Influence of the design of Experiments on the robustness, data hunger, and predictive power of metamodels on the example of a minimal model for passive occupant safety

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1 Introduction

This report will present the development of the project that has as the mean goal. First, will be approached how the data was created regarding the design of the experiment and also the data analysis. The experiments made to reach the results keep into consideration the analysis of the performance of the regression and classification methods. An analysis of the results will provide the best machine learning method for the mean problem.

2 Design of Experiment

The first step was to define the parameters that would be used for the FE simulations, being them the features regarding the body and environment configurations. For the body configurations, the anthropometric parameters used are Body Mass Index (BMI), Sitting Height to Stature (SHS), Stature, Age, and for the environment was varied the impact speed, backrest angle, and the shoulder belt limiter load.

Then, to build the database for use as input on the FE simulation was settled the maximum, minimum, and average values for the human body configuration (Table 1). For the simulation, we used the Latin Hypercube Sampling Method to create an anthropometric features variation of 1000 samples in a range between the maximum and the minimum configuration values. Later, we added at the final attaching the standard configurations, summing up 1003 samples as input.

Building the simulation batches was defined the usage of different environment configurations (Table 2). Varying the environment features were obtained seven different environment configurations, in which each one of them had the own FE simulation. Therefore the final simulation result is seven databases, one for each environment where each one has 1003 samples.

Table 1: Dummy body configurations

	BMI	SHS	Stature	Age
Min	18	0.4	1450	20
Avg	29	0.5	1675	55
Max	40	0.6	1900	90
Unit	kg/m^2	No unit	mm	$years$

Table 2: Environment configurations

	Impact Speed	Backrest Angle	Should Belt Limiter Load	Environment
	64	23	4.5	1
	56	23	4.5	2
	40	23	4.5	3
	48	33	3.5	4
	24	12	7	5
	48	23	4.5	6
	24	33	3.5	7
Unit	kg/m^2	Degrees	kN	-

3 Data Analysis

With the simulation done, is given the beginning of the data analysis on the simulation results. The data pre-processing is responsible of prepare the raw data for the feature selection and the applications with the machine learning methods. Then, correlation and outliers analysis was done in order to obtain more knowledge about the database. So, the data was ready to be applied to the machine learning methods.

The first analysis consists of analysis about the outliers (Figure 1) present at the raw data with some selected features regarding the head and chest output channels from the FE simulation. Later, we removed the outliers based on the *Tukey Method*, whose boxplot is responsible define the lower bounds and upper bounds from the interquartile range (IQR) and the first and third quartiles. As reference two remove the outliers was used the output channels chest acceleration ("a3ms_x_acceleration@15-spine_0_mass", "a3ms_y_acceleration@15-spine_0_mass") and head acceleration ("a3ms_x_acceleration@12-neck", "a3ms_y_acceleration@12-neck"), then the result can be observed on the Figure 2.
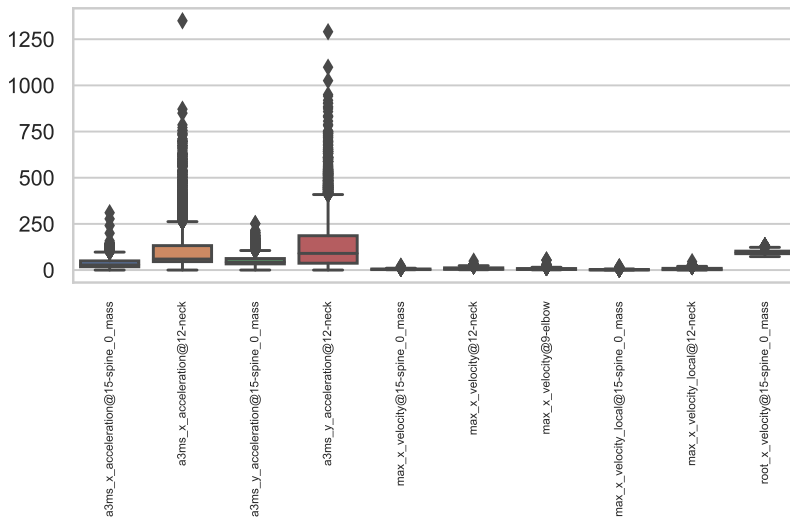

Figure 1: Boxplot with outliers.

Therefore, with the outliers removed, the next step was to do the correlation analysis between the output channels of the FE simulations and the anthropometric features. With this, it is possible to see the correlation matrix of the most correlated features in the database in Figure 3. The strongest correlation is between the Stature and head acceleration ("head_a3ms"), BMI, and the chest velocity

Having the final database in hand after removing the outliers and analyze the correlation between the features, we analyze the critical and non-critical distribution in each environment
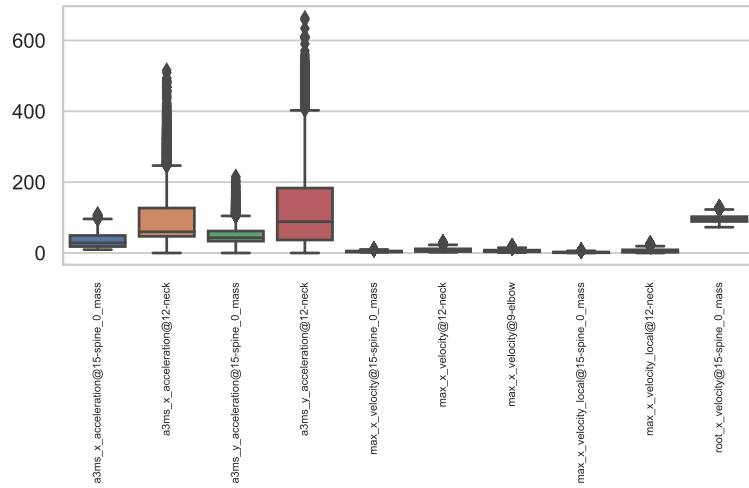
Figure 2: Boxplot without the outliers.

Figure 3: Correlation matrix

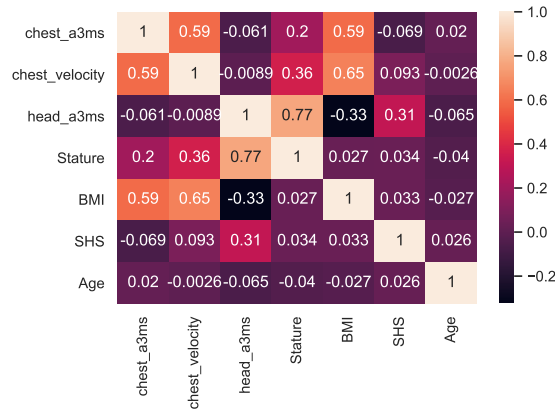configuration used in the FE simulations. The figures 4a and 4b show the distribution of the non-balanced cases, respectively the first figure using chest acceleration there is a balance in environments 1 and 2 but not in the others, in the second figure, the distribution is a little better using head displacement with environment 4.

