Age of Abalone Prediction from Physical Measurements Using ANN

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Abstract: Abalones have long been a valuable food source for humans in every area of the world where a species is abundant. Predicting the age of abalone is done using physical measurements. The age of abalone is determined by cutting the shell through the cone, staining it, and counting the number of rings through a microscope -- a boring and time-consuming task. Other measurements, which are easier to obtain, are used to predict the age of abalone is using Artificial Neural Network (ANN) which is a branch of Artificial Intelligence. The dataset was collected form UCI Machine learning Repository. To predict the age of abalone using physical measurements, an ANN with multi-layer model using JustNN (JNN) tool is proposed. The proposed model was trained and tested and the accuracy was obtained. The best accuracy rate was 92.22%.

Keywords: Abalones, Age, physical measurements, ANN, JNN

1. Introduction

Abalone is marine snails. Their taxonomy puts them in the family Haliotidae, which contains only one genus, Haliotis, which once contained six subgenera. These subgenera have become alternate representations of HaliotisThe number of species recognized worldwide ranges between 30 and 130 with over 230 species-level taxa described. The most comprehensive treatment of the family considers 56 species valid, with 18 additional subspecies [1].

The shells of abalones have a low, open spiral structure, and are characterized by several open respiratory pores in a row near the shell's outer edge. The thick inner layer of the shell is composed of nacre (mother-of-pearl), which in many species is highly iridescent, giving rise to a range of strong, changeable colors, which make the shells attractive to humans as decorative objects, jewelry, and as a source of colorful mother-of-pearl [3].

The flesh of abalones is widely considered to be a desirable food, and is consumed raw or cooked by a variety of cultures.

Abalone varies in size from 20 mm (0.79 in) (Haliotis pulcherrima) to 200 mm (7.9 in) while Haliotis rufescens is the largest of the genus at 12 in (30 cm) [6].

The shell of abalones is convex, rounded to oval in shape, and may be highly arched or very flattened. The shell of the majority of species has a small, flat spire and two to three whorls. The last whorl, known as the body whorl, is auriform, meaning that the shell resembles an ear, giving rise to the common name "ear shell". Haliotis asinina has a somewhat different shape, as it is more elongated and distended. The shell of Haliotis cracherodii cracherodii is also unusual as it has an ovate form, is imperforate, shows an exserted spire, and has prickly ribs [4].

A mantle cleft in the shell impresses a groove in the shell, in which is the row of holes characteristic of the genus. These holes are respiratory apertures for venting water from the gills and for releasing sperm and eggs into the water column. They make up what is known as the selenizone, which forms as the shell grows. This series of eight to 38 holes is near the anterior margin. Only a small number is generally open. The older holes are gradually sealed up as the shell grows and new holes form. Each species has a typical number of open holes, between four and 10, in the selenizone. An abalone has no operculum. The aperture of the shell is very wide and nacreous [5].

The exterior of the shell is striated and dull. The color of the shell is very variable from species to species, which may reflect the animal's diet. The iridescent nacre that lines the inside of the shell varies in color from silvery white, to pink, red and green-red to deep blue, green to purple [2].

The animal has fimbriated head lobes and side lobes that are fimbriated and cirrated. The radula has small median teeth, and the lateral teeth are single and beam-like. They have about 70 uncini, with denticulated hooks, the first four very large. The rounded foot is very large in comparison to most molluscs. The soft body is coiled around the columellar muscle, and its insertion, instead of being on the columella, is on the middle of the inner wall of the shell. The gills are symmetrical and both well developed [7].

These snails cling solidly with their broad, muscular foot to rocky surfaces at sublittoral depths, although some species such as Haliotis cracherodii used to be common in the intertidal zone. Abalones reach maturity at a relatively small size. Their fecundity is

high and increases with their size, laying from 10,000 to 11 million eggs at a time. The spermatozoa are filiform and pointed at one end, and the anterior end is a rounded head [7].

The adults provide no further assistance to the larvae and they are described as lecithotrophic. The adults are herbivorous and feed with their rhipidoglossan radula on macroalgae, preferring red or brown algae.

