. National Capital Region (NCR)
dt	287.63	7.28e+06	429.41	0.44	0.44	0.25	0.02	Milkfish.. Region V (Bicol Region)
par	1929,78	1.99e+10	2668.53	-0.32	0.36	0.35	0.02	Milkfish.. Region XI (Davao Region)
xgboost	10.86	1.5e+05	12.14	-3.85	0.53	13.54	0.02	Snail (Suso).. Region V (Bicol Region)
llar	0.74	1.31e+04	1.17	-0.28	0.04	2.67	0.02	Snail (Suso).. Region XI (Davao Region)

With the results, PyCaret was suitable for the volume data Time-series forecast. It was able to provide an accurate and reduced error model such as the Lasso Least Angle Regression which can be used in that time series as well as other time series.

3.2. Model integration and prototype designs

3.2.1. Model integration

The integration of the Time Series Forecasting Model using Voila was able to display the appropriate graph upon selecting the Geolocation and Species. The graph contains the actual and predicted values of the application which is shown in Fig. 4. However, due to the limitations of the researcher's computational device, displaying the graphs takes a long time since every time the user chooses a combination of Geolocation and Species, it processes and generates a new model.

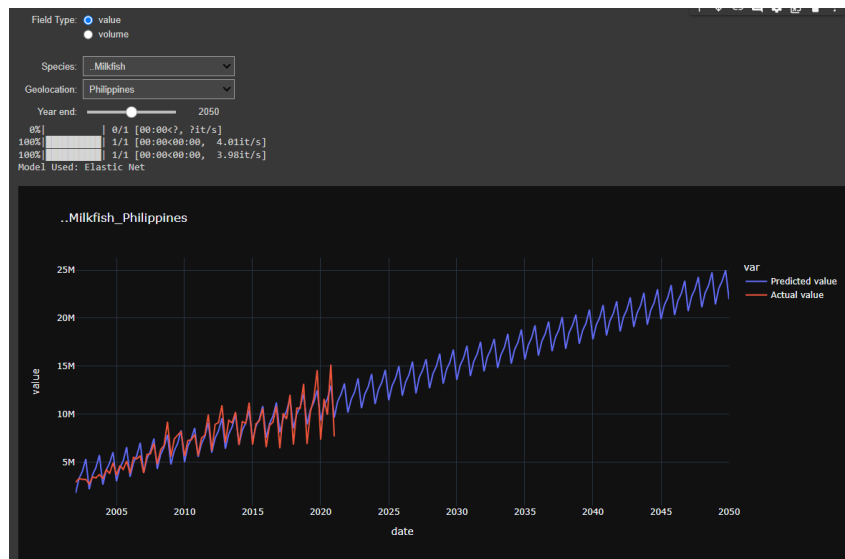


Fig. 4. Model integration in a web-based prototype.

3.2.2. Prototype designs

Figure 5 shows the dashboard which presents various types of charts containing a general overview of all the fish species in all regions' volume and value of production collectively.

It presents a bar graph on the top fish species with the highest volume and highest values during the latest quarter, a line chart for the volume and value forecasts, and a comparison for the forecasted and actual results of the stated fields. Lastly, a stacked area graph for both volume and value that spans throughout previous different years.

It also presents news regarding changes in volume and value that have taken over during the latest quarters. A textual forecast also comes, which gives information regarding changes that might happen in the future. The news and predictions elements can be clicked on, which redirects users to either the news or

predictions page, which can be seen on Fig. 6. The page contains the list of all news and predictions that have occurred.



Fig. 5. Prototype home page – dashboard.

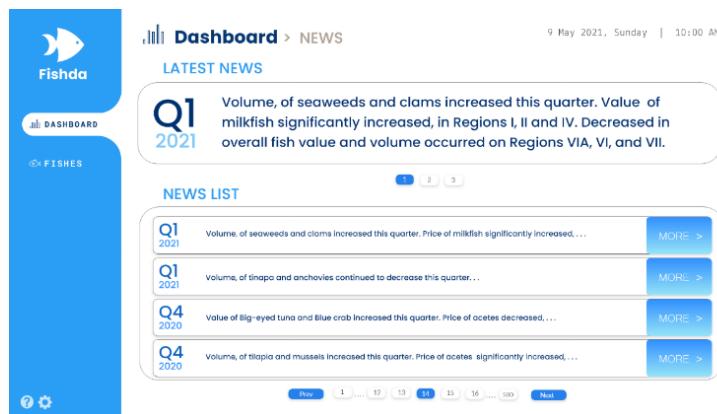


Fig. 6. News page.

