

Machine Learning

Course Project Report (Phase-I)

Title of the project: Cryotherapy Dataset

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ML Category: Classification

1. Introduction

A brief description of the problem statement.

Cryotherapy is a treatment procedure used to freeze and remove abnormal tissue cells. The effectiveness of this treatment can vary based on numerous factors such as the patient's age, sex, the time they have had the disease, the number of warts, the type of wart, and the surface area affected by the warts

The goal of this project is to develop a machine learning model that can predict the success of cryotherapy treatment based on these factors. The dataset provided contains these variables, with the 'Result_of_Treatment' as the target variable, which is binary (0 indicating unsuccessful treatment and 1 indicating successful treatment).

The predictive classifier model developed from this dataset could assist in determining the likelihood of successful cryotherapy treatment for future patients, based on their individual characteristics and conditions. This could lead to more personalised and effective treatment plans.

2. Dataset and Features

Details of the dataset - Description about the features and total number of samples available. Dimension of dataset [90 \times 7]. No missing values found.

The Cryotherapy dataset contains 90 samples, each representing a patient who underwent cryotherapy treatment. Each sample has seven features, described as follows:

Sex: This is a binary variable representing the patient's gender. In this dataset, '1' represents male [Total 47 men] and '2' represents female [Total 43 Women].



Age (year): This is a continuous variable representing the patient's age values ranging from 15–67.

Time elapsed before treatment (month): This is a continuous variable representing the duration (in months) the patient has had the disease before undergoing cryotherapy. Here, values range from 0–12.

Number_of_Warts: This is a continuous variable representing the number of warts the patient had before the treatment. Here, the values range from 1–12.

Types of wart (Count): This is a categorical variable representing the type of wart. The dataset uses the values '1', '2', and '3' to represent different types of warts. Where:

- 1- Common (54),
- 2- Plantar (9),
- 3- Both (27) [Patients have both types of common and plantar warts]

Surface area of the warts [Surface area of biggest wart] (mm2): This is a continuous variable representing the size (in square millimetres) of the affected area before the treatment. Here, values range from 4–750.

Result_of_Treatment: This is the target variable, a binary variable representing the result of the cryotherapy treatment. '0' indicates the treatment was unsuccessful, and '1' indicates the treatment was successful.

3. Methods

Following are the various methods used in this project.

In the Phase-I, the experiments are run using the default settings of the Scikit-Learn library. In the Phase-II, hyperparameter tuning is performed.

The dataset is split into 75% training set and 25% testing set. Standard feature scaling is performed.

3.1 Baseline - Logistic Regression

Brief description of the method:

Logistic Regression is a machine learning algorithm used for binary classification. It uses a statistical method for predicting binary outcomes. It models the probability that a given input point belongs to a certain class by applying the logistic function to a linear



combination of the input features. In this case, the model predicts whether cryotherapy treatment is successful (1) or unsuccessful (0).

Library/Class Used: sklearn.linear_model.LogisticRegression What It Does: Predicts binary outcomes by fitting a logistic curve to the data.

• Result obtained: Accuracy = 0.8695652173913043

3.2 Support Vector Machines

• Brief description of the method:

Support Vector Machines (SVM) are supervised learning models used for classification and regression tasks. Its aim is to find a hyperplane in an N-dimensional space (N — the number of features) that distinctly classifies the data points. The best hyperplane for an SVM means the one with the largest margin between the two classes. SVMs can use different kernel functions (linear, polynomial, and RBF) to transform the input space into higher dimensions where a linear separator can be found.

Library/Class Used: sklearn.svm.SVC

What It Does: Finds the optimal hyperplane to classify the data points with maximum margin.

- Results obtained using Linear, Polynomial and RBF kernels respectively:
 - o SVM (Linear): Accuracy = 0.8695652173913043
 - SVM (Polynomial): Accuracy = 0.7391304347826086
 - o SVM (RBF): Accuracy = 0.9130434782608695

3.3 Decision Tree

• Brief description of the method.

Decision Trees are a non-parametric supervised learning method used for classification and regression. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. The tree is built by splitting the data into subsets based on the feature that results in the most significant information gain or the greatest reduction in impurity.



