CCT College Dublin

Assessment Cover Page

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Declaration

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Introduction

Health is a major concern among all societies, rich and poor, impacting on the quality of life, economic productivity and social stability. Since the beginning of time humanity has tried to overcome diseases and even death, looking for answers in nature and using all the available resources around.

The oldest record about medical conditions is an ancient Egyptian work produced by Imhotep and dated from around 3000 BC. Hippocrates was one of the first to suggest that diseases could have natural causes instead of supernatural (University of Glasgow, 2020). Data has been a key feature of the evolution of science, especially in the health field and The National Center for Health Statistics has contributed hugely for the american society through its exceptional work in gathering and organising data.

Health is not the same for all age groups and the predominance of diseases vary on different stages of life. It is important to study how health conditions and ageing are related to get a better understanding of how diseases behave with different ages so health authorities can draw prevention strategies and allocate resources to researchers for more effective treatments.

Objective

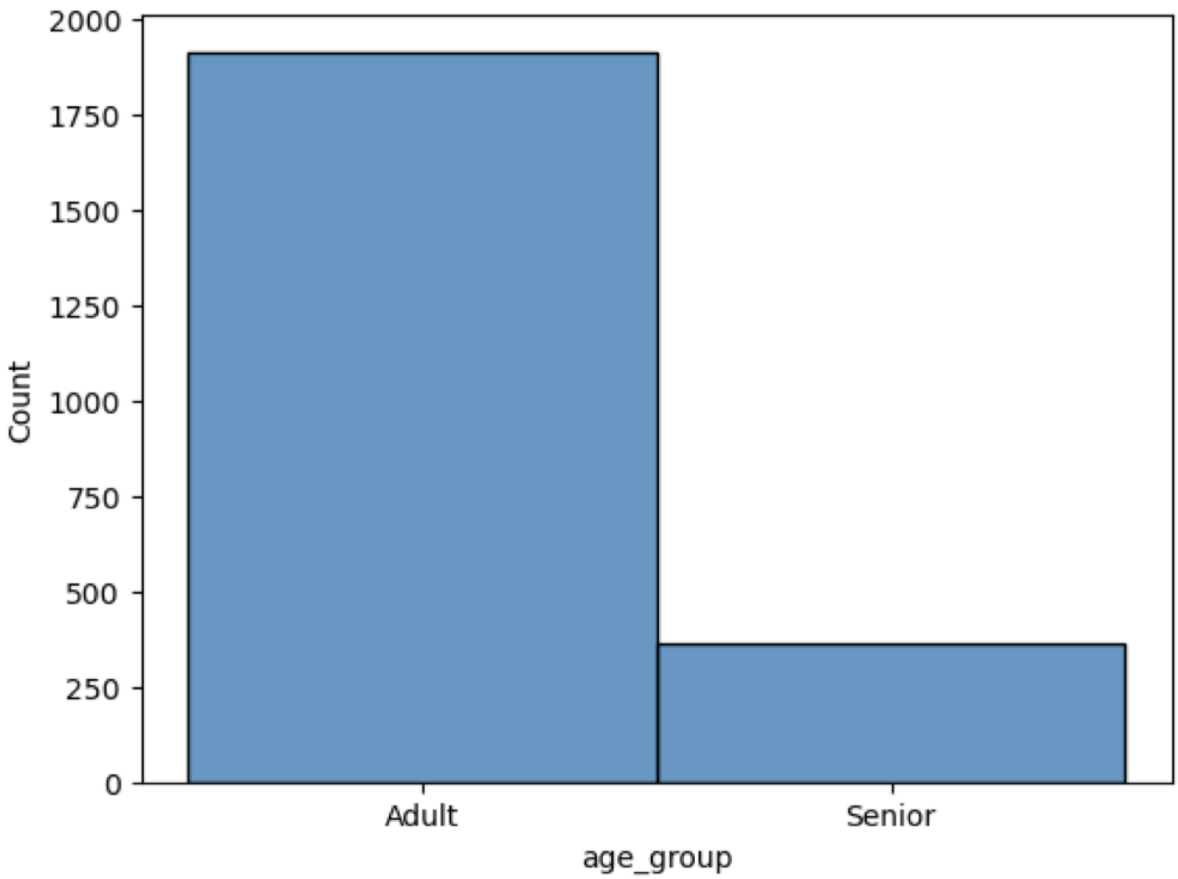
The objective is to predict in which age group (Senior or Non-Senior) the respondents will be, given their health and nutritional information. Even though the problem can be dealt with Regression, Classification or Clustering, this project will focus on the first two and their performances will be compared. Two dimensionality reduction techniques will be performed - PCA and LDA - and two methods for imbalanced data - SMOTE and Near-Miss.