(a)

(b)
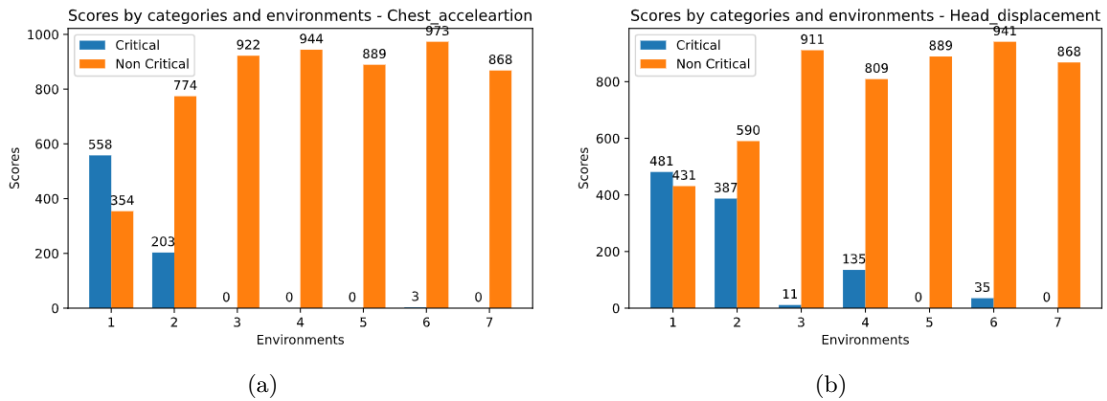
Figure 4: Scores by categories for each environment.

The approach used to try to get a better distribution was to put some noise (10% of noise used) on the database, and we can see the result for the chest acceleration in the Figure 5a and for the head displacement in the Figure 5b. Therefore, we conclude that the noise helped somewhat, but not as we had hoped, that is, as the environments were more balanced between cases.

(a)

(b)

Figure 5: Scores by categories for each environment for the database with noise.

4 Methodology

The work methodology was based on two main approaches, regression and classification methods predict the injury in a frontal collision. The first experimen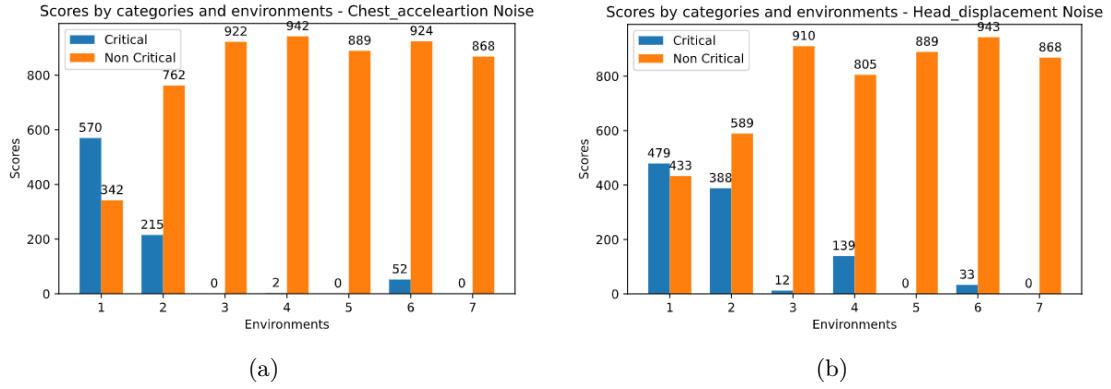t consists of bringing all seven environments together in a single database. Then, add noise to this database and apply different regression and classification methods. To validate the performance of the methods used, we used a comparison based on error metrics and using four different input subsets (IS - Input Subset) in Table 3. Each subset consists of FE simulation results for the minimum, maximum, and average body configurations among the anthropometric characteristics of the given body we want to predict, and also was created subsets just with results for the average bodies were created.

Table 3: Feature Subsets

Set	BMI	SHS	Stature	Age	Head Acceleration	Chest Acceleration	Chest Velocity
IS 1	*	*	*	*	*	*	*
IS 2	*	*	*	*	*		
IS 3	*	*	*	*		*	*
IS 4	*	*	*	*	*	*	

The model target is chest acceleration and head displacement for the regression and classification methods. For the classifiers, the target was classified into two categories, critical and non-critical. The critical situation is the result of a chest acceleration higher than 60g and head displacement values higher than 650mm.

The second experiment was given by choosing the best regression and classification experiment along with the best input subset for each of the used targets based on the error metric. This approach consists basically of one question, being *"How many environments we need to do the FE simulations to predict the injury degree of a car occupant in new environments?"*.

Besides, in this experiment the separate environment database was used, so that at first one environment was used to validate the method and another to predict. Thus, different combinations with two, three, four, five and six validate the method and after predict with one environment.

5 Results

This section has been separated into two sections. These sections will be divided into two parts, one regarding the results where we use the database without noise and the other with noise.

This section is about the results collected by the two experiments approached in the last section.

5.1 First Experiment

5.1.1 Normal Data

This section is regarded to the experiment using the data without noise.

Regression   From the Tables 4 e 5, we can see the results for the regression methods using as target the chest acceleration. The idea behind using just average body results is to see if the results are better than if we use all the results of the standard body, looking for a cost reduction. For the two tables using the chest acceleration as the target of the models, the best results are with random forest and MLP 2 (Multilayer Perceptron), with kNN we achieved good results but without a number of neighbors defined, which means that for each input subset we had different numbers of neighbors on the methods with better results. The input subsets that detain the best results based on the error metrics are the input subset 3 and 4.

Table 4: Results from the regression methods using the average, minimum and maximum body results.

Input Subsets	Metrics	Random Forest	SVM	kNN	Linear Regression	MLP 1	MLP 2
1	RMSE	5.42	5.66	5.60	0.00	6.29	6.02
	R2	0.91	0.91	0.91	0.00	0.88	0.89
	MAE	3.31	2.78	3.13	0.00	4.11	3.88
2	RMSE	6.09	5.86	6.10	8.54	6.28	6.17
	R2	0.90	0.91	0.89	0.76	0.88	0.89
	MAE	3.59	2.91	3.51	6.56	3.96	3.86
3	RMSE	6.15	5.64	5.59	8.13	6.29	6.07
	R2	0.89	0.91	0.91	0.78	0.89	0.90
	MAE	3.88	2.79	3.13	6.29	4.07	3.84
4	RMSE	5.30	5.61	5.60	8.13	6.12	6.13
	R2	0.92	0.92	0.91	0.79	0.89	0.89
	MAE	2.99	2.73	3.16	6.38	3.89	3.78

On the Tables 6 e 7, we can see the results for the regression methods using as target the head displacement. For the two tables, the best results came from the SVM and the MLP 1 and 2 (Multilayer Perceptron), because these methods own the higher value for the R^2 and also the lowest RMSE and MAE values. The input subsets 3 and 4 still being the subsets with the best results. What differs from the MLP methods is the configuration, in that they have three layers, two of which are hidden layers with ten neurons, but MLP layer one has five neurons, and MLP layer two has ten neurons.

Classification   For the classification methods using as target the chest acceleration we have the results on the Tables 8 and 9. The best results came from the MLP and decision tree, the input subsets with the best results here are also the ones of the regression methods, 3 and 4.

Using as target the head displacement we have the results on the Tables 10 and 11. The best results came from the MLP and the SVM, MLP detains the best performance in all the input subsets less the subset 3 in which the SVM has the better result. We can say the input subsets with the best results here still being the 3 and 4.

Table 5: Results from the regression methods using the average body results.

Input Subsets	Metrics	Random Forest	SVM	kNN	Linear Regression	MLP 1	MLP 2
1	RMSE	5.02	5.55	5.61	8.29	7.28	5.94
	R2	0.93	0.91	0.91	0.78	0.84	0.89
	MAE	2.58	2.72	3.20	6.43	5.29	3.81
2	RMSE	5.08	6.40	8.93	9.60	8.27	6.75
	R2	0.92	0.89	0.73	0.68	0.78	0.86
	MAE	2.71	3.47	5.55	6.91	5.15	4.64
3	RMSE	5.03	5.94	8.20	9.58	6.34	6.16
	R2	0.93	0.91	0.79	0.68	0.88	0.89
	MAE	2.61	3.32	4.55	6.91	4.29	3.98
4	RMSE	5.03	5.61	5.90	8.29	6.26	5.59
	R2	0.93	0.91	0.89	0.78	0.88	0.91
	MAE	2.61	2.76	3.71	6.42	3.99	3.63

Table 6: Results from the regression methods using the average body results and head displacement as target.