Library/Class Used: sklearn.tree.DecisionTreeClassifier **What It Does:** Splits data into subsets based on the most significant features, creating a tree structure for prediction.

• Result obtained: Decision Tree: Accuracy = 0.8260869565217391

3.4 Random Forest

• Brief description of the method:

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes for classification tasks. It reduces overfitting by averaging multiple decision trees trained on different parts of the same training set and generally improves the model's performance.

Library/Class Used: sklearn.ensemble.RandomForestClassifier **What It Does:** Constructs multiple decision trees and averages their predictions to improve accuracy and reduce overfitting.

• Result obtained: Random Forest: Accuracy = 0.8695652173913043

3.5 AdaBoost

• Brief description of the method:

AdaBoost, short for Adaptive Boosting, is an ensemble technique that combines multiple weak classifiers to create a strong classifier. It adjusts the weights of incorrectly classified instances, allowing the algorithm to focus more on difficult cases in subsequent rounds. Each weak classifier is trained on the weighted training data, and the final model is a weighted sum of these weak classifiers.

Library/Class Used: sklearn.ensemble.AdaBoostClassifier What It Does: Combines multiple weak classifiers, adjusting weights to focus on difficult cases, resulting in a stronger classifier.

• *Result obtained:* AdaBoost: Accuracy = 0.8260869565217391



3.6 Gradient Boosting

• Brief description of the method:

Gradient Boosting is an ensemble technique that builds models sequentially. Each new model attempts to correct the errors made by the previous models. It combines the strengths of multiple weak learners to create a strong learner by focusing on the residual errors of the combined ensemble. It is particularly effective for classification tasks on structured data.

Library/Class Used: sklearn.ensemble.GradientBoostingClassifier **What It Does:** Builds models sequentially, correcting errors from previous models to create a strong overall learner.

Result obtained: Gradient Boosting: Accuracy = 0.8260869565217391

4. Results

Baseline results:

- Feature scaling significantly improved the performance of models, particularly SVM polynomial and RBF. Logistic Regression did not benefit from feature scaling, as the improvement was not particularly pronounced. The Decision Tree and Ensemble model's performance were also relatively stable with or without feature scaling.
- Baseline model of SVM (Using RBF kernel) seems to yield the best predictions with an accuracy of **91.3%** [0.9130434782608695 rounded to three significant decimal places in percentage form].
- The SVM with the RBF kernel outperformed other models in predicting the success of cryotherapy treatment mostly due to its ability to handle non-linear relationships, its flexibility in adjusting hyperparameters, its sensitivity to feature scaling, and its effectiveness in high-dimensional spaces.

These characteristics seem to make the RBF kernel SVM a powerful tool for classification tasks involving complex datasets like the cryotherapy dataset, as of the baseline standard model results seen so far.



• Tables and plots for various experiments.

Fig1: Snippet of console output of the results obtained from the experiments, with standard scaling applied.

With Scaling - Logistic Regression: Accuracy = 0.8695652173913043 Classification Report: precision recall f1-score support 0 0.85 0.92 0.88 12
Classification Report: precision recall f1-score support
precision recall f1-score support
**
0 0.85 0.92 0.88 12
1 0.90 0.82 0.86 11
accuracy 0.87 23
macro avg 0.87 0.87 23
weighted avg 0.87 0.87 23
With Scaling - SVM (Linear): Accuracy = 0.8695652173913043
Classification Report:
precision recall f1-score support
0.05
0 0.85 0.92 0.88 12 1 0.90 0.82 0.86 11
1 0.90 0.82 0.86 11
accuracy 0.87 23
macro avg 0.87 0.87 23
weighted avg 0.87 0.87 23
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With Scaling - SVM (Polynomial): Accuracy = 0.7391304347826086
Classification Report:
precision recall f1-score support
0 0.88 0.58 0.70 12
1 0.67 0.91 0.77 11
accuracy 0.74 23
macro avg 0.77 0.75 0.73 23
weighted avg 0.78 0.74 0.73 23
1