Figure 7 shows the interface where users are able to check and find details regarding the status of fisheries that have occurred during the previous years and quarters. Users must first select values from the tags above (Fish species, Region, Volume, Value, Year, Quarter). They can choose multiple values on a single tag. All chosen tag values will be used for the selection and filtering out results that will be displayed in the results area. Users can also search from the given results as well as click on the “More” button to view more specific and detailed information about the chosen record.

Figure 8 shows the interface that the screen will transition to if users had clicked the “More” button from the previous interface. Users can view more specific information for a particular fish species they have chosen. A query interface can be used by the users for the purpose of searching for more details regarding the fish. Tags are also implemented in the query interface where users can pick from a group of regions, years, and quarters. A line graph on the fish species’ volume and value

is presented below the query interface which updates and renders according to the chosen tags. The shaded portion of the line graph presents the forecasted values for the query.

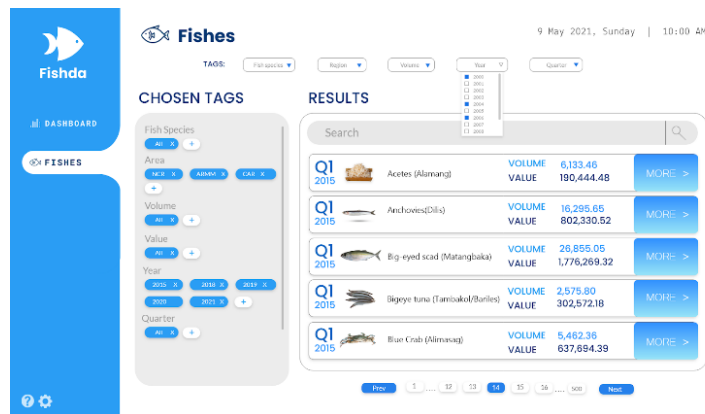


Fig. 7. Prototype fishes page.



Fig. 8. Prototype detailed fish record page.

On the right side of the screen, a leaderboard system is created where it shows the top regions which have the highest and lowest volumes, as well as the highest and lowest values of production for that fish species. Below the leaderboards, is a stacked area graph that presents the comparison and evolution of the fish species' value and volume that have transpired throughout the course of the previous years.

4. Conclusion

Preserving and maintaining the quality of fisheries in general through thorough monitoring enables people from all over the world to compensate for our ecosystem's resources fully. Fish monitoring provides a more significant opportunity for many countries to keep and grow their economies and provide for their people. As stated previously, despite many challenges, there has been considerable improvement in the global production of fish for quite some time now

and it will continue to grow if the performance of the industry is retained. Furthermore, the researchers have decided to create Fishda, which is a prototype for a fish monitoring and forecasting application. The said application will serve as a data-based decision-making tool for all users, to help control fishing and trading activities, efficiently manage the country's total fish production and quality, and help users know what, where, and when to buy fish.

Forecasted value and volume can be used to predict the fish prices on a certain month from the data set downloaded from Philippine Statistics Authority Website. Furthermore, by using the Pycaret Library, models are recommended for each geolocation and fish species time series for forecasting which also identifies the forecast errors of each. With this, models can be assessed if it is suitable for the application. Using these models, the application has the capability to forecast future value and volume of the species depending on the geolocation.

The application would be further enhanced when provinces are considered in its data set. In addition, daily or monthly data can also improve the application as the data only provide a quarterly overview of the volume and value of the fish. In the testing of models, other forecast errors should also be taken into consideration. Other models and libraries are also recommended to guarantee the accuracy of the generated forecasting models. The application may be further developed and even be implemented in other applications which will be able to make full use of its monitoring and forecasting abilities. A possible venture would be an online market that will be able to guide and give market insights to customers who are interested in purchasing fish. Furthermore, other valuable information such as environmental components can be also considered for more accurate, in-depth, and holistic forecasts. Another thing to note is that the benefits of deploying the application as a web-based application make it more feasible to use for its intended users.

Abbreviations

FPI	Fish Price Index
GDP	Gross Domestic Product
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
R ²	Coefficient of Determination
RMSE	Root Mean Squared Error
RMSLE	Root Means Squared Log Error

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