Data Understanding

The National Center for Health Statistics (NCHS) at the Center for Disease Control and Prevention (CDC) is responsible for collecting a wide-ranging set of nutritional and health information through surveys across The United States territory. The sub-dataset provided for this project was extracted in the UC Irvine Machine Learning Repository with DOI 10.24432/C5BS66 and is licensed under a Creative Commons Attribution 4.0 International (CC BY 4.0) licence. It contains 2278 observations and 10 features related to lifestyle choices and biochemical markers (such as Blood Insulin Levels) and they were selected based on their hypothetical correlation with age, which is the target variable labelled into two categories.

The dataset has no missing values and the column “SEQN”, which contain the respondent sequence number, was dropped for its insignificance for the analysis. This information is only useful for gathering and organising the dataset during the survey fase. The target variable in “age_group” is divided into two groups: individuals over 65 years were labelled as “senior” while the “non-senior” contains the individuals under 65 years. The One-Hot Encoding was used to transform the target variable from categorical to numerical to avoid to force an ordinal relationship between the groups (Brownlee, 2020). This method create two new features where “age_goup_adult" will be 1 when the "adult" value is true and 0 when is false and “age_group_Senior” will be the opposite. The new variable “age_group_Senior” will be dropped so we have just one target variable and the Machine Learning models can perform their mathematical procedures.

Figure 1 - Target Variable Distribution



The graphic above shows that the target variable is imbalanced where the amount of "Adult" represents 84.02% against 15.98% of the "Senior" group. The imbalance of the dataset might affect the performance of the Machine Learning algorithms, when the minority class tends to be ignored over the majority leading to an overfitting model (Truong, 2022). There are two ways to make the number of observations in the groups equal: by creating synthetic data of the minority group or reducing the number of the majority group (Imarticus, 2021). Both ways will be explored through the SMOTE (Synthetic Minority Oversampling Technique) and Near-Miss techniques.

The column "RIDAGEYR" contains the ages of the respondents, the distribution is not normal, even though the media and the median are the same, with a higher concentration on the left side. The average is 41 years old with a standard deviation of approximately 20, the youngest person is 12 years old and the oldest is 80. The dataset is quite balanced for genders, with 1113 males and 1165 females.