Classification			_	
	precision	recall	f1-score	support
0	0.86	1.00	0.92	12
1	1.00	0.82	0.90	11
accuracy			0.91	23
macro avg	0.93	0.91	0.91	23
weighted avg	0.93	0.91	0.91	23
With Scaling - Classification		Tree: Accu	ıracy = 0.8	2608695652173
	precision	recall	f1-score	support
0	0.90	0.75	0.82	12
1	0.77	0.91	0.83	11
accuracy			0.83	23
macro avg	0.83	0.83	0.83	23
weighted avg	0.84	0.83	0.83	23
With Scaling - Classification	Report:			
	precision	recall	f1-score	support
0	0.90	0.75	0.82	12
1	0.77	0.91	0.83	11
accuracy			0.83	23
macro avg	0.83	0.83	0.83	23
weighted avg	0.84	0.83	0.83	23



	precision	recall	f1-score	support
0	0.90	0.75	0.82	12
1	0.77	0.91	0.83	11
accuracy			0.83	23
macro avg	0.83	0.83	0.83	23
weighted avg	0.84	0.83	0.83	23
	- Gradient			
With Scaling Classificatio	- Gradient	Boosting:		0.8260869
	- Gradient on Report: precision	Boosting:	Accuracy = f1-score	0.8260869
Classificatio	- Gradient on Report: precision 0.90	Boosting: recall	Accuracy = f1-score	0.8260869 support
Classificatio	- Gradient on Report: precision 0.90 0.77	Boosting: recall 0.75	Accuracy = f1-score 0.82	0.8260869 support 12
Classificatio	- Gradient on Report: precision 0.90 0.77	Boosting: recall 0.75	Accuracy = f1-score 0.82 0.83	support

Fig2: Snippet of console output of the results obtained from the experiments, without feature scaling.

```
Without Scaling - Logistic Regression: Accuracy = 0.8695652173913043 Classification Report:
             precision recall f1-score support
                  0.90
                                     0.86
                                                11
                                     0.87
0.87
                                                23
   accuracy
                  0.87
                           0.87
macro avg
weighted avg
                           0.87
                                     0.87
Without Scaling - SVM (Linear): Accuracy = 0.8695652173913043 Classification Report:
                         recall f1-score support
             precision
                  0.85
                           0.92
                                                11
                  0.90
                           0.82
                                     0.86
   accuracy
                                     0.87
                                                23
                  0.87
                           0.87
                                     0.87
weighted avg
                                     0.87
                 0.87
                           0.87
0.65
                                                11
macro avg
weighted avg
                  0.24
                                     0.32
                                                23
```