Input Subsets	Metrics	Random Forest	SVM	kNN	Linear Regression	MLP 1	MLP 2
1	RMSE	48.30	8.05	18.76	0.00	33.10	27.74
	R2	0.93	1.00	0.99	0.00	0.97	0.98
	MAE	25.00	6.50	12.55	0.00	24.37	21.40
2	RMSE	32.62	11.16	37.89	66.08	41.44	31.35
	R2	0.97	1.00	0.96	0.88	0.96	0.98
	MAE	18.43	9.24	24.78	51.99	30.85	21.76
3	RMSE	38.17	7.90	18.62	45.24	27.24	24.90
	R2	0.96	1.00	0.99	0.95	0.98	0.99
	MAE	20.74	6.32	12.53	35.82	19.96	18.67
4	RMSE	38.77	13.90	34.63	45.33	25.90	21.60
	R2	0.96	0.99	0.97	0.95	0.98	0.99
	MAE	20.96	11.69	22.38	35.75	18.35	14.79

Table 7: Results from the regression methods using the average body results and the head displacement as target.

Input Subsets	Metrics	Random Forest	SVM	kNN	Linear Regression	MLP 1	MLP 2
1	RMSE	97.25	17.89	25.84	64.40	60.09	46.53
	R2	0.93	0.91	0.91	0.78	0.84	0.89
	MAE	0.70	0.99	0.98	0.89	0.90	0.95
2	RMSE	5.08	6.40	8.93	9.60	8.27	6.75
	R2	0.75	0.75	0.57	0.53	0.52	0.51
	MAE	38.98	58.51	93.40	101.47	101.12	101.30
3	RMSE	95.53	26.03	60.73	77.07	58.16	30.61
	R2	0.71	0.98	0.89	0.83	0.91	0.98
	MAE	41.62	22.90	40.86	64.03	46.09	22.75
4	RMSE	95.58	45.00	74.09	103.17	102.80	38.71
	R2	0.71	0.94	0.82	0.64	0.64	0.96
	MAE	41.66	34.73	52.31	86.78	85.58	29.35

Table 8: Classification methods using the average, minimum and maximum body results using as target the chest acceleration.

Input Subsets	Metrics	Random Forest	Decision Tree	SVM	kNN	Naive Bayes	Logistic Regression	MLP
1	Accuracy	0.92	0.96	0.96	0.96	0.84	0.95	0.95
	Precision	0.64	0.83	0.85	0.87	0.42	0.78	0.84
	Recall	0.7	0.78	0.77	0.78	0.99	0.83	0.74
	F1	0.67	0.81	0.81	0.82	0.59	0.81	0.79
	AUC	0.83	0.88	0.88	0.88	0.91	0.9	0.86
2	Accuracy	0.93	0.96	0.96	0.96	0.84	0.95	0.97
	Precision	0.78	0.87	0.85	0.84	0.42	0.74	0.89
	Recall	0.59	0.79	0.84	0.78	0.99	0.84	0.81
	F1	0.67	0.83	0.84	0.81	0.59	0.79	0.85
	AUC	0.79	0.89	0.91	0.88	0.91	0.9	0.9
3	Accuracy	0.92	0.91	0.96	0.96	0.84	0.95	0.95
	Precision	0.63	0.58	0.87	0.88	0.42	0.78	0.8
	Recall	0.72	0.86	0.78	0.78	0.99	0.82	0.77
	F1	0.67	0.69	0.82	0.83	0.59	0.8	0.78
	AUC	0.83	0.89	0.88	0.88	0.91	0.9	0.87
4	Accuracy	0.92	0.91	0.96	0.96	0.84	0.95	0.96
	Precision	0.64	0.58	0.85	0.87	0.42	0.77	0.84
	Recall	0.7	0.86	0.81	0.78	0.99	0.84	0.84
	F1	0.67	0.69	0.83	0.82	0.59	0.8	0.84
	AUC	0.83	0.89	0.89	0.88	0.91	0.9	0.91

Table 9: Classification methods using the average body results using as target the chest acceleration.

Input Subsets	Metrics	Random Forest	Decision Tree	SVM	kNN	Naive Bayes	Logistic Regression	MLP
2	Accuracy	0.93	0.96	0.96	0.96	0.91	0.95	0.95
	Precision	0.85	0.87	0.87	0.87	0.58	0.78	0.76
	Recall	0.49	0.79	0.81	0.78	0.93	0.83	0.79
	F1	0.62	0.83	0.84	0.82	0.71	0.80	0.78
	AUC	0.74	0.89	0.90	0.88	0.92	0.90	0.88
2	Accuracy	0.92	0.96	0.96	0.91	0.92	0.94	0.96
	Precision	1.00	0.86	0.81	0.66	0.59	0.80	0.83
	Recall	0.27	0.80	0.80	0.42	0.93	0.69	0.80
	F1	0.43	0.83	0.81	0.51	0.72	0.74	0.82
	AUC	0.64	0.89	0.89	0.69	0.92	0.83	0.89
3	Accuracy	0.89	0.96	0.96	0.91	0.92	0.95	0.96
	Precision	1.00	0.84	0.82	0.66	0.59	0.78	0.86
	Recall	0.01	0.80	0.82	0.53	0.91	0.78	0.83
	F1	0.02	0.82	0.82	0.59	0.72	0.78	0.85
	AUC	0.50	0.89	0.90	0.75	0.91	0.88	0.91
4	Accuracy	0.93	0.96	0.96	0.96	0.89	0.95	0.97
	Precision	0.86	0.84	0.88	0.88	0.50	0.79	0.87
	Recall	0.50	0.80	0.81	0.78	0.98	0.82	0.82
	F1	0.63	0.82	0.84	0.83	0.66	0.80	0.85
	AUC	0.74	0.89	0.90	0.88	0.93	0.89	0.90

Table 10: Classification methods using the average, minimum and maximum body results using as target the head displacement.

Input Subsets	Metrics	Random Forest	Decision Tree	SVM	kNN	Naive Bayes	Logistic Regression	MLP
1	Accuracy	0.92	0.98	0.99	0.98	0.82	0.96	0.99
	Precision	0.93	0.94	0.97	0.94	0.44	0.85	0.98
	Recall	0.48	0.92	0.97	0.90	0.82	0.90	0.96
	F1	0.63	0.93	0.97	0.92	0.58	0.87	0.97
	AUC	0.74	0.95	0.98	0.94	0.82	0.94	0.98
2	Accuracy	0.93	0.98	0.99	0.98	0.83	0.96	0.99
	Precision	0.97	0.92	0.95	0.93	0.45	0.85	0.97
	Recall	0.53	0.92	0.98	0.90	0.82	0.90	0.97
	F1	0.68	0.92	0.96	0.92	0.58	0.87	0.97
	AUC	0.76	0.95	0.99	0.94	0.83	0.94	0.98
3	Accuracy	0.93	0.95	0.99	0.98	0.82	0.96	0.99
	Precision	0.90	0.80	0.97	0.94	0.44	0.86	0.97
	Recall	0.56	0.89	0.97	0.90	0.82	0.89	0.96
	F1	0.69	0.84	0.97	0.92	0.58	0.88	0.97
	AUC	0.77	0.93	0.99	0.94	0.82	0.93	0.98
4	Accuracy	0.93	0.98	0.99	0.98	0.82	0.96	0.99
	Precision	0.90	0.93	0.96	0.94	0.44	0.86	0.96
	Recall	0.58	0.91	0.97	0.90	0.82	0.90	0.97
	F1	0.70	0.92	0.97	0.92	0.58	0.88	0.97
	AUC	0.78	0.95	0.98	0.94	0.82	0.94	0.98

Table 11: Classification methods using the average body results using as target the head displacement.