The haliotid family has a worldwide distribution, along the coastal waters of every continent, except the Pacific coast of South America, the Atlantic coast of North America, the Arctic, and Antarctica. The majority of abalone species are found in cold waters, such as off the coasts of New Zealand, South Africa, Australia, Western North America, and Japan [8].

The shell of the abalone is exceptionally strong and is made of microscopic calcium carbonate tiles stacked like bricks. Between the layers of tiles is a clingy protein substance. When the abalone shell is struck, the tiles slide instead of shattering and the protein stretches to absorb the energy of the blow. Material scientists around the world are studying this tiled structure for insight into stronger ceramic products such as body armor. The dust created by grinding and cutting abalone shell is dangerous; appropriate safeguards must be taken to protect people from inhaling these particles [9].

Abalones have long been a valuable food source for humans in every area of the world where a species is abundant. The meat of this mollusc is considered a delicacy in certain parts of Latin America, France, New Zealand, East Asia and Southeast Asia. In the Greater China region and among Overseas Chinese communities, abalone is commonly known as bao yu, and sometimes forms part of a Chinese banquet. In the same way as shark fin soup or bird's nest soup, abalone is considered a luxury item, and is traditionally reserved for special occasions such as weddings and other celebrations. However, the availability of commercially farmed abalone has allowed more common consumption of this once rare delicacy [10].

Abalones have been identified as one of the many classes of organism threatened with extinction due to overfishing and the acidification of oceans from anthropogenic carbon dioxide, as reduced pH erodes their shells. It is predicted that abalones will become extinct in the wild within 200 years at current rates of carbon dioxide production. Currently the white, pink, and green abalone is on the federal endangered species list, and possible restoration sites have been proposed for the San Clemente Island and Santa Barbara Island areas. The possibility of farming abalone to be reintroduced into the wild has also been proposed, with these abalone having special tags to help track the population [11].

Usually predicting the age of abalone is done using physical measurements. The age of abalone is determined by cutting the shell through the cone, staining it, and counting the number of rings through a microscope -- a boring and time-consuming task. Other measurements, which are easier to obtain, are used to predict the age using Artificial Neural Network (ANN).

2. Artificial Neural Network

An Artificial Neural Network (ANN) is a mathematical model that is driven by the functional feature of biological neural networks. A neural network contains an interconnected set of artificial neurons, and it processes information using a connectionist form to computation. As a rule, an ANN is an adaptive system that adjusts its structure based on external or internal data that runs over the network during the learning process. Current neural networks are non-linear numerical data modeling tools. They are usually used to model tricky relationships among inputs and outputs or to uncover patterns in data. ANN has been applied in several applications with significant accomplishment. For example, ANN has been effectively applied in the area of prediction, and handwritten character recognition [12-25].

Neurons are often come together into layers. Layers are groups of neurons that perform similar functions. There are three kinds of layers. The input layer is the layer of neurons that take input from the user program. The layer of neurons that send data to the user program is the output layer. Between the input layer and output layer there are hidden layers. Hidden layer neurons are connected only to other neurons and never directly interact with the user program. The input and output layers are not just there as interface points. Every neuron in a neural network has the opportunity to affect processing. Processing can occur at any layer in the neural network. Not every neural network has this many layers. The hidden layer is optional. The input and output layers are required, but it is possible to have a layer that act as both an input and output layer [26-35].

ANN learning can be either supervised or unsupervised. Supervised training is accomplished by giving the neural network a set of sample data along with the expected outputs from each of these samples. Supervised training is the most common form of neural network training. As supervised training proceeds, the neural network is taken through several iterations, or epochs, until the actual output of the neural network matches the expected output, with a reasonably small error. Each epoch is one pass through the training samples. Unsupervised training is similar to supervised training except that no expected outputs are provided. Unsupervised training usually occurs when the neural network is to classify the inputs into several groups[36-46].

The training progresses through many epochs, just as in supervised training. As training progresses, the classification groups are "discovered" by the neural network [47-57]. Training is the process by which these connection weights are assigned. Most training algorithms begin by assigning random numbers to the weight matrix. Then the validity of the neural network is tested. Next, the

weights are adjusted based on validation results. This process is repeated until the validation error is within an acceptable limit [58-61]. Validation of the system is done once a neural network has been trained and it must be evaluated to see if it is ready for actual use. This final step is important so that it can be determined if additional training is required. To properly validate a neural network validation data must be set aside that is completely separate from the training data [62].