Classification ۱ pı	recision	recall	f1-score	support
_				
0 1	1.00	0.08	0.15	12
1	0.50	1.00	0.67	11
accuracy			0.52	23
macro avg	0.75	0.54	0.41	23
weighted avg	0.76	0.52	0.40	23
Without Scaling		on Tree: Ad	ccuracy = 0	0.826086956
Classification				
р	recision	recall	f1-score	support
0	0.90	0.75	0.82	12
1	0.77	0.91	0.83	11
accuracy			0.83	23
macro avg	0.83	0.83	0.83	23
weighted avg	0.84	0.83	0.83	23
Without Scaling Classification (Forest: A	ccuracy = 0	826086956
рі	recision	recall	f1-score	support
p 0		recall 0.75	f1-score 0.82	support 12
	recision			
0	necision 0.90	0.75	0.82	12
0	necision 0.90	0.75	0.82 0.83	12 11
0 1 accuracy macro avg	0.90 0.77	0.75 0.91	0.82 0.83	12 11 23
0 1 accuracy macro avg weighted avg	0.90 0.77 0.83	0.75 0.91 0.83	0.82 0.83 0.83	12 11 23 23
0 1 accuracy macro avg weighted avg	0.90 0.77 0.83 0.84	0.75 0.91 0.83 0.83	0.82 0.83 0.83 0.83 0.83	12 11 23 23 23
accuracy macro avg weighted avg	0.90 0.77 0.83 0.84	0.75 0.91 0.83 0.83	0.82 0.83 0.83 0.83 0.83	12 11 23 23 23
accuracy macro avg weighted avg Without Scalin, Classification	0.90 0.77 0.83 0.84 g - AdaBoo Report:	0.75 0.91 0.83 0.83	0.82 0.83 0.83 0.83 0.83	12 11 23 23 23 23
accuracy macro avg weighted avg Without Scalin, Classification	0.90 0.77 0.83 0.84	0.75 0.91 0.83 0.83	0.82 0.83 0.83 0.83 0.83	12 11 23 23 23 23
accuracy macro avg weighted avg Without Scalin Classification	0.90 0.77 0.83 0.84 g - AdaBoc Report: precision	0.75 0.91 0.83 0.83 0st: Accura	0.82 0.83 0.83 0.83 0.83 acy = 0.826 f1-score	12 11 23 23 23 23 23 50869565217 support
accuracy macro avg weighted avg Without Scaling Classification	0.90 0.77 0.83 0.84 g - AdaBoc Report: precision	0.75 0.91 0.83 0.83 est: Accura	0.82 0.83 0.83 0.83 0.83 acy = 0.826 f1-score	12 11 23 23 23 23 23 50869565217 support
accuracy macro avg weighted avg Without Scalin Classification	0.90 0.77 0.83 0.84 g - AdaBoc Report: precision	0.75 0.91 0.83 0.83 0st: Accura	0.82 0.83 0.83 0.83 0.83 acy = 0.826 f1-score 0.82 0.83	12 11 23 23 23 23 23 50869565217 support
accuracy macro avg weighted avg Without Scalin Classification 0 1 accuracy	0.90 0.77 0.83 0.84 g - AdaBoc Report: precision 0.90 0.77	0.75 0.91 0.83 0.83 0st: Accurr recall 0.75 0.91	0.82 0.83 0.83 0.83 0.83 acy = 0.826 f1-score 0.82 0.83	12 11 23 23 23 23 50869565217 support 12 11
accuracy macro avg weighted avg Without Scalin, classification 0 1 accuracy macro avg	0.90 0.77 0.83 0.84 g - AdaBoc Report: precision 0.77	0.75 0.91 0.83 0.83 0.83 0.83	0.82 0.83 0.83 0.83 0.83 acy = 0.826 f1-score 0.82 0.83 0.83	12 11 23 23 23 23 23 50869565217 support 12 11 23 23
accuracy macro avg weighted avg Without Scalin Classification 0 1 accuracy	0.90 0.77 0.83 0.84 g - AdaBoc Report: precision 0.90 0.77	0.75 0.91 0.83 0.83 0st: Accurr recall 0.75 0.91	0.82 0.83 0.83 0.83 0.83 acy = 0.826 f1-score 0.82 0.83 0.83	12 11 23 23 23 23 23 50869565217 support 12 11 23 23
accuracy macro avg weighted avg Without Scaling Classification 0 1 accuracy macro avg weighted avg	0.90 0.77 0.83 0.84 g - AdaBoc Report: precision 0.77 0.83 0.84	0.75 0.91 0.83 0.83 0.83 0.75 0.91 0.83 0.83	0.82 0.83 0.83 0.83 0.83 acy = 0.826 f1-score 0.82 0.83 0.83 0.83	12 11 23 23 23 23 50869565217 support 12 11 23 23 23
accuracy macro avg weighted avg Without Scalin, classification 0 1 accuracy macro avg	0.90 0.77 0.83 0.84 g - AdaBoc Report: precision 0.77 0.83 0.84 g - Gradie	0.75 0.91 0.83 0.83 0.83 0.75 0.91 0.83 0.83	0.82 0.83 0.83 0.83 0.83 acy = 0.826 f1-score 0.82 0.83 0.83 0.83	12 11 23 23 23 23 50869565217 support 12 11 23 23 23

 $\textbf{Fig3:} \ \textit{A tabular visualisation comparing results obtained from different models, both with and without scaling}$ respectively.

recall f1-score 0.75

0.83 0.83

0.83 0.84

macro avg weighted avg

0.82

0.83

0.83 0.83

11

23

23 23

Model	Without Scaling	With Scaling
Logistic Regression	0.869565	0.869565
SVM (Linear)	0.869565	0.869565
SVM (Polynomial)	0.478261	0.73913
SVM (RBF)	0.521739	0.913043
Decision Tree	0.826087	0.826087
Random Forest	0.826087	0.826087
AdaBoost	0.826087	0.826087
Gradient Boosting	0.826087	0.826087



Fig4: A bar plot chart comparing results obtained from the experiments, with accuracy of the models rounded to having three significant decimal digits.

