Machine Learning

Course Project Report

(Phase-I)

Title of the project: Abalone

Student : Ekta Sai Meda Meda Ekta Sai

ML Category: Regression

---

1. Introduction

- Abalone is a marine snail inhabiting cold coastal waters, highly valued based on its age, usually determined through time-consuming laboratory procedures. In this regard, this work aims to construct predictive models for fast and accurate abalone age estimation using advanced machine learning techniques. Algorithms applied to a dataset of physical characteristics included Linear Regression, Decision Tree, Random Forest, and Support Vector Machine. Model performance was measured using R-squared with R^2 and RMSE. The proposed method is a replaceable alternative to the conventionally technique-based methods with data-driven efficient solutions, which contribute to the advancement of studies in abalone ecological research and commercial operations in the abalone industry.

2. Dataset and Features

The Abalone dataset used for this project was sourced directly from the UC Irvine Machine Learning Repository, originally published in 1995. The dataset can be found here. It contains 4,176 samples, each of which shows different physical attributes of abalones.Labels for all other eight numerical features are present in each row of the dataset and correspond to the following physical characteristics of abalone:

- sex: Categorical feature with three subcategories—male, female, and infant. Notably, "infant" refers to the age of the abalone rather than its sex, indicating a potential limitation in the dataset.
- length: Measured in millimetres, representing the longest shell measurement.
- diameter : Measured in millimetres, representing the shell width perpendicular to length.
- Height : Measured in millimetres, representing the height with meat in the shell.
- Whole Weight : Measured in grams, representing the weight of the whole abalone.
- Shucked Weight : Measured in grams, representing the weight of the abalone meat.

- Viscera Weight : Measured in grams, representing the gut weight after bleeding.Shell Weight : Measured in grams, representing the weight of the shell after drying.

	sex	length	diameter	height	whole_weight	shucked_weight	viscera_weight	shell_weight	rings
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.1500	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.0700	7
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.2100	9
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.1550	10
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0550	7
...	...	...	...	...	...	...	...	...	...
4172	F	0.565	0.450	0.165	0.8870	0.3700	0.2390	0.2490	11
4173	M	0.590	0.440	0.135	0.9660	0.4390	0.2145	0.2605	10
4174	M	0.600	0.475	0.205	1.1760	0.5255	0.2875	0.3080	9
4175	F	0.625	0.485	0.150	1.0945	0.5310	0.2610	0.2960	10
4176	M	0.710	0.555	0.195	1.9485	0.9455	0.3765	0.4950	12

4177 rows × 9 columns

Also, the dataset contains a feature "Rings" that were hand-counted under a microscope by researchers. To determine the age of an abalone, just add 1.5 years to the number of rings.
Although it was created in 1995, this dataset is still very relevant today due to the biological characteristics of abalone, as with many animals, that change very slowly over thousands to millions of years due to evolutionary processes. Thus, predictive models trained off of this dataset are still very much applicable to today's abalone populations.
The data is preprocessed so that all values are numerical attributes. Categorical feature "Sex" is also encoded. The missing values will be removed and continuous values scaled by dividing by 200. Thus, the dataset is ready to be used with most of the machine learning models. It makes sure that these preprocessing steps ensure the cleanliness and normalisation of the dataset for the effective training of machine learning models used in this project.

3. Methods

3.1 Baseline - Linear Regression or Logistic/Softmax Regression based on the ML category

- Linear Regression is another core machine learning algorithm developed to establish the relationship between a dependent variable (target) and one or more independent variables, referred to as features. The relationship is assumed to be linear, and the model should find that best-fitting line which minimises the sum of the squared residuals of observed and predicted values. Mathematically, it can be expressed in the following form:

$$y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_p x_{ip} + \varepsilon_i = X_i^T \beta + \varepsilon_i, \quad i = 1, 2, \ldots, n$$

Where, yi represents the continuous numeric response for the ith observation, βj is the regression coefficient for the jth variable, xij shows the jth variable for the ith observation, and i is called the random error or the noise that is not able to be explained by the linear model.The parameters β are estimated using the Ordinary Least Squares (OLS) method, which minimises the residual sum of squares (RSS).