Figure 2 - Age Distribution

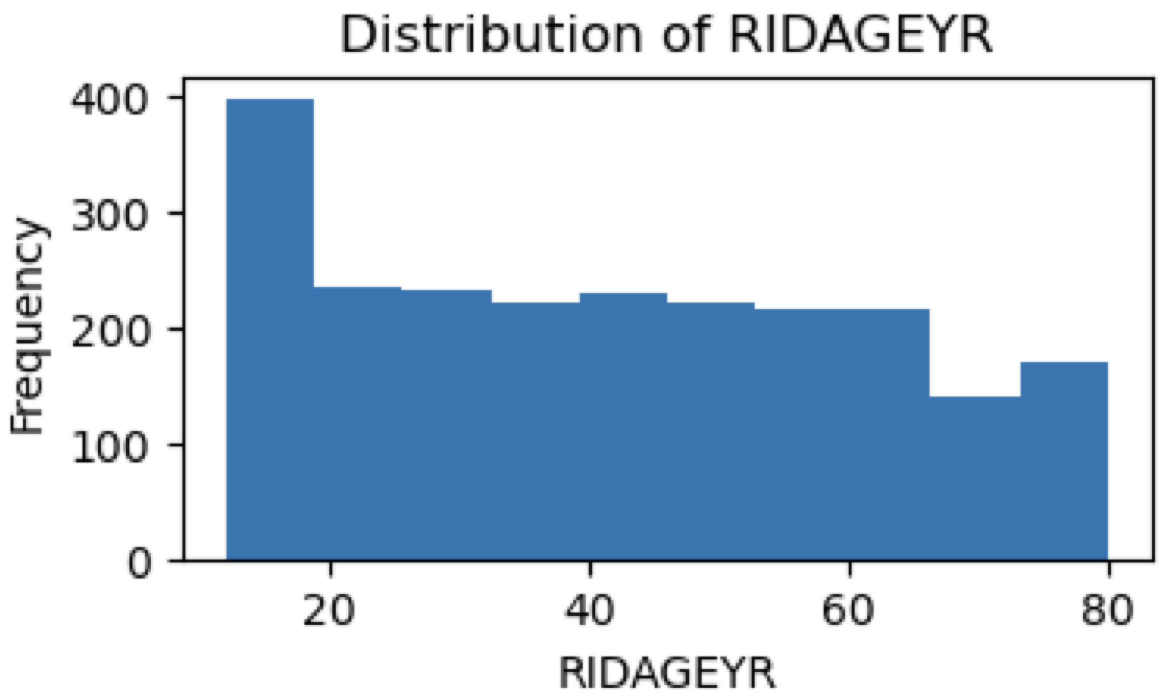
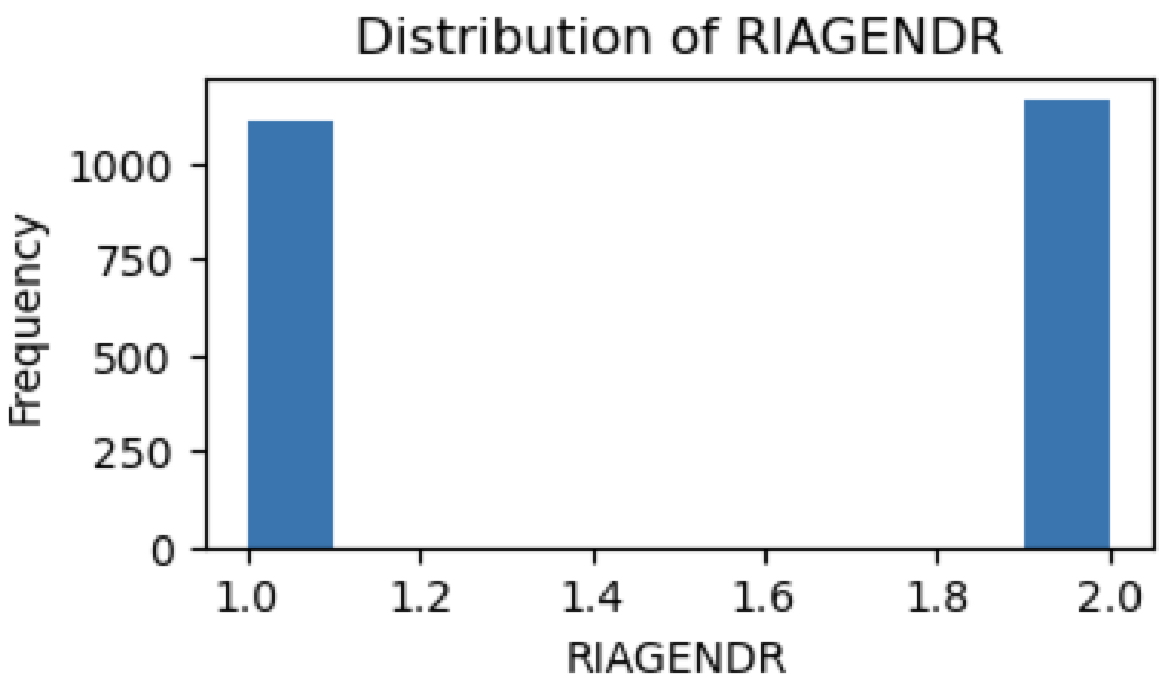
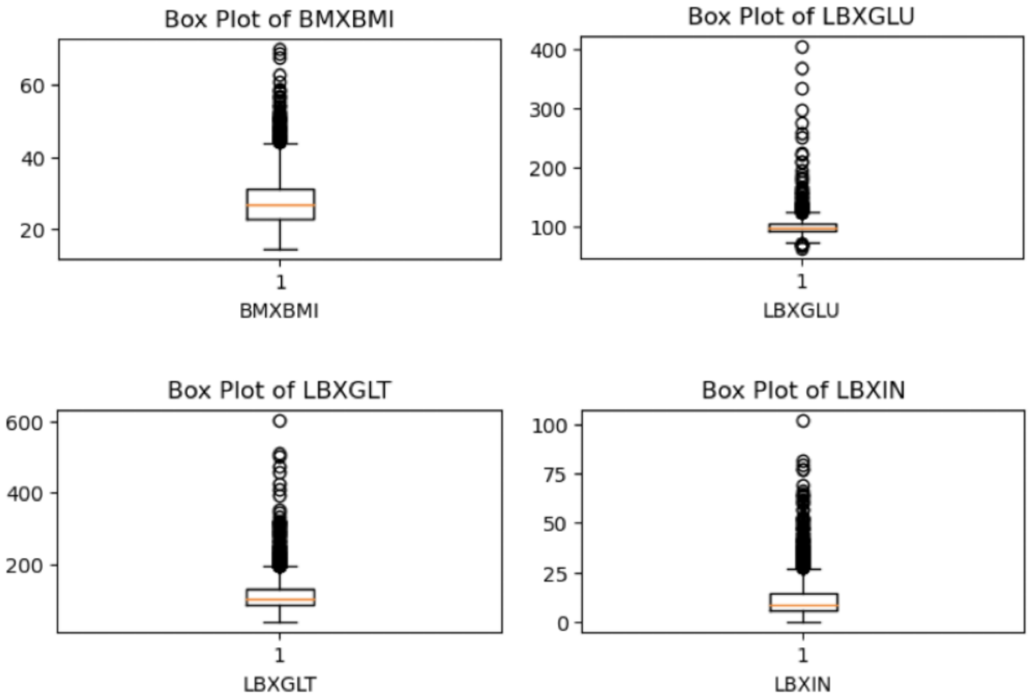


Figure 3 - Gender Distribution



The presence of outliers are significant in four columns: “BMXBMI” (Body Mass Index), “LBXGLU” (Blood Glucose after fasting), “LBXGLT” (Oral Health) and “LBXIN” (Blood Insulin Levels).