3. Methodology

A data set refer to Department of Primary Industry and Fisheries, Tasmania [63] was used; it contains a number of factors that are considered to have an effect on predicting the age of abalone from physical measurements. These factors were classified as input variables. The output variable represents the predicted age of abalone based on those inputs.

3.1 The Input Variables

This database includes 4177 cases. Each case represents the features of the age of the abalone. It was found that each of these cases belonged to one of 16 classes (number of the rings). These features are shown in table 1.

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#	Name	Data Type	Measurement	Description	Attribute
			Unit		Туре
1	Sex	Categorical		M, F, and I (infant)	Input
2	Length	Continuous	mm	Longest shell measurement	Input
3	Diameter	Continuous	mm	perpendicular to length	Input
4	Height	Continuous	mm	with meat in shell	Input
5	Whole weight	Continuous	mm	whole abalone	Input
6	Shucked weight	Continuous	mm	weight of meat	Input
7	Viscera weight	Continuous	mm	gut weight (after bleeding)	Input
8	Shell weight	Continuous	mm	after being dried	Input
9	Rings	integer		+1.5 gives the age in years	Output

Once the most appropriate raw input data has been selected, it must be preprocessed; otherwise, the neural network will not produce accurate forecasts.

Transformation and normalization are two widely used preprocessing methods. Transformation involves manipulating raw data inputs to create a single input to a network, while normalization is a transformation performed on a single data input to distribute the data evenly and scale it into an acceptable range for the network. Acceptable rang of value, in *JNN tool*, varies in the range between zero and one.

3.2 Data Normalization

Linear scaling of data is one of the methods of data normalization. Linear scaling requires that a minimum and maximum values associated with the facts for a single data input be found. Let's call these values Xmin and Xmax, respectively. The formula for transforming each data value to an input value X is:

$$X_i = (X_i - X_{min}) / (X_{man} - X_{min})$$
 eq.(1)

Our desired range varies in the interval between zero and one. In this study we normalized the number of rings variable to be in the range between 0 and 1. We converted the categorical attribute Sex to numeric values then the numeric value was normalized to be between zero and one. We used the equation eq. (1) for the normalization.

3.3 Building the ANN Model

We have used Just Neural Network (JNN) tool [64] to build a multilayer ANN model. The proposed model consists of five Layers: Input Layer with 8 nodes, First Hidden Layer with 5 nodes, Second Layer with 1 one, Third Layer with 7 nodes, and Output Layer with one node as can be seen in Figure 3.

We have sat the parameters of the proposed model as follows: Learning Rate 0.06 and the Momentum to be 0.08, and Average Error rate to be 0.01 (as shown in Figure 2).

3.4 Evaluating the ANN model

The abalone dataset consists of 4177 samples with 9 attributes as in Table 1. We imported the preprocessed CSV file of the abalone dataset into the JNN environment (as seen in Figure 1). We divided the imported dataset into two sets (Training and

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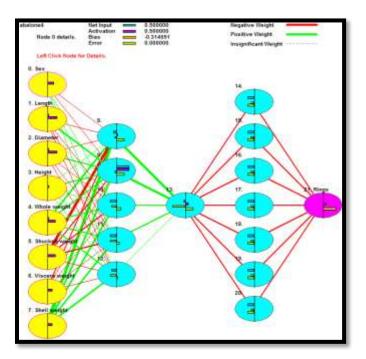
Validation) randomly using the JNN tool. The Training consists of approximately 67% (2827 samples) and the validation set consists of 33% of the dataset (1350 samples). After making sure that the parameter control was sat properly, we started training the ANN model and kept eye on the learning curve, error loss and validation accuracy. We trained the ANN model for 687 cycles. The best accuracy we got was 92.22% (as seen in Figure 4). We determined the most influential factors in the abalone dataset as in Figure 5. Figure 6 shows the summary of the proposed model.