- **Mean Squared Error(MSE):** 4.675903975878888
- **R^2 Score(R2):** 0.5454718270324019
- **Mean absolute error(MAE):** 1.5693587109234113

3.2 Support Vector Machines

- Support Vector Machines are non-parametric classifiers useful in both cases: classification and regression. SVM functions like a linear binary classifier designating the class label to test data based upon the maximum span between the two classes. It is possible to apply them on nonlinear data using kernel methods. An SVM creates a hyperplane in infinitely dimensional space. This infinite dimensional space separates classes or fits them into a line of regression. Essentially, the hyperplane will be determined by the closest training data points because it aims to maximise the distance between the two classes. This makes SVMs especially powerful models that could achieve high accuracy with a relatively small number of training examples.
- **Result:**

kernel	**MSE**	**MAE**	**MAPE**	**R2**
linear	4.788017	1.526880	0.147777	0.534574
poly	5.423970	1.547286	0.147386	0.472755
rbf	4.627016	1.480766	0.142497	0.550224

3.3 Decision Tree

- Another easy supervised learning method applicable for both classification and regression problems is the decision tree. It recursively breaks down the data into smaller subsets based on certain criteria until the final decision is made based on a voting mechanism. Decision trees are mainly classified into classification trees and regression trees. In classification trees, the output variable is discrete while, in regression trees, the output variable is continuous. Entropy and information gain are normally used to develop decision trees. At every node, the data is divided iteratively until all the leaves are pure. To avoid overfitting, a depth limit is usually imposed on the decision tree. Information gain for each attribute is calculated by using certain equations.

$$G_i = 1 - \sum_{k=1}^{n} {p_{i,k}}^2$$

pi,k is the ratio of class k instances among training instances in i th node

- **Mean Squared Error (MSE):** 8.807655502392345
- **R-squared (R2) Score:** 0.14383879902539387
- **Mean absolute error(MAE):** 2.04

3.4 Random Forest

- The Random Forest algorithm is one of the robust tree-based learning algorithms in machine learning. It works by creating many Decision Trees during the training process. Each tree is created on a random subset of the dataset, and at each split, features are chosen randomly. All this randomness will bring variety to the trees, hence reducing overfitting risks and increasing the accuracy of predictions. The results from all trees are combined during prediction, either by voting in the case of classification tasks or by averaging in the case of regression tasks. Once more, it is the ensemble approach that is behind the magic, this time supported by multiple trees, for achieving stable results with accuracy. Random Forests are used for classification as well as regression and, therefore, can be regarded as an efficient method factory since it is able to cope with complex data, avoid overfitting, and make reliable predictions in many applications.
- **Mean Squared Error (MSE)**: 4.805265550239234
- **R-squared (R2) Score:** 0.5328970435574765
- **Mean absolute error(MAE):** 1.56

3.5 AdaBoost

- AdaBoost, also called Adaptive Boosting, is one of a kind method of ensemble learning that falls under the broader family of machine learning for both classification and regression tasks. The basic idea motivating AdaBoost is iteratively training weak classifiers on the training dataset, where each subsequent classifier increases the weight of the data points that were misclassified in the previous run. The final model of AdaBoost is a combination of all the individually used weak classifiers during the training process. In such a way, weights are assigned to the models under consideration based on their accuracy. In other words, the greatest weight will be applied to the weak model with the highest accuracy, while the model with the lowest accuracy is given less weight.
- **Mean Squared Error (MSE):** 9.01497758062926

- **R-squared (R2) Score:** 0.12368574927865306
- **Mean absolute error(MAE) :**2.60

3.6 Gradient Boosting

- Thus, gradient boosting is a form of ensemble technique in which models are built sequentially, with each new model making corrections on residual errors on the previous one. Here, gradient descent has to be used to minimise a loss function.
- **Mean Squared Error (MSE):** 4.7367260255976165
- **R-squared (R2) Score:** 0.5395595295863018
- **Mean absolute error(MAE) :**1.54

4. Results

Among all of the methods, that of the **Support Vector Machine** with a **Radial Basis Function kernel (SVM(rbf))** is the best for predicting the age of abalone.

MSE: This is the average of squared differences between observed actual outcomes and predicted outcomes.

R-squared (R2): It tells the proportion of variance for the dependent variable explained by the independent variables in a model.