Input Subsets	Metrics	Random Forest	Decision Tree	SVM	kNN	Naive Bayes	Logistic Regression	MLP
2	Accuracy	0.88	0.98	0.99	0.98	0.88	0.96	0.99
	Precision	1.00	0.92	0.97	0.94	0.56	0.84	0.97
	Recall	0.20	0.92	0.97	0.90	0.82	0.90	0.98
	F1	0.33	0.92	0.97	0.92	0.67	0.87	0.98
	AUC	0.60	0.95	0.99	0.94	0.85	0.93	0.99
2	Accuracy	0.86	0.97	0.98	0.90	0.90	0.90	0.99
	Precision	1.00	0.89	0.92	0.63	0.64	0.65	0.97
	Recall	0.07	0.92	0.93	0.74	0.65	0.63	0.93
	F1	0.13	0.90	0.92	0.68	0.65	0.64	0.95
	AUC	0.53	0.95	0.96	0.83	0.80	0.79	0.96
3	Accuracy	0.85	0.98	0.99	0.94	0.90	0.92	0.98
	Precision	0.00	0.92	0.97	0.83	0.66	0.71	0.94
	Recall	0.00	0.92	0.97	0.78	0.72	0.77	0.94
	F1	0.00	0.92	0.97	0.80	0.69	0.74	0.94
	AUC	0.50	0.95	0.99	0.88	0.83	0.86	0.96
4	Accuracy	0.91	0.98	0.99	0.98	0.89	0.95	0.99
	Precision	1.00	0.92	0.97	0.94	0.59	0.82	0.97
	Recall	0.37	0.91	0.97	0.89	0.82	0.81	0.97
	F1	0.54	0.92	0.97	0.92	0.68	0.81	0.97
	AUC	0.69	0.95	0.99	0.94	0.86	0.89	0.98

5.1.2 Noise Data

This section is regarded to the experiment using the data with noise.

Regression From the Tables 12 e 13, we can see the results for the regression methods using as target the chest acceleration. For the two tables using the chest acceleration as the model target, the best results are with random forest and MLP 2. The input subsets that detain the best results based on the error metrics are the input subset 3 and 4, the only result better than the MLP 2 using the random forest is with the input subset 3.

Table 12: Results from the regression methods using the average, minimum and maximum body results.

Input Subsets	Metrics	Random Forest	SVM	kNN	Linear Regression	MLP 1	MLP 2
	RMSE	9.47	10.00	8.68	10.53	8.78	8.55
1	R2	0.74	0.75	0.77	0.64	0.77	0.78
	MAE	2.58	2.78	3.13	0.00	3.69	3.70
	RMSE	8.96	10.05	9.73	10.94	9.64	9.48
2	R2	0.77	0.73	0.70	0.60	0.70	0.72
	MAE	8.34	10.63	9.17	10.85	9.39	8.84
	RMSE	5.03	5.64	5.59	8.13	6.46	6.09
3	R2	0.80	0.71	0.74	0.61	0.73	0.76
	MAE	6.36	7.98	6.90	8.55	7.11	6.69
	RMSE	9.76	9.09	8.61	10.54	8.99	8.46
4	R2	0.72	0.78	0.77	0.64	0.75	0.79
	MAE	7.48	6.89	6.57	8.30	6.91	6.52

Table 13: Results from the regression methods using the average body results.

Input Subsets	Metrics	Random Forest	SVM	kNN	Linear Regression	MLP 1	MLP 2
	RMSE	8.19	9.10	8.87	10.79	9.34	9.31
1	R2	0.81	0.78	0.76	0.61	0.72	0.73
	MAE	6.23	6.96	6.86	8.52	7.18	7.14
	RMSE	12.04	11.77	11.74	12.60	11.54	11.18
2	R2	0.51	0.53	0.52	0.39	0.50	0.56
	MAE	8.92	8.58	8.72	9.78	8.56	8.29
	RMSE	11.11	11.73	11.23	12.58	11.44	11.43
3	R2	0.60	0.57	0.59	0.39	0.51	0.51
	MAE	8.14	8.53	8.25	9.78	8.50	8.48
	RMSE	8.27	8.93	9.06	10.79	9.51	8.85
4	R2	0.80	0.78	0.74	0.61	0.71	0.76
	MAE	6.28	6.77	6.97	8.53	7.30	6.81

From the Tables 14 e 15 show the results for the machine learning methods using the head displacement as target. For the two tables using the chest acceleration as the target of the models, the best results are with the random forest, SVM, and MLP 2. The input subsets that detain the best results based on the error metrics are the input subset 3 and 4, the only result better than the MLP 2 using the random forest is with the input subset 3.

Classification For the classification methods using as target the chest acceleration we have the results on the Tables 16 and 17. The best results came from the MLP and logistic regression, the input subsets with the best results here are the 3 and 4. In this case, the MLP prevails with the best performance overall of the other methods in all the input subsets.

Table 14: Results from the regression methods using the average body results and head displacement as target.

Input Subsets	Metrics	Random Forest	SVM	kNN	Linear Regression	MLP 1	MLP 2
1	RMSE	19.94	21.76	32.36	67.98	52.90	25.03
	R2	0.99	0.99	0.97	0.87	0.93	0.99
	MAE	14.42	16.31	21.87	53.53	39.11	18.92
2	RMSE	46.38	55.00	70.28	90.46	89.51	36.06
	R2	0.94	0.92	0.84	0.75	0.75	0.97
	MAE	18.43	9.24	24.78	51.99	30.85	21.76
3	RMSE	27.53	33.14	41.46	73.69	62.09	27.06
	R2	0.98	0.97	0.95	0.85	0.89	0.98
	MAE	15.36	21.98	26.12	58.38	47.41	19.80
4	RMSE	19.81	32.66	54.82	82.98	77.63	20.32
	R2	0.99	0.97	0.91	0.80	0.82	0.99
	MAE	14.33	22.98	36.22	67.43	60.88	14.26

Table 15: Results from the regression methods using the average body results and the head displacement as target.

Input Subsets	Metrics	Random Forest	SVM	kNN	Linear Regression	MLP 1	MLP 2
1	RMSE	32.22	41.19	68.51	85.62	82.29	80.10
	R2	0.97	0.95	0.86	0.79	0.80	0.81
	MAE	17.07	26.55	41.46	67.08	62.55	60.75
2	RMSE	128.24	127.12	128.70	124.04	123.62	123.65
	R2	0.38	0.56	0.34	0.39	0.39	0.39
	MAE	104.46	94.09	108.59	106.09	105.86	105.76
3	RMSE	97.41	98.62	100.44	103.47	100.36	100.34
	R2	0.71	0.74	0.67	0.65	0.67	0.67
	MAE	68.43	66.10	74.31	83.80	79.96	80.11
4	RMSE	55.50	64.20	88.98	107.37	106.94	106.92
	R2	0.91	0.88	0.71	0.60	0.60	0.60
	MAE	28.60	39.01	63.35	89.06	88.95	88.91

Table 16: Classification methods using the average, minimum and maximum body results.