Figure 4 - Boxplot with the highest concentration of outliers



Success Criteria

The success of the regression models can be evaluated using the following methods: the R-squared (R2), the Adjusted R-squared, Mean Squared Error (MSE), the Cross-Validation Score, the comparison between the MSE on the train and on the test data and Huber Loss, from Sklearn and Tensorflow libraries (Pedregosa et al., 2011) (TensorFlow Developers, 2023).

The R-squared is usually used to measure and to indicate the quality of a regression model, it is a proportion of the variance in the target variable that is explained by the features of the model (Frost, 2018). Meanwhile the Adjusted R-squared takes into consideration the numbers of features used in the model and measures if adding additional features would be better, penalising if it does not (Bhandari, 2020). The MSE is a method to calculate the error with the squared difference between the actual and the predicted value (M, 2021).

The Cross-Validation Score is a helpful technique to reduce bias and to avoid overfitting by estimating how well the model will perform and generalise in new unseen data (Brownlee, 2018). The comparison between the MSE on the train test data is also helpful to check overfitting by having those two as close as possible (Bishop, 2006). The Huber Loss has the same goal as the MSE and it is normally used in a dataset with the presence of outliers (M, 2021).

When dealing with classification models the success will be measured by the Accuracy score, Precision, Recall, f1-score and Cross-Validation Accuracy. The Accuracy score is the ratio of the total of corrected predictions to the total predictions of the model. It is a very straightforward concept and it is usually visualised with the help of a confusion matrix, which summarises the model's predictions and organises in a table by class with the correctly predicted values and their errors (Brownlee, 2019).

Precision and Recall are two simple and useful score measures. The first one takes the true positives and divides them for all the positives while the second one is the true positives divided by the sum of the true positives and the false negatives, giving us a ratio of the true predictions by the model (Huilgol, 2020). The f1-score is the harmonic mean between precision and recall as a higher value indicating a better performance considering both precision and recall (Pedregosa et al., 2019).

The ultimate goal of any machine learning algorithm is to achieve such a performance that predicts new and unseen data as it did on the original one. Most of the time this unseen data is not available in such cases the train test split for validation is a good choice to test if the model generalises well (Galarnyk, 2022). It is a good practice to experiment with different sizes of train test split, in this project the percentages that will be used are: 10%, 20% and 30%.

A tuning in the hyperparameters of the algorithms are also important in the pursuit of the best model. There are several ways to do it but the one chosen for this project was the Grid Search from Sklearn library. After specifying the range for the hyperparameters, the method tries different combinations and calculates their performance; it might be time-consuming depending on the number of hyperparameters that is being tested (Shah, 2021).

Dimensionality Reduction

Principal Component Analysis and Linear Discriminant Analysis are both dimensionality reduction techniques that help with complex datasets. PCA is an unsupervised machine learning useful to deal with the curse of dimensionality, which is the difficulty to get meaningful patterns within the data due its large numbers of features (dimensions). This method is commonly used when it is important to reduce the amount of time that the algorithm takes to process high-dimensional data and also reduces the amount of noise by reducing the overfitting and improving the generalisation of the model. Its importance lays down on the simplicity of its applicability and the useful resource of keeping as much of the original variance as possible (S, 2022).

Another dimensionality reduction technique that will be implemented in this project is Linear Discriminant Analysis. LDA is generally used in classification problems for feature extraction patterns. The idea is to reduce the number of dimensions by reducing the variability within classes while maximising it between the classes. Different from PCA, LDA is a supervised method which considers the classes labels to identify the directions that best discriminate them (Dash, 2021).

It is important to test both techniques in different models and compare their results through the success criteria chosen.

Imbalanced Data

The imbalance in the target variable of a dataset might cause overfitting and bias on the success criteria. This problem can be dealt with by equalising both classes through the augmentation of the minor class or the reduction of the majority.

The Synthetic Minority Over-Sampling Technique, or SMOTE, balances the dataset by generating synthetic observations of the minority class with its nearest neighbours. While this technique is compatible with various machine learning algorithms and simple to use, the synthetic data might have the opposite desirable effect and generate an overfitting model (Brownlee, 2020b).