One of the metrics is the **Mean Absolute Error (MAE)**, which takes a mean of the absolute values of all errors in the predictions without considering their directions.

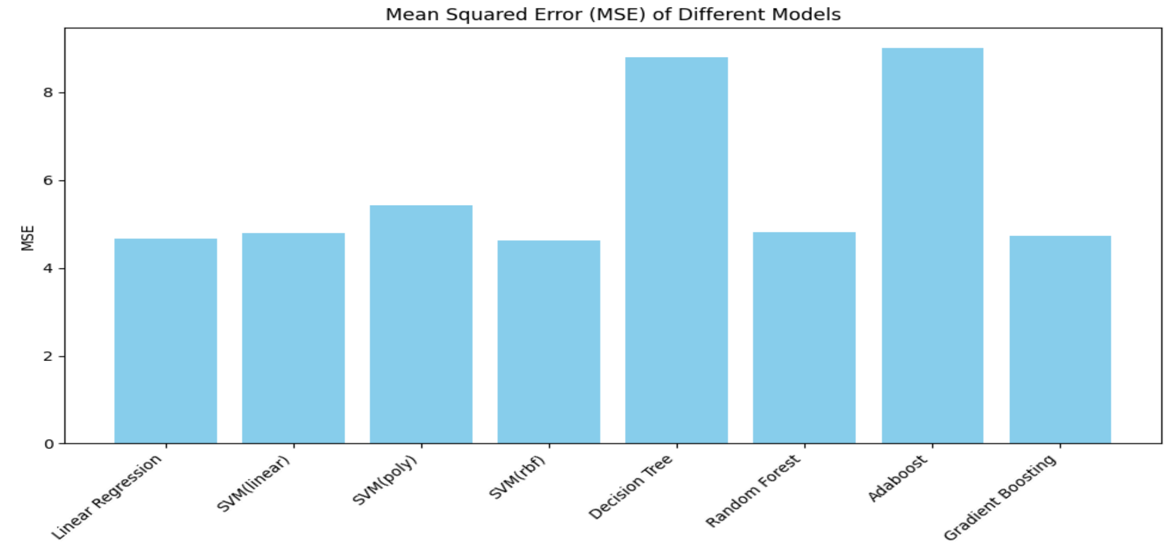
	Model	MSE	R2	MAE	MAPE
0	Linear Regression	4.6759	0.5454	1.5693	0.15960
1	SVM(linear)	4.7880	0.5345	1.5268	0.14777
2	SVM(poly)	5.4239	0.4727	1.5472	0.14738
3	SVM(rbf)	4.6270	0.5502	1.4807	0.14249
4	Decision Tree	8.8076	0.1438	2.0400	0.20000
5	Random Forest	4.8052	0.5328	1.5600	0.16000
6	Adaboost	9.0149	0.1236	2.6000	0.29000
7	Gradient Boosting	4.7367	0.5395	1.5400	0.15000

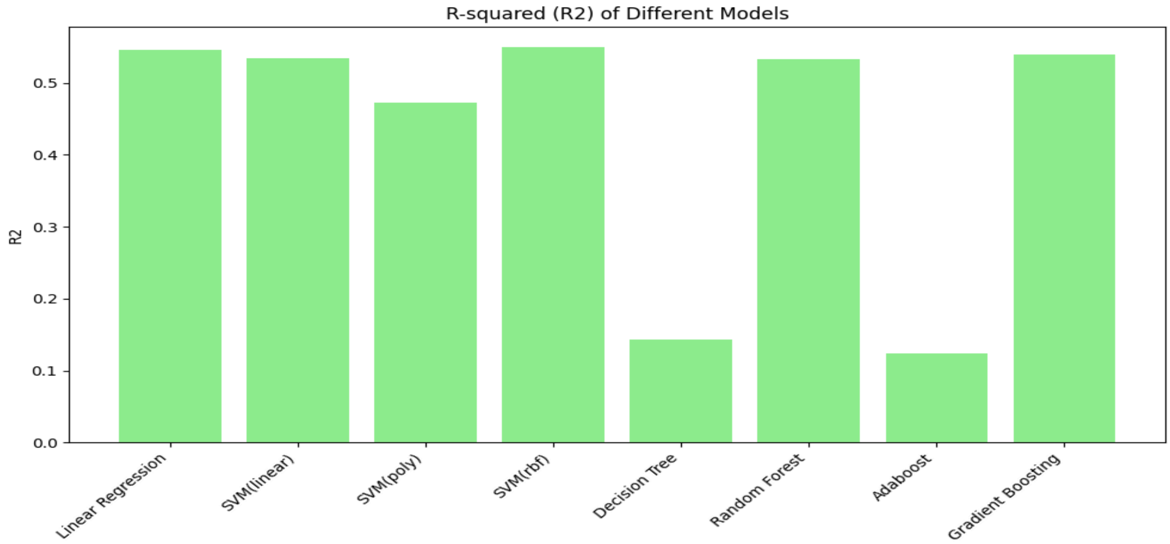
MSE: The SVM with RBF kernel has the lowest MSE (4.6270), indicating it has the smallest average squared errors among the models.