Input Subsets	Metrics	Random Forest	Decision Tree	SVM	kNN	Naive Bayes	Logistic Regression	MLP
1	Accuracy	0.91	0.83	0.92	0.93	0.84	0.94	0.95
	Precision	0.62	0.39	0.65	0.74	0.42	0.71	0.82
	Recall	0.68	0.73	0.75	0.67	0.96	0.76	0.74
	F1	0.65	0.50	0.70	0.70	0.59	0.73	0.78
	AUC	0.81	0.79	0.85	0.82	0.89	0.86	0.86
2	Accuracy	0.88	0.92	0.91	0.92	0.85	0.93	0.93
	Precision	0.00	0.64	0.61	0.66	0.44	0.68	0.72
	Recall	0.00	0.75	0.66	0.63	0.95	0.73	0.72
	F1	0.00	0.69	0.64	0.64	0.60	0.70	0.72
	AUC	0.50	0.85	0.80	0.79	0.89	0.84	0.84
3	Accuracy	0.91	0.92	0.92	0.92	0.85	0.93	0.94
	Precision	0.84	0.63	0.66	0.69	0.43	0.71	0.73
	Recall	0.30	0.74	0.68	0.61	0.94	0.73	0.76
	F1	0.44	0.68	0.67	0.65	0.59	0.72	0.74
	AUC	0.64	0.84	0.82	0.79	0.89	0.84	0.86
4	Accuracy	0.91	0.83	0.93	0.94	0.84	0.94	0.95
	Precision	0.61	0.38	0.68	0.74	0.42	0.72	0.80
	Recall	0.68	0.72	0.76	0.71	0.96	0.77	0.77
	F1	0.64	0.50	0.72	0.73	0.59	0.74	0.78
	AUC	0.81	0.78	0.85	0.84	0.89	0.86	0.87

Table 17: Classification methods using the average body results.

Input Subsets	Metrics	Random Forest	Decision Tree	SVM	kNN	Naive Bayes	Logistic Regression	MLP
1	Accuracy	0.88	0.93	0.94	0.94	0.88	0.93	0.95
	Precision	0.00	0.66	0.76	0.76	0.50	0.72	0.82
	Recall	0.00	0.75	0.73	0.71	0.90	0.73	0.76
	F1	0.00	0.70	0.75	0.74	0.65	0.72	0.79
	AUC	0.50	0.85	0.85	0.84	0.89	0.84	0.87
2	Accuracy	0.88	0.85	0.90	0.89	0.89	0.89	0.91
	Precision	0.00	0.39	0.60	0.52	0.55	0.57	0.70
	Recall	0.00	0.46	0.34	0.38	0.52	0.41	0.38
	F1	0.00	0.42	0.44	0.44	0.53	0.48	0.49
	AUC	0.50	0.68	0.66	0.67	0.73	0.69	0.68
3	Accuracy	0.88	0.86	0.89	0.88	0.88	0.89	0.91
	Precision	0.00	0.40	0.54	0.50	0.50	0.54	0.69
	Recall	0.00	0.46	0.38	0.40	0.66	0.38	0.39
	F1	0.00	0.43	0.45	0.44	0.57	0.44	0.50
	AUC	0.50	0.68	0.67	0.67	0.79	0.67	0.68
4	Accuracy	0.90	0.92	0.94	0.94	0.89	0.94	0.95
	Precision	1.00	0.66	0.74	0.76	0.51	0.73	0.80
	Recall	0.15	0.74	0.79	0.70	0.91	0.76	0.76
	F1	0.26	0.70	0.77	0.73	0.66	0.74	0.78
	AUC	0.57	0.85	0.88	0.84	0.90	0.86	0.87

Using head displacement as target the results are being shown in the Tables 18 and 19, the best results came from the MLP in all the input subsets overcoming the other methods, mainly with the input subset 4.

Table 18: Classification methods using the average, minimum and maximum body results.

Input Subsets	Metrics	Random Forest	Decision Tree	SVM	kNN	Naive Bayes	Logistic Regression	MLP
1	Accuracy	0.88	0.96	0.98	0.96	0.83	0.96	0.98
	Precision	0.95	0.87	0.91	0.88	0.45	0.84	0.97
	Recall	0.22	0.87	0.92	0.84	0.84	0.88	0.92
	F1	0.36	0.87	0.92	0.86	0.59	0.86	0.94
	AUC	0.61	0.93	0.95	0.91	0.83	0.93	0.96
2	Accuracy	0.85	0.96	0.96	0.95	0.88	0.94	0.97
	Precision	0.00	0.87	0.84	0.84	0.55	0.80	0.92
	Recall	0.00	0.84	0.91	0.78	0.83	0.83	0.87
	F1	0.00	0.86	0.87	0.81	0.66	0.81	0.89
	AUC	0.76	0.95	0.99	0.94	0.83	0.94	0.98
3	Accuracy	0.50	0.91	0.94	0.88	0.86	0.90	0.93
	Precision	0.86	0.96	0.97	0.95	0.85	0.95	0.98
	Recall	1.00	0.88	0.88	0.86	0.50	0.83	0.91
	F1	0.08	0.85	0.94	0.82	0.84	0.87	0.92
	AUC	0.14	0.87	0.91	0.84	0.63	0.85	0.91
4	Accuracy	0.92	0.96	0.98	0.96	0.83	0.95	0.98
	Precision	0.88	0.85	0.93	0.89	0.46	0.83	0.96
	Recall	0.53	0.88	0.92	0.84	0.84	0.84	0.92
	F1	0.66	0.87	0.93	0.86	0.59	0.84	0.94
	AUC	0.76	0.93	0.96	0.91	0.83	0.91	0.96

5.2 Second Experiment

This section is about the second experiment performed. At the beginning of this experiment, we needed to choose the machine learning method and also the input subset with the best results, this choice was made based on the analysis done in the first experiment. In general, in the first experiment, the best results we got came from the multilayer perceptron for the regression and classification methods, using the configuration of three hidden layers each with 10 neurons and activation function *relu*.

The input subset was chosen to be used as subset four. For the regression methods, we applied different approaches, one using a normal application of a regression model trying to predict the value and another analysis using post-labeling. Later, with these results, we could see if even with an output different from the actual value we could classify the outcome into critical or non-critical with the threshold values, 60g for chest acceleration and 650mm for head displacement.

5.2.1 Normal Data

Regression The results with the regression method for the first approach are firstly showed in the Figure 6a and 6b where we have the result using as target the chest acceleration. The Figures 6c and 6d are the results for the usage of head displacement as the target of the methods. The regression results for this approach are not good, because as we can see in those figures the error values are high where the methods just had the better performance using environments 1 and 6 for training.

The results for the regression post-labeling method are exposed in the Figure 7a for the standard body configurations and 7b for the average body, showing the results using as target the chest acceleration. The Figures 7c for the standard body configurations and 7d for the average body,are the results for the usage of head displacement as the target of the methods. The regression results for the post labeling approach are not better than the first one, because as we can

Table 19: Classification methods using the average body results.