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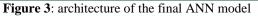
Figure 1: Imported dataset into JNN environment

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Figure 2: Control of the parameters of the proposed ANN model



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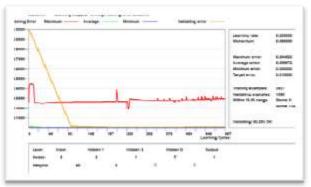


Figure 4: Training and validation curves of the proposed ANN model

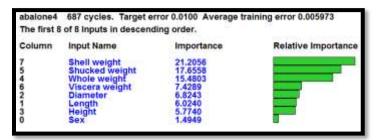


Figure 5: The most influential Feature in the proposed ANN model

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Excluded columns: 0	Hidden layer 1 nodes: 5		
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Figure 6: Details of the proposed ANN model

4. Conclusion

An Artificial Neural Network model for predicating predicting the age of abalone from physical measurements using features obtained from UCI Machine Learning Repository was presented. The model used feed forward backpropagation algorithm for training the proposed ANN model using JNN tool. The factors for the model were obtained from dataset which represents abalone features. The model was tested and the accuracy rate was 92.22%. This study showed that artificial neural network is capable of predicating age of abalone from physical measurements accurately.

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References

- Gofas, Serge; Tran, Bastien; Bouchet, Phillippe (2014). "WoRms Taxon Details: Haliotis Linnaeus, 1758". WoRMS (World Register of Marine Species). Retrieved16 August 2020. 1 2
- Beesley, P. L.; Ross, G. J. B.; Wells, A. (1998). Mollusca: The Southern Synthesis: An Essential Reference. Melbourne, Australia: CSIRO Publishing. pp. 667–669. Dauphin, Y.; Cuif, J. P.; Mutvei, H.; Denis, A. (1989). "Mineralogy, Chemistry and Ultrastructure of the External Shell-layer in Ten Species of Haliotis With Reference to Haliotis 3
- tuberculata (Mollusca, Archaeogastropoda)". Bulletin of the Geological Institutions of the University of Uppsala. 15: 7-38. 4 Cox, Keith W. (1962). "California abalone, family Haliotidae". The Resources Agency of California Department of Fish and Game: Fish Bulletin. 118.ISSN 6306-2593.
- Abu Nada, A. M., et al. (2020). "Age and Gender Prediction and Validation Through Single User Images Using CNN." International Journal of Academic Engineering Research 5 (IJAER) 4(8): 21-24.
- Abu Nada, A. M., et al. (2020). "Arabic Text Summarization Using AraBERT Model Using Extractive Text Summarization Approach." International Journal of Academic 6 Information Systems Research (IJAISR) 4(8): 6-9.
- Abu-Saqer, M. M., et al. (2020). "Type of Grapefruit Classification Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 4(1): 1-5. 7 8
- Afana, M., et al. (2018). "Artificial Neural Network for Forecasting Car Mileage per Gallon in the City." International Journal of Advanced Science and Technology 124: 51-59. Al Barsh, Y. I., et al. (2020). "MPG Prediction Using Artificial Neural Network." International Journal of Academic Information Systems Research (IJAISR) 4(11): 7-16.
- 10 Alajrami, E., et al. (2019). "Blood Donation Prediction using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 3(10): 1-7.
- Alajrami, E., et al. (2020). "Handwritten Signature Verification using Deep Learning." International Journal of Academic Multidisciplinary Research (IJAMR) 3(12): 39-44. 11
- Al-Araj, R. S. A., et al. (2020). "Classification of Animal Species Using Neural Network." International Journal of Academic Engineering Research (IJAER) 4(10): 23-31. 12
- Al-Atrash, Y. E., et al. (2020). "Modeling Cognitive Development of the Balance Scale Task Using ANN." International Journal of Academic Information Systems Research 13 (IJAISR) 4(9): 74-81.
- Alghoul, A., et al. (2018). "Email Classification Using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 2(11): 8-14. 14
- Al-Kahlout, M. M., et al. (2020). "Neural Network Approach to Predict Forest Fires using Meteorological Data." International Journal of Academic Engineering Research (IJAER) 15 $4(9) \cdot 68-72$