Undersampling methods do the opposite as described above, in order to balance the dataset they remove part of the observations from the majority class. Although it is an interesting technique it should be handled carefully because useful information might be lost due to the randomness of the process. The Near-Miss is one of the methods available and works based on the distance between the majority class examples to the minority class (Brownlee, 2020c).

Both techniques are worthwhile testing as experiment is key to good science, however a closer look into the results are demanded to check if they are reliable.

Models - Linear Regression

For Regression 07 models were performed:

- Linear Regression;
- Linear Regression Polynomial Second Degree;
- Random Forest;
- Support Vector Regression;
- K-Nearest Neighbours;
- Bagging Regressor with KNN;
- Decision Tree.

When applying LDA all the models performed better with a 10% split and the best result was KNN with a R2 of 0.9221, Cross-Validation score of 0.8622 and no overfitting as the difference between the MSE on the train and on the test was small.

For PCA 04 out of 07 models performed better with a 10% split and the other 03 with a 30% split. The best performance overall was Random Forest with R2 of 0.9895 and 10% split, followed by Decision Tree with 30% split and R2 of 0.9738. Even though the Grid Search was used to find the best hyperparameters in both cases, the first model cannot be used due its small Adjusted R2 of -0.229 and big difference between the R2. The second model is more reliable with no overfitting, no difference between R2 and Adjusted R2 and a Cross-Validation score of 0.9473.

Overall PCA had better results than LDA in 4 models: Random Forest, KNN, Bagging Regressor with KNN and Decision Tree. Linear Regression had the worst performance in all scenarios but improved considerably with its derivation when Polynomial with second degree is applied.

Table 1 - Regression with LDA and PCA

LDA					PCA			
10%	20%	30%	BEST		10%	20%	30%	BEST
R2 LN: 0.5618881510394962	R2 LN: 0.5041900982150748	R2 LN: 0.4927866255820207	10%		R2 LN: 0.5282121813594496	R2 LN: 0.4753742755353033	R2 LN: 0.46568286690897653	10%
R2 LNP2: 0.8071489417811208	R2 LNP2: 0.7612939803295771	R2 LNP2: 0.7510945668752906	10%		R2 LNP2: 0.7993926928925605	R2 LNP2: 0.7795515454599702	R2 LNP2: 0.7698297738540906	10%
R2 RF: 0.8957097930140704	R2 RF: 0.8624796667270428	R2 RF: 0.8547897694606474	10%		R2 RF: 0.9895033026113671	R2 RF: 0.9735693971063258	R2 RF: 0.970571667544113	10%
R2 SVR: 0.8945388097791866	R2 SVR: 0.8352821121231669	R2 SVR: 0.8334051561957369	10%		R2 SVR: 0.8652449665458792	R2 SVR: -1.0195804195804197	R2 SVR: 0.8354034987443396	10%
R2 KNN: 0.9221710189452125	R2 KNN: 0.8639440559440559	R2 KNN: 0.8606565562216599	10%		R2 KNN: 0.9545997610513739	R2 KNN: 0.942916342916343	R2 KNN: 0.959343104121733	30%
R2 KNN BGG: 0.9027336280134173	R2 KNN BGG: 0.8567059607059607	R2 KNN BGG: 0.8606001870884047	10%		R2 KNN BGG: 0.9378162324837769	R2 KNN BGG: 0.9292749155606298	R2 KNN BGG: 0.9429404765659469	30%
R2 DT: 0.8603816908227705	R2 DT: 0.8268961504398012	R2 DT: 0.8420032937063441	10%		R2 DT: 0.9686922003824572	R2 DT: 0.9626003626003626	R2 DT: 0.9738634240782569	30%

As mentioned before, the target variable is imbalanced and there are two ways to deal with it: oversampling the minority class or undersampling the majority one. Both techniques were performed with LDA and PCA and the best results, considering only the R2, were obtained with oversampling, the highlights are: Random Forest, K-Nearest Neighbours, Bagging Regressor with KNN and Decision Tree with R2 higher than 0.97 in all three splits with PCA. These models did not show overfitting when the Training Mean Square Errors and the Validation MSE were compared but they all performed poorly for Cross-Validation with a score no higher than 0.58, which might indicate that the models do not generalise well to new unseen data. The results for the Cross-Validation score with undersampling were even lower, with LDA and PCA, with some being negative.