Input Subsets	Metrics	Random Forest	Decision Tree	SVM	kNN	Naive Bayes	Logistic Regression	MLP
2	Accuracy	0.85	0.97	0.99	0.96	0.91	0.96	0.98
	Precision	0.00	0.91	0.94	0.89	0.64	0.84	0.94
	Recall	0.00	0.89	0.96	0.85	0.82	0.87	0.94
	F1	0.00	0.90	0.95	0.87	0.72	0.86	0.94
	AUC	0.50	0.94	0.97	0.92	0.87	0.92	0.96
2	Accuracy	0.85	0.86	0.89	0.87	0.89	0.89	0.90
	Precision	0.00	0.53	0.59	0.56	0.65	0.65	0.62
	Recall	0.00	0.54	0.77	0.61	0.51	0.54	0.77
	F1	0.00	0.53	0.67	0.58	0.57	0.59	0.69
	AUC	0.50	0.73	0.84	0.76	0.73	0.75	0.84
3	Accuracy	0.85	0.87	0.91	0.89	0.89	0.90	0.92
	Precision	0.00	0.55	0.65	0.63	0.66	0.68	0.69
	Recall	0.00	0.58	0.81	0.67	0.51	0.61	0.78
	F1	0.00	0.56	0.72	0.65	0.57	0.65	0.74
	AUC	0.50	0.75	0.87	0.80	0.73	0.78	0.86
4	Accuracy	0.85	0.97	0.98	0.96	0.91	0.94	0.98
	Precision	0.00	0.91	0.90	0.90	0.65	0.78	0.94
	Recall	0.00	0.91	0.96	0.82	0.82	0.78	0.93
	F1	0.00	0.91	0.93	0.86	0.73	0.78	0.94
	AUC	0.50	0.94	0.97	0.90	0.87	0.87	0.96

(a)

(b)

(c)

(d)
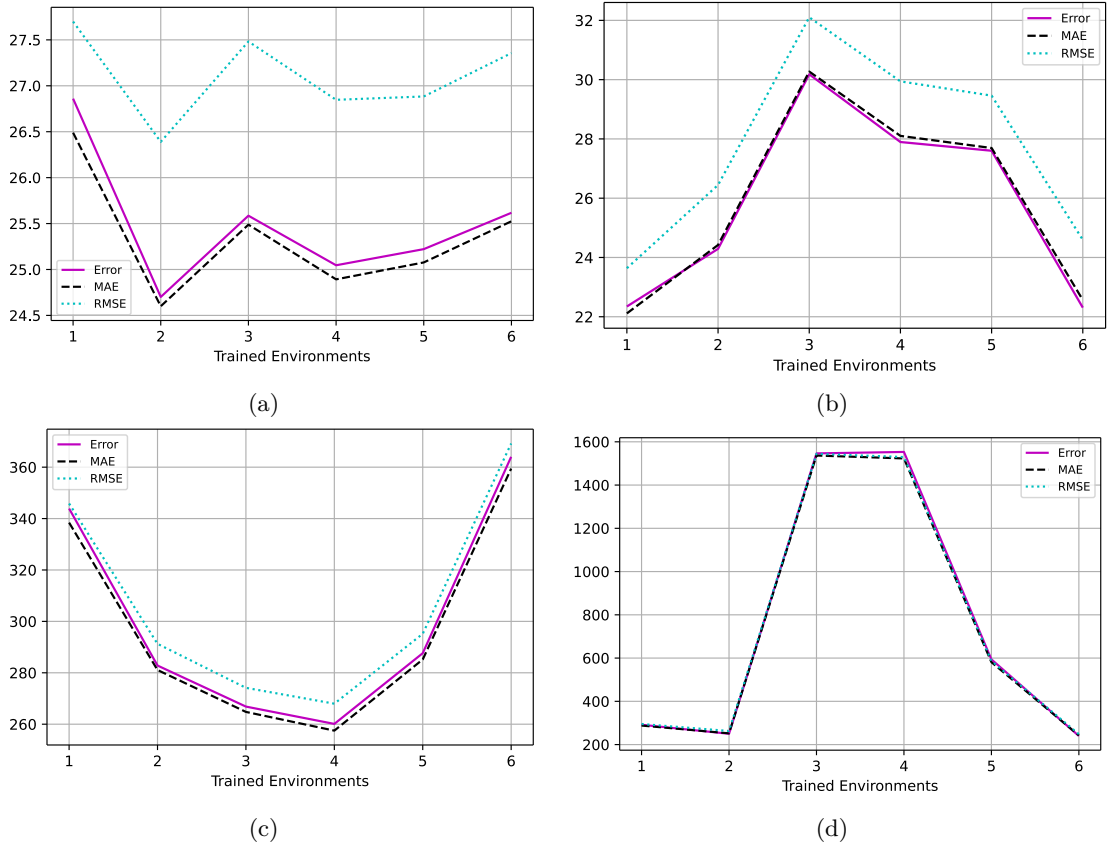
Figure 6: Scores by categories for each environment in the first regression approach and the normal database.

see in those figures the better results are when we used one environment for the training and the reason for that is the non-balanced distribution of the critical and non-critical cases (Figures 4a and 4b) affecting the model performance.

These figures are shown on the axis x the number of environments used to validate the model, and the axis y the error metric values. The number of environments trained doesn't mean that we used three specifical environments to train, but all the possible combinations between the seven we have. Therefore, the error metrics regard the error average of all models validated by all environment combinations.
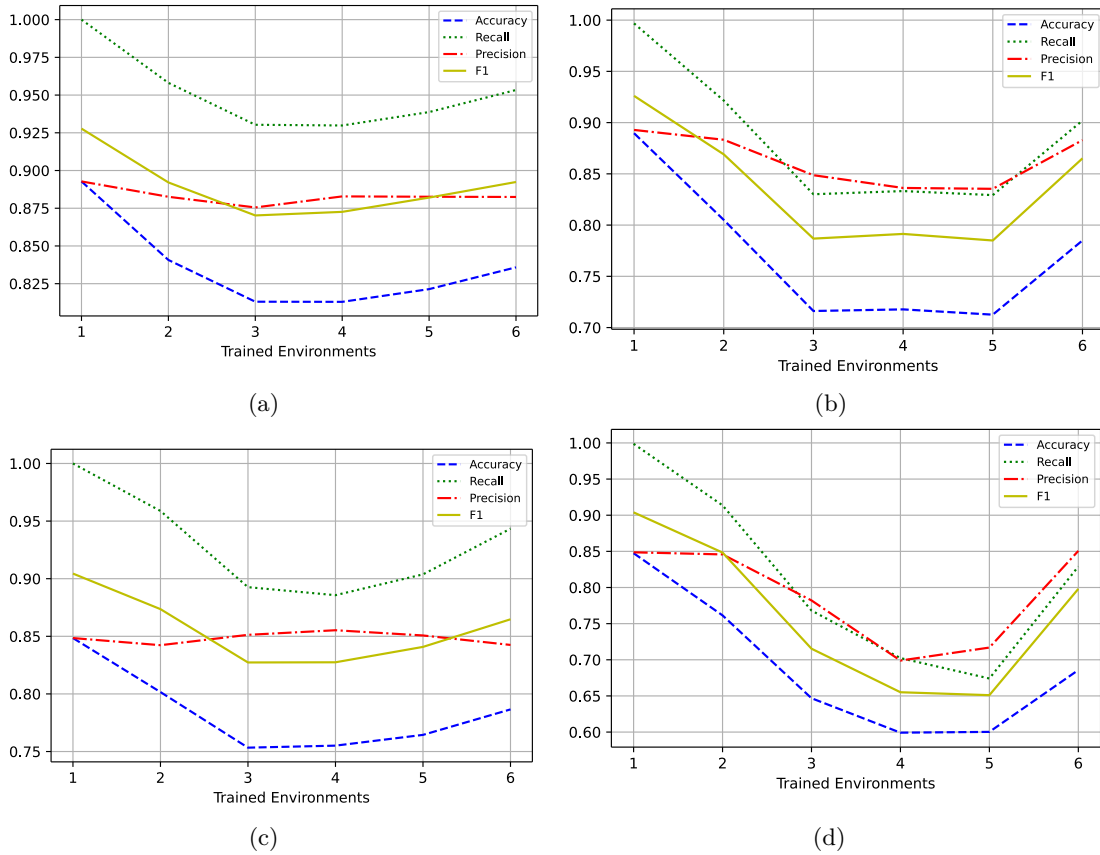
Figure 7: Scores by categories for each environment in the post labeling approach and the normal database.