- Alkronz, E. S., et al. (2019). "Prediction of Whether Mushroom is Edible or Poisonous Using Back-propagation Neural Network." International Journal of Academic and Applied 16 Research (IJAAR) 3(2): 1-8.
- Al-Madhoun, O. S. E.-D., et al. (2020). "Low Birth Weight Prediction Using JNN." International Journal of Academic Health and Medical Research (IJAHMR) 4(11): 8-14. 17 18 Al-Massri, R., et al. (2018). "Classification Prediction of SBRCTs Cancers Using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER)
- 2(11): 1-7. 19 Al-Mobayed, A. A., et al. (2020). "Artificial Neural Network for Predicting Car Performance Using JNN." International Journal of Engineering and Information Systems (IJEAIS) 4(9): 139-145.
- 20 Al-Mubayyed, O. M., et al. (2019). "Predicting Overall Car Performance Using Artificial Neural Network." International Journal of Academic and Applied Research (IJAAR) 3(1): 1-5.
- 21 Alshawwa, I. A., et al. (2020). "Analyzing Types of Cherry Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 4(1): 1-5.
- Al-Shawwa, M., et al. (2018). "Predicting Temperature and Humidity in the Surrounding Environment Using Artificial Neural Network." International Journal of Academic 22 Pedagogical Research (IJAPR) 2(9): 1-6.
- Ashqar, B. A., et al. (2019). "Plant Seedlings Classification Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 3(1): 7-14. Bakr, M. A. H. A., et al. (2020). "Breast Cancer Prediction using JNN." International Journal of Academic Information Systems Research (IJAISR) 4(10): 1-8. 23
- 24
- Barhoom, A. M., et al. (2019). "Predicting Titanic Survivors using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 3(9): 8-12. 25 26 Belbeisi, H. Z., et al. (2020). "Effect of Oxygen Consumption of Thylakoid Membranes (Chloroplasts) From Spinach after Inhibition Using JNN." International Journal of Academic Health and Medical Research (IJAHMR) 4(11): 1-7.
- Dalffa, M. A., et al. (2019). "Tic-Tac-Toe Learning Using Artificial Neural Networks." International Journal of Engineering and Information Systems (IJEAIS) 3(2): 9-19. 27
- Dawood, K. J., et al. (2020). "Artificial Neural Network for Mushroom Prediction." International Journal of Academic Information Systems Research (IJAISR) 4(10): 9-17. 28
- Dheir, I. M., et al. (2020). "Classifying Nuts Types Using Convolutional Neural Network." International Journal of Academic Information Systems Research (IJAISR) 3(12): 12-18. 29
- 30 El-Khatib, M. J., et al. (2019). "Glass Classification Using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 3(2): 25-31.
- El-Mahelawi, J. K., et al. (2020). "Tumor Classification Using Artificial Neural Networks." International Journal of Academic Engineering Research (IJAER) 4(11): 8-15. 31
- 32 El-Mashharawi, H. Q., et al. (2020). "Grape Type Classification Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 3(12): 41-45.
- 33 Elzamly, A., et al. (2015). "Classification of Software Risks with Discriminant Analysis Techniques in Software planning Development Process." International Journal of Advanced Science and Technology 81: 35-48.
- 34 Elzamly, A., et al. (2015). "Predicting Software Analysis Process Risks Using Linear Stepwise Discriminant Analysis: Statistical Methods." Int. J. Adv. Inf. Sci. Technol 38(38): 108-115.
- 35 Elzamly, A., et al. (2017). "Predicting Critical Cloud Computing Security Issues using Artificial Neural Network (ANNs) Algorithms in Banking Organizations." International Journal of Information Technology and Electrical Engineering 6(2): 40-45.
- Habib, N. S., et al. (2020). "Presence of Amphibian Species Prediction Using Features Obtained from GIS and Satellite Images." International Journal of Academic and Applied 36 Research (IJAAR) 4(11): 13-22.
- 37 Harz, H. H., et al. (2020). "Artificial Neural Network for Predicting Diabetes Using JNN." International Journal of Academic Engineering Research (IJAER) 4(10): 14-22.
- 38 Hassanein, R. A. A., et al. (2020). "Artificial Neural Network for Predicting Workplace Absenteeism." International Journal of Academic Engineering Research (IJAER) 4(9): 62-67