Table 2 - Regression with LDA, PCA and Oversampling

LDA - Over Sampling					PCA - Over Sampling			
10%	20%	30%	BEST		10%	20%	30%	BEST
R2 LN: 0.7635925495609067	R2 LN: 0.7475267940774699	R2 LN: 0.7439193356990967	10%		R2 LN: 0.7369995676749912	R2 LN: 0.7373150824242898	R2 LN: 0.7286196676676804	20%
R2 LNP2: 0.8283614540695288	R2 LNP2: 0.7950646052829744	R2 LNP2: 0.8028222702205406	10%		R2 LNP2: 0.8230878657126647	R2 LNP2: 0.8217220680819086	R2 LNP2: 0.8177087367073441	10%
R2 RF: 0.9063086092105765	R2 RF: 0.8788981374045148	R2 RF: 0.8846655331310294	10%		R2 RF: 0.9906451612903225	R2 RF: 0.9886071871009943	R2 RF: 0.9868253859348199	10%
R2 SVR: 0.9151153467813481	R2 SVR: 0.8904595217125015	R2 SVR: 0.8879652120337375	10%		R2 SVR: 0.0	R2 SVR: 0.0	R2 SVR: 0.0	
R2 KNN: 0.924826762246117	R2 KNN: 0.8906438746438746	R2 KNN: 0.9045092433771679	10%		R2 KNN: 0.98805256869773	R2 KNN: 0.9851851851851852	R2 KNN: 0.9824661711454165	10%
R2 KNN BGG: 0.9025916172920782	R2 KNN BGG: 0.884436420722135	R2 KNN BGG: 0.8943396226415095	10%		R2 KNN BGG: 0.9816282642089094	R2 KNN BGG: 0.9849345892203035	R2 KNN BGG: 0.9824937865369132	20%
R2 DT: 0.8941198420825917	R2 DT: 0.8528596405798787	R2 DT: 0.8561793160501606	10%		R2 DT: 0.9885752688172043	R2 DT: 0.9763532763532764	R2 DT: 0.9858967028778349	10%

Table 3 - Regression with LDA, PCA and Undersampling

LDA - Under Sampling					PCA - Under Sampling			
10%	20%	30%	BEST		10%	20%	30%	BEST
R2 LN: 0.7524543977902298	R2 LN: 0.6786802216427132	R2 LN: 0.663615555682719	10%		R2 LN: 0.7214445089990282	R2 LN: 0.7400765044385769	R2 LN: 0.7305304112238034	20%
R2 LNP2: 0.7277140678345341	R2 LNP2: 0.6956373357267776	R2 LNP2: 0.6859051023776452	10%		R2 LNP2: 0.6476387214490104	R2 LNP2: 0.7690086279751207	R2 LNP2: 0.7559104093017317	20%
R2 RF: 0.8201000619402062	R2 RF: 0.7501886326820648	R2 RF: 0.7603797062261229	10%		R2 RF: 0.965654335451356	R2 RF: 0.9581946807072087	R2 RF: 0.9468944805747759	10%
R2 SVR: 0.8567145391833357	R2 SVR: 0.7558895475676481	R2 SVR: 0.7681677863063485	10%		R2 SVR: 0.0	R2 SVR: 0.0	R2 SVR: 0.0	
R2 KNN: 0.870899470899471	R2 KNN: 0.7671380471380471	R2 KNN: 0.7624642464246425	10%		R2 KNN: 0.9470899470899471	R2 KNN: 0.9595959595959596	R2 KNN: 0.9361936193619362	20%
R2 KNN BGG: 0.8411467444120505	R2 KNN BGG: 0.7382374768089053	R2 KNN BGG: 0.768729036168923	10%		R2 KNN BGG: 0.9312925170068027	R2 KNN BGG: 0.9428509585652443	R2 KNN BGG: 0.9358698727015559	20%
R2 DT: 0.7369733290141454	R2 DT: 0.7030605134871009	R2 DT: 0.731904057185764	10%		R2 DT: 0.9828042328042328	R2 DT: 0.9663299663299664	R2 DT: 0.9603960396039604	10%

Models - Classification

For Classification 07 models were performed:

- Logistic Regression;
- Decision Tree;
- Random Forest;
- Support Vector Machine;
- K-Nearest Neighbours;
- Naive Bayes;
- Artificial Neural Networks.

The LDA and PCA were applied again but with no over and under sampling techniques once all the accuracy scores without them were higher than 0.95. The 10% split was the most common but the differences were not so significant, suggesting that the models were stable with different train test splits. The Cross-Validation score was close to the accuracy score in all scenarios.

The presence of overfitting was evaluated by the difference between precision and recall for both classes, in this case the models with PCA performed better with almost no difference while for the ones with LDA the range of the difference was between 0.07 and 0.15. The best models with LDA, with high accuracy and low overfitting, were Logistic Regression, Support Vector Machine and K-Nearest Neighbours. When PCA is applied the best performances were obtained with Decision Tree and Random Forest.