Classification The second experiment showed good results with the classifier making good predictions. It can be seen in Figure 8a regarding the default body settings and Figure 8b for the average body using the thorax acceleration as the target. The figures 7c for the standard body configurations and 7d for the average body, are the results for using head displacement as the target. We can see that for target chest acceleration the results are better than head displacement as well because they make more sense when we see the curve increasing as the method increases the number of environments in the training, especially in Figures 8a and 8b.
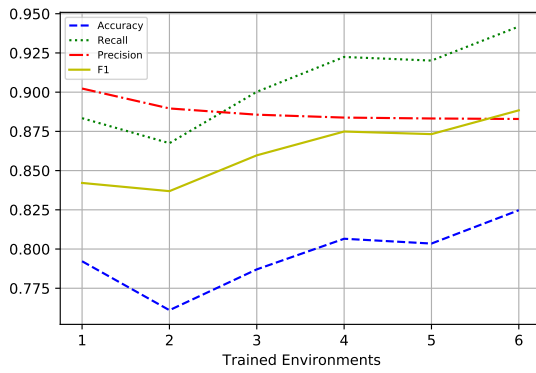
(a)
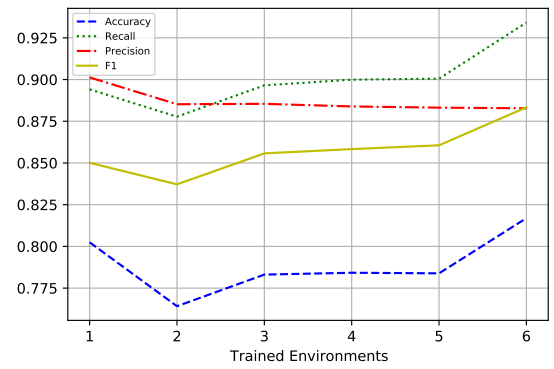
(b)
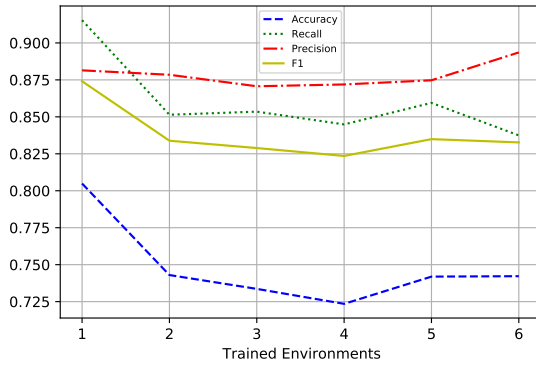
(c)
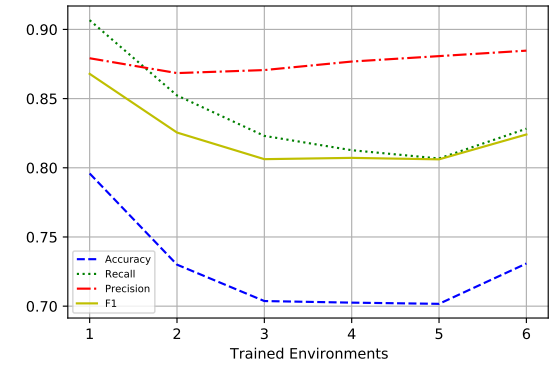
(d)

Figure 8: Scores by categories for each environment in the classification method and the normal database

5.2.2 Noise Data

Regression The results with the regression method with the data with noise and for the first approach are firstly showed in the Figure 9a and 9b where we have the result using as target the chest acceleration. The Figures 9c and 9d are the results for the usage of head displacement as the target of the methods. The regression results for this approach are better than the methods that used the normal database regarding the shape of the curves and the error values are lower. We can see in the Figure 9b and 9d has lower errors using six environments for the training and validation than using just one, what makes sense if you think in the case that you are giving more data for the model on the training stage.
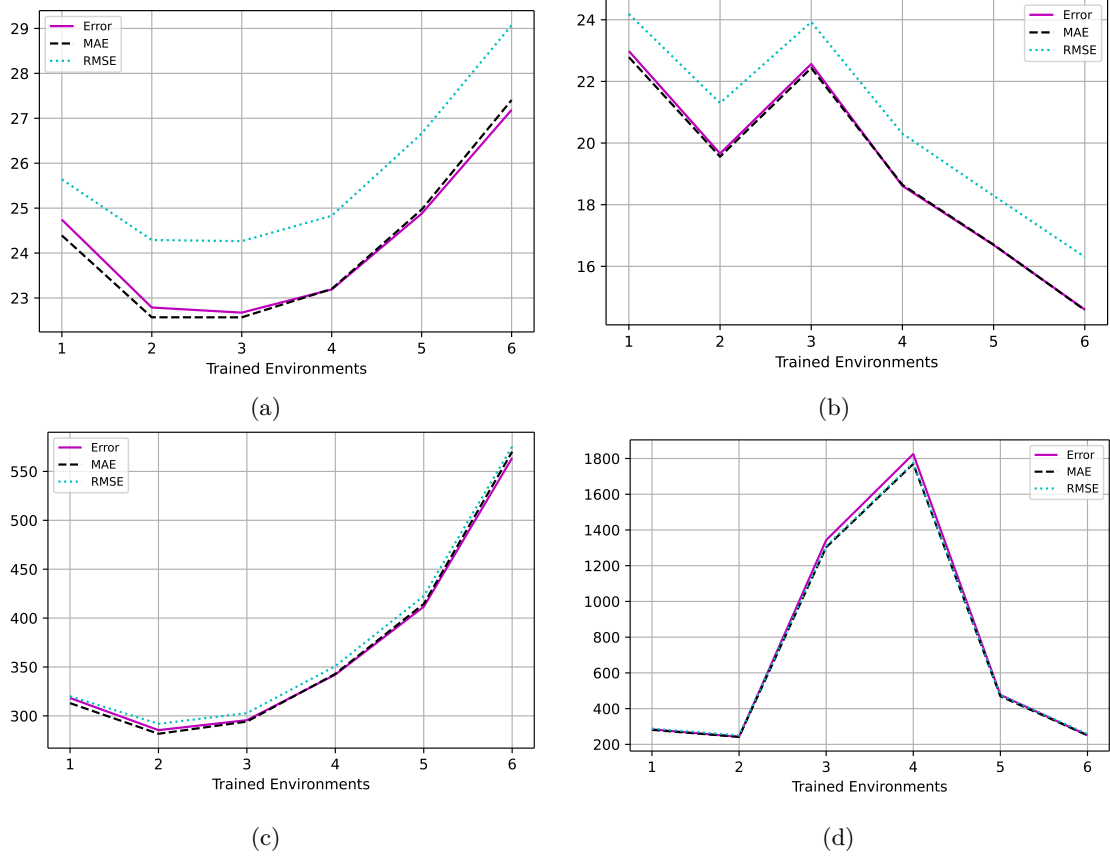
Figure 9: Scores by categories for each environment in the first regression approach and the noise database.

The results for the regression post labeling method are exposed in the Figure 10a for the standard body configurations and 10b for the average body, showing the results using as target the chest acceleration. The Figures 10c for the standard body configurations and 7d for the average body,are the results for the usage of head displacement as the target of the methods. The regression results for the post-labeling approach are worst than the first one using the normal database because as we can see in those figures the better results are when we used one environment, in other words, is the same problem that we had with the normal data.