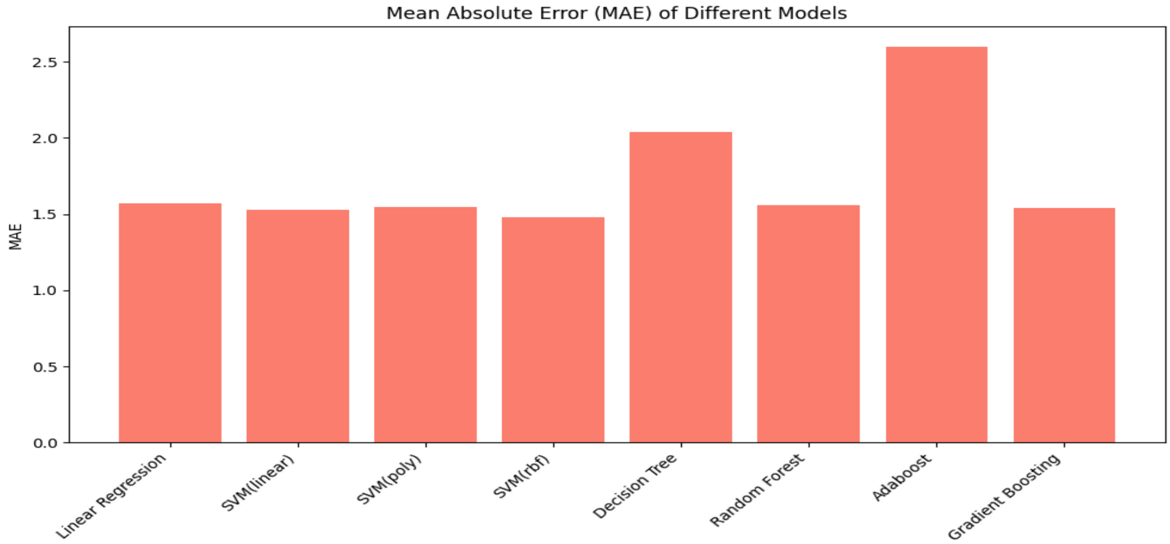
R2: The SVM with RBF kernel also has the highest R2 value (0.5502), indicating it explains the highest proportion of variance in the age of abalone.

MAE: The SVM with RBF kernel has the lowest MAE (1.4807), indicating the smallest average absolute errors.

Considering the MSE, R2, and MAE metrics, the **SVM with RBF kernel** emerges as the best-performing model for predicting the age of abalone. It achieves the best balance between accuracy and error minimization, making it the most reliable method among the ones tested


Mean Squared Error (MSE) of Different Models
MSE
0
2
4
6
8
Linear Regression
SVM(linear)
SVM(poly)
SVM(rbf)
Decision Tree
Random Forest
Adaboost
Gradient Boosting


R-squared (R2) of Different Models
R2
0.0
0.1
0.2
0.3
0.4
0.5
Linear Regression
SVM(linear)
SVM(poly)
SVM(rbf)
Decision Tree
Random Forest
Adaboost
Gradient Boosting


Mean Absolute Error (MAE) of Different Models
MAE
0.0
0.5
1.0
1.5
2.0
2.5
Linear Regression
SVM(linear)
SVM(poly)
SVM(rbf)
Decision Tree
Random Forest
Adaboost
Gradient Boosting

SAI UNIVERSITY