Table 4 - Classification with LDA and PCA

LDA					PCA			
10%	20%	30%	BEST		10%	20%	30%	BEST
Accuracy_lg: 0.9868	Accuracy_lg: 0.9759	Accuracy_lg: 0.9781	10%		Accuracy_lg: 0.9781	Accuracy_lg: 0.9868	Accuracy_lg: 0.9898	30%
Accuracy_dt: 0.9605	Accuracy_dt: 0.9627	Accuracy_dt: 0.9561	20%		Accuracy_dt: 1.0000	Accuracy_dt: 0.9956	Accuracy_dt: 0.9971	10%
Accuracy_rf: 0.9605	Accuracy_rf: 0.9649	Accuracy_rf: 0.9605	20%		Accuracy_rf: 1.0000	Accuracy_rf: 0.9978	Accuracy_rf: 0.9956	10%
Accuracy_svm: 0.9868	Accuracy_svm: 0.9759	Accuracy_svm: 0.9781	10%		Accuracy_svm: 0.9956	Accuracy_svm: 0.9956	Accuracy_svm: 0.9956	TODOS
Accuracy_knn: 0.9825	Accuracy_knn: 0.9737	Accuracy_knn: 0.9795	10%		Accuracy_knn: 0.9956	Accuracy_knn: 0.9956	Accuracy_knn: 0.9942	10% ou 20%
Accuracy_gnb: 0.9825	Accuracy_gnb: 0.9737	Accuracy_gnb: 0.9751	10%		Accuracy_gnb: 0.9825	Accuracy_gnb: 0.9912	Accuracy_gnb: 0.9912	20% ou 30%
Accuracy_ann: 0.9868	Accuracy_ann: 0.9781	Accuracy_ann: 0.9766	10%		Accuracy_ann: 0.9912	Accuracy_ann: 0.9978	Accuracy_ann: 0.9927	20%

The last experiment performed was with the original data with no dimensionality reduction or sampling techniques. For Regression all models got R2 smaller than the best ones in the previous scenarios, the exceptions were Random Forest and Decision Tree. Although the first one got a R2 of 1.00, the Adjusted R2 was -0.014 making the model not a good choice. However, the second one got a 1.00 score for R2, Adjusted R2 and Cross-Validation with no presence of overfitting across all train test splits.

Table 5 - Regression with Original Data

Regression		
10%	20%	30%
R2 LN: 0.5618881510394962	R2 LN: 0.5041900982150747	R2 LN: 0.49278662558202013
R2 LNP2: 0.8051823695564234	R2 LNP2: 0.7865151627989853	R2 LNP2: 0.7737980964040417
R2 RF: 1.0	R2 RF: 1.0	R2 RF: 1.0
R2 SVR: 0.8082321417670297	R2 SVR: 0.7962631481558756	R2 SVR: 0.7923535186535011
R2 KNN: 0.9069943676395289	R2 KNN: 0.9097684537684537	R2 KNN: 0.9063471630181886
R2 KNN BGG: 0.9039487131258033	R2 KNN BGG: 0.9000622234907949	R2 KNN BGG: 0.9161898985431851
R2 DT: 1.0	R2 DT: 1.0	R2 DT: 1.0

Once more the classification models performed better than the regression models on an overall view with scores higher than 0.96. Decision Tree and Random Forest were the best ones again but this time both of them got good results in all scores: accuracy, precision, recall, Cross-Validation and no overfitting.

Table 6 - Classification with Original Data

Classification		
10%	20%	30%
Accuracy_lg: 0.9781	Accuracy_lg: 0.9868	Accuracy_lg: 0.9868
Accuracy_dt: 1.0000	Accuracy_dt: 1.0000	Accuracy_dt: 1.0000
Accuracy_rf: 1.0000	Accuracy_rf: 1.0000	Accuracy_rf: 1.0000
Accuracy_svm: 0.9956	Accuracy_svm: 0.9956	Accuracy_svm: 0.9956
Accuracy_knn: 0.9868	Accuracy_knn: 0.9934	Accuracy_knn: 0.9927
Accuracy_gnb: 0.9649	Accuracy_gnb: 0.9715	Accuracy_gnb: 0.9591
Accuracy_ann: 0.9912	Accuracy_ann: 0.9912	Accuracy_ann: 0.9708

Models - Overall Analysis

In an overview with the best model for each combination taking into account just the two main success criteria - R2 for regression and accuracy for classification - the most recurrent ones are: K-Nearest Neighbours, Decision Tree and Random Forest. A more in depth analysis, considering others success criteria, was debated on the previous section leaving this one to explain about the highlighted models.