Classification It's possible to see the results for the noise data of the second experiment in the Figure 11a regarding the standard body configurations and 11b for the average body using the chest acceleration as the target. The Figures 11c for the standard body configurations and 11d for the average body,are the results for the usage of head displacement as the target. We can see that for the chest acceleration as target the results are better than the head displacement also because they make more sense, when we see the curve increasing while the method increases the
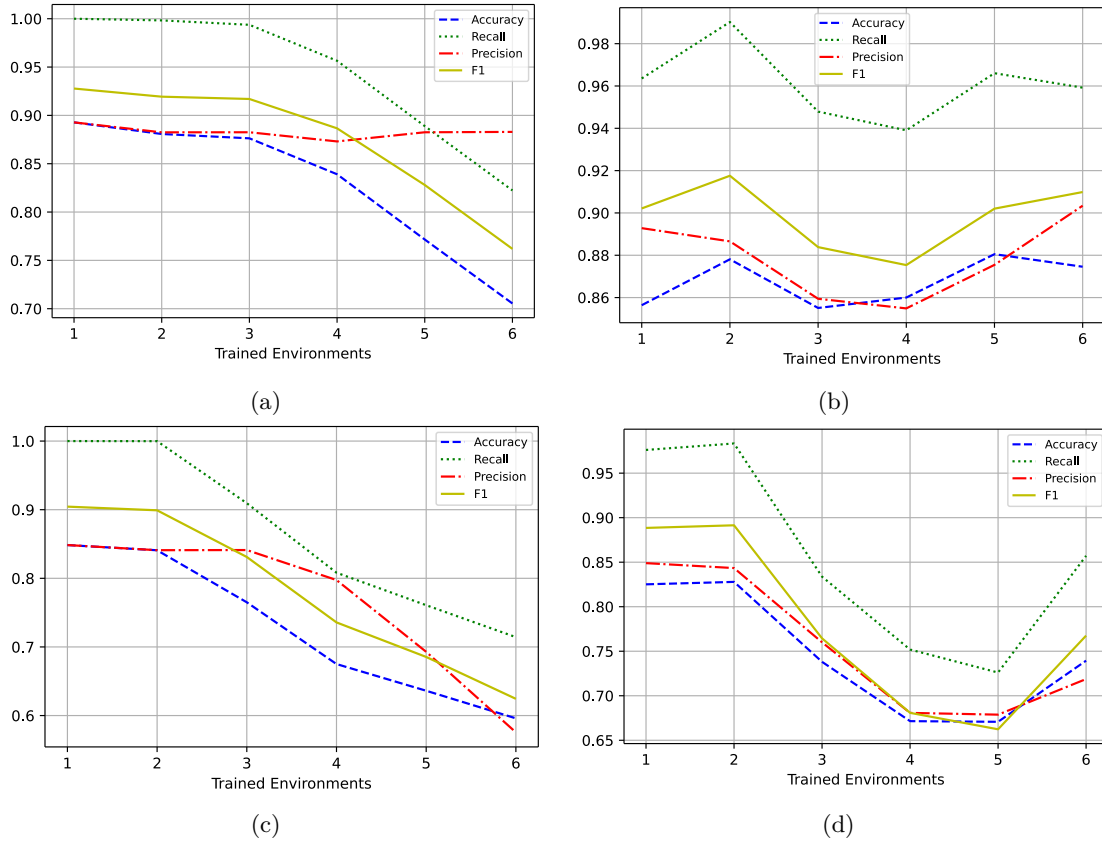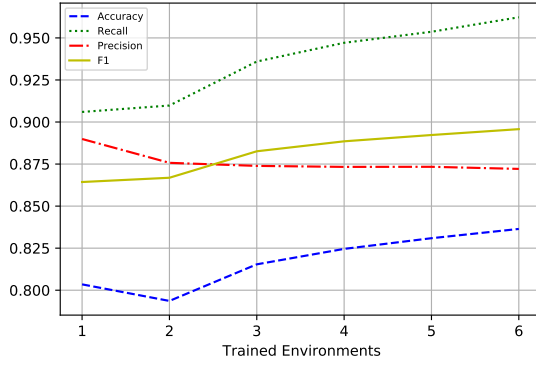
Figure 10: Scores by categories for each environment in the post labeling approach and the noise database.

number of environments on the training especially in the Figures 8a and 8b.

With the Figures 7c, 7d, 11b and 11a we can see that the best results were achieve with six environment trained, but we can also accept that with three environments it's possible to validate the model to predict new data. The other point here is that the results for both body results approach are good and if you use more data as input means more information for the model consequently bring better performance for the models.

All those results presented in this section could give us some conclusions about the best methods and the reasons why the results for the regression methods and the results using just one environment on the validation of the methods at the most of the time are worst than the others.

The reason why the regression methods had the worst performance than the classification methods it's because the distribution of the database created by the FE simulations split the results into two distinguished classes creating a gap between them. The consequence of that is the problem that we had with some models with better performance using just one environment at the validation stage, because some environments have just non-critical cases, being easy for the model with one environment to predict the classes of this environment in case.
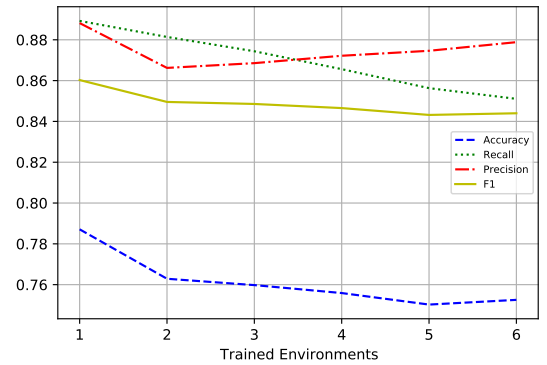
18
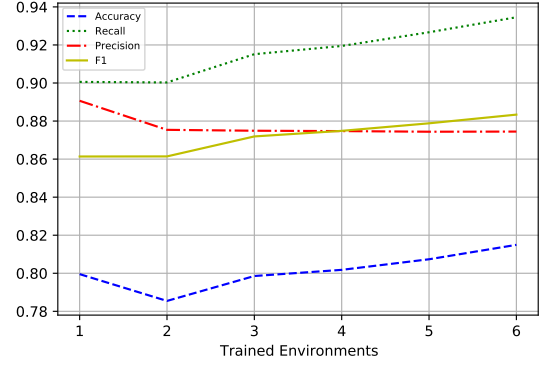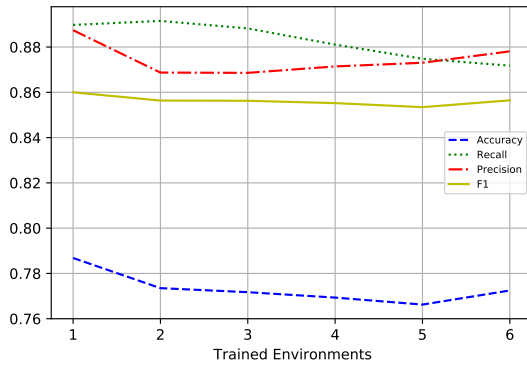
Figure 11: Scores by categories for each environment with the classification methods and the noise database.

6 Conclusion

As a conclusion, for now, the classification approach detain a better performance than the others in the second experiment, and in the first experiment the performance of both, regressor and classifier methods are very similar. With the obstacle found with the development of this work, we can say that the problem to be solved with this project is a classification problem.

As a final conclusion of this work, it's possible to predict the car crash as critical or non-critical for body configurations that the meta-model doesn't know, but that are in one of the environments that the meta-model knows. About the usage of the results of all standard body configurations or just the average, it's feasible to use just the average but have in mind that use more data as input is always better.

For future work the question is "What can be improved ?", first the complexity of the Finite Element Model, the second is create a meta-model with varied dummy body configurations (*5th*, *50th*, *95th*) and different configurations of the Finite Element Simulations to create a better distribution of the database. The last point would be to make an analysis comparing the performance of the meta-models using different databases.