- 39 Heriz, H. H., et al. (2018). "English Alphabet Prediction Using Artificial Neural Networks." International Journal of Academic Pedagogical Research (IJAPR) 2(11): 8-14.
- 40 Jaber, A. S., et al. (2020). "Evolving Efficient Classification Patterns in Lymphography Using EasyNN." International Journal of Academic Information Systems Research (IJAISR) 4(9): 66-73.
- Kashf, D. W. A., et al. (2018). "Predicting DNA Lung Cancer using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 2(10): 6-13. 41
- Khalil, A. J., et al. (2019). "Energy Efficiency Predicting using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 3(9): 1-8. 42
- 43
- Kweik, O. M. A., et al. (2020). "Books' Rating Prediction Using Just Neural Network." International Journal of Academic Engineering Research (JJAER) 4(10): 17-22. 44
- Mettleq, A. S. A., et al. (2020). "Mango Classification Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 3(12): 22-29. 45
- 46
- Metwally, N. F., et al. (2018). "Diagnosis of Hepatitis Virus Using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 2(11): 1-7. Mohammed, G. R., et al. (2020). "Predicting the Age of Abalone from Physical Measurements Using Artificial Neural Network." International Journal of Academic and Applied 47 Research (IJAAR) 4(11): 7-12.
- 48 Musleh, M. M., et al. (2019). "Predicting Liver Patients using Artificial Neural Network." International Journal of Academic Information Systems Research (IJAISR) 3(10): 1-11.
- Oriban, A. J. A., et al. (2020). "Antibiotic Susceptibility Prediction Using JNN." International Journal of Academic Information Systems Research (IJAISR) 4(11): 1-6. 49 Qwaider, S. R., et al. (2020). "Artificial Neural Network Prediction of the Academic Warning of Students in the Faculty of Engineering and Information Technology in Al-Azhar 50
- University-Gaza." International Journal of Academic Information Systems Research (IJAISR) 4(8): 16-22.
- 51 Sadek, R. M., et al. (2019). "Parkinson's Disease Prediction Using Artificial Neural Network." International Journal of Academic Health and Medical Research (IJAHMR) 3(1): 1-
- Salah, M., et al. (2018). "Predicting Medical Expenses Using Artificial Neural Network." International Journal of Engineering and Information Systems (IJEAIS) 2(20): 11-17. 52
- 53 Salman, F. M., et al. (2020). "COVID-19 Detection using Artificial Intelligence." International Journal of Academic Engineering Research (IJAER) 4(3): 18-25.
- Samra, M. N. A., et al. (2020). "ANN Model for Predicting Protein Localization Sites in Cells." International Journal of Academic and Applied Research 54 (IJAAR) 4(9): 43-50.
- Shawarib, M. Z. A., et al. (2020). "Breast Cancer Diagnosis and Survival Prediction Using JNN." International Journal of Engineering and Information 55 Systems (IJEAIS) 4(10): 23-30.
- Zaqout, I., et al. (2015). "Predicting Student Performance Using Artificial Neural Network: in the Faculty of Engineering and Information Technology." 56 International Journal of Hybrid Information Technology 8(2): 221-228.

International Journal of Academic Engineering Research (IJAER) ISSN: 2643-9085

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- 57 Geiger, Daniel L.; Owen, Buzz (2012). Abalone: Worldwide Haliotidae. Hackenheim, Germany: Conchbooks.
- Hoiberg, Dale H., ed. (1993). Encyclopædia Britannica. 1: A-ak Bayes (15th ed.). Chicago, IL: Encyclopædia Britannica, Inc.
- 59 Tryon, Jr., George W. (1880). Manual of Conchology; Structural and Systematic With Illustrations of the Species (PDF). II: Muricinæ, Purpurinæ. Philadelphia, PA: Academy of Natural Sciences.
- Anon (2014g). "Distribution Map: Haliotis". Ocean Biogeographic Information System. Retrieved 22 August 2020.
- 61 Leatherman, Stephen (2012). National Geographic Field Guide to the Water's Edge. National Geographic Field Guides. National Geographic. p. 93. ISBN 978-1426208683.
- 62 "Hypersensitivity Pneumonitis". www.clevelandclinicmeded.com. Retrieved 17 January 2020.
- 63 UCI Machine Learning repository (https://archive.ics.uci.edu/ml/datasets.html)
- 64 EasyNN Tool