Table 7 - Overall Analysis

Overall Analysis	
Combination	Model
Regression and LDA	KNN
Regression and PCA	Decision Tree
Regression, LDA and Undersampling	KNN
Regression, PCA and Undersampling	Decision Tree
Regression, LDA and Oversampling	KNN
Regression, PCA and Oversampling	Random Forest
Classification and LDA	Logistic Regression, Support Vector Machine and Artificial Neural Networks
Classification and PCA	Decision Tree and Random Forest
Regression with Original Data	KNN
Classification with Original Data	Decision Tree and Random Forest

The K-Nearest Neighbours is known for using proximity in order to make classifications or predictions with the assumption that similar points are found close to each other. The Euclidean distance is often used in both regression and classification models. In the first case, the average of the distance of the continuous values are used while for classification the distance between the data points and the class label. KNN is easy to implement due its simplicity with few hyperparameters. The disadvantages are the proneness to overfitting and the curse of dimensionality. Its usage has been broad, for example: on finances (risk of a loan), healthcare (risk of a heart attack) and pattern recognition (handwriting) (IBM, 2022).

Decision Tree is another supervised machine learning algorithm that can be used for classification and regression problems. Through a built flowchart, the algorithm splits the training data into subsets in accordance with the attributes values and just stops with the set criteria, for example: maximum depth and minimum number of samples. The entropy or Gini impurity is used to help to optimise the model, maximising information gain and minimising impurity. Its usage is very popular due the similarity with the human process of decision making and due the power of thinking in all possible outcomes. Decision Tree often faces the overfitting problem and computational complexity for a broader range of class labels, which can be dealt with using Random Forest (GeeksForGeeks, 2017).

Random Forest is an aggregation of Decision Trees that reaches one single result by combining their outputs. Classification problems are solved with the most frequent class while regression problems are solved with the computed mean of predictions, in both cases the random feature selection is used at each node of the decision tree bringing diversity to the model. The often high accuracy and low overfitting make this algorithm a powerful one, even though with its computational expensiveness and less interpretability when compared with a Decision Tree (IBM, 2023).

Conclusion

On average the models performed better with a 10% train test split, with higher R2 or accuracy, smaller difference between the Training and Validation MSE (no overfitting), good Cross-Validation score and a lower Huber Loss. All the experiments performed in the pursuit of the best models and their results can be found in separated Jupyter Notebooks or in the Github Repository, the links are provided in the main file and on the appendix.

A total of 14 machine learning algorithms were tested, 07 for regression and 07 for classification, along with two dimensionality reduction methods and two techniques to balance the target variable. Among all the combinations made, Decision Tree and Random Forest were the ones with the highest frequency of good results. Even though LDA is more appropriate for classification problems, this method was tested on regression algorithms with the hypothesis that the results would be considerably low but it turned out to be surprisingly good. The results with PCA were predominantly better than the ones with LDA among all combinations. The imbalance of the dataset was not a crucial problem once the models without the balance techniques performed better in all success criteria.

The classification algorithms outperformed the regression ones and one of the hypotheses is the low correlation between the variables. As the target variable is separated into two classes and the values are not continuous, a classification approach might be more straightforward in regards to the relationship between the independent and the dependent variables.

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Appendix

All the experiments performed in the pursuit of the best models and their results can be found in separated Jupyter Notebooks or in the Github Repository, the links are provided in the main file.

LDA with Regression Algorithms: http://localhost:8888/notebooks/Documents/GitHub/ML/LDA.ipynb

LDA with Classification Algorithms: http://localhost:8888/notebooks/Documents/GitHub/ML/LDA_Classification.ipynb

LDA with Oversampling and Regression: http://localhost:8888/notebooks/Documents/GitHub/ML/LDA_Over.ipynb

LDA with Undersampling and Regression: http://localhost:8888/notebooks/Documents/GitHub/ML/LDA_Under.ipynb

PCA with Regression Algorithms: http://localhost:8888/notebooks/Documents/GitHub/ML/PCA.ipynb

PCA with Classification Algorithms: http://localhost:8888/notebooks/Documents/GitHub/ML/PCA_Classification.ipynb

PCA with Oversampling and Regression: http://localhost:8888/notebooks/Documents/GitHub/ML/PCA_Over.ipynb

PCA with Undersampling and Regression: http://localhost:8888/notebooks/Documents/GitHub/ML/PCA_Under.ipynb

Original Data with Regression and Classification Algorithms: http://localhost:8888/notebooks/Documents/GitHub/ML/Original%20Data.ipynb

Summary of R2 and Accuracy of all Models: https://docs.google.com/spreadsheets/d/1_jueJid0ULbd2rgHKxMRD1Jy-Ke8bujUO5ozr00IkL4/edit#gid=0

Github Repository: https://github.com/izazaka/ML