# Using Machine Learning to Predict Poverty Status in Costa Rican Households

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Abstract – This study presents two supervised multiclassification machine learning models to predict the poverty status of Costa Rican households as a way to support government and business sectors make decisions in a rapidly changing social and economic environment. Using the Costa Rican household dataset collected via the proxy means test conducted by the Inter-American Development Bank, Random Forest and Gradient Boosted Trees achieved F1 scores of 64.9% and 68.4%, respectively. This study also reveals that education has the greatest impact on predicting poverty status.

Keywords – Poverty Prediction, Supervised Machine Learning, Multiclassification, Random Forest, Gradient Boosted Trees

# I. INTRODUCTION

Over the past two decades, Costa Rica has removed their foreign investment restrictive measures and liberalized their international trade policies [1]. These efforts have brought economic growth to Costa Rica and have led Costa Rica to become an upper-middle-income country. According to the World Bank Group [1], when the poverty line of upper-middle-income countries was set to \$5.50 per day, Costa Ricans with incomes below the poverty line decreased, from 12.9% in 2010 to 10.6% in 2019. Despite strong economic growth, Costa Rica has recently been experiencing economic hardships due to the COVID-19 pandemic. Costa Rica's gross domestic product (GDP) decreased by 4.1% in 2020. A sharp increase in unemployment pushed an estimated 124,000 people into poverty, which raised the poverty rate to 13.0% in the same year [1].

To minimize the social and economic impacts of unexpected crises, it is necessary to consider introducing data-driven technology capable of making dynamic predictions. According to the United Nations Development Programme (UNDP) [2], traditional statistical methods may require two years of data collection and analysis to predict poverty. Machine learning will be a great way to empower government and business sectors to make more intelligent and strategic decisions, ultimately supporting the lives of vulnerable people in society and leading towards a sustainable future.

To build a machine learning model for poverty prediction, this study referenced a research paper titled "Poverty Classification Using Machine Learning: The Case of Jordan," which presents a machine learning model to predict poverty among Jordanian households [3]. Alsharkawi *et al.* [3] implemented a classification model that is robust enough to deal with changes in political, social, and economical factors. This study achieved an F1 score of 81.0% using Gradient Boost implemented with Light GBM, which is an acceptable level of accuracy compared to the average F1 score of 87.1% among poverty prediction classification models (i.e., Naïve Bayes, Decision Tree, K-Nearest Neighbors, Logistic Regression, and ID3) in other countries (i.e., Lagangilang, Abra, and Philippines) [4]. This paper aims to build a machine learning model to predict the poverty status of Costa Rican households.

# II. EXPLORATORY DATA ANALYSIS

In this study, the Inter-American Development Bank's Costa Rican household dataset was used to build a machine learning model for predicting the poverty status of Costa Rican households. The dataset was compiled through a proxy means test that includes questionnaires related to household composition, observable characteristics of the household (e.g., material of roof), and ownership of electronic devices.

As shown in **Appendix - Exhibit 1**, the dataset has 143 columns (i.e., a mix of categorical and numerical variables) and 9,557 rows. Of the 143 variables, the variable titled "Target" is used as a dependent variable to predict poverty status. This variable consists of four classes (i.e., extreme poverty, moderate poverty, vulnerable households, and non-vulnerable households). To examine whether the dataset is imbalanced, univariate analysis is conducted. As shown in **Exhibit 2**, of the 9,557 survey participants, 5,996 were non-vulnerable households. This represents about 62.7% of the total, which indicates that this is the majority class of the dataset.

#### EXHIBIT 2. DEPENDENT VARIABLE UNIVARIATE ANALYSIS



As shown in **Exhibit 3**, 6,829 of the 9,557 survey participants live in urban areas, which represents about 71.4% of the total.

EXHIBIT 3. GEOGRAPHICAL REPRESENTATION OF THE SAMPLES



As shown in **Appendix - Exhibit 1**, seven variables (i.e., v2a1, v18q1, dependency, edjefe, edjefa, meaneduc, and SQBmeaned) have missing values. In particular, v2a1 and v18q1 have estimated missing values percentages of 72.0% and 75.0%, respectively.

# III. APPROACH

In this study, five models are considered (i.e., Decision Tree, Random Forest, Gradient Boosted Trees, Naïve Bayes, and K-Nearest Neighbors).

# A. Decision Tree

# EXHIBIT 4. DECISION TREE STRUCTURE



A Decision Tree is a model that utilizes the tree-like model for analyzing and forecasting the data. The tree consists of the root node, internal nodes, and leaf nodes, and is recursively split into sub-trees [5]. A Decision Tree is one of the most widely used machine learning models because the model can handle categorical and numerical datasets, as well as a mix of categorical and numerical datasets. It can also be applied by non-expert users more easily than other machine learning models, as it requires less skill in data pre-processing, and because the model has a built-in resistance to outliers [6]. Decision Trees can be utilized for datasets with missing values; many studies have found the method to work with such datasets [7], [8]. However, because Decision Trees require careful parameter tuning to prevent the model from becoming biased towards the majority class [9], they were not used in this study.

#### B. Random Forest

EXHIBIT 5. RANDOM FOREST STRUCTURE [10]



Random Forest creates multiple independent trees using a random sample of data and aggregates trees that are created using a Decision Tree model. By aggregating the results of different trees into one result, Random Forest can limit overfitting without increasing errors that are caused by bias [11]. As Decision Trees can be utilized to overcome missing values, Random Forest is also a well-known algorithm that can handle datasets with missing values. Because Random Forest can decrease the risk of overfitting [12], and because it works well with non-linear data [13], it was used in this study to predict the poverty status of Costa Rican households.

# C. Gradient Boosted Trees

EXHIBIT 6. GRADIENT BOOSTED TREES STRUCTURE [14]



Gradient Boosted Trees can be used to improve the predictive performance of a Decision Tree. Gradient Boosted Trees generate the trees sequentially, and new trees correct previously trained trees iteratively [15], [16]. Gradient Boosted Trees are prone to overfitting, as they develop the models based on the previous trees. However, regularization parameters (e.g., learning rate or shrinkage parameter) prevent overfitting by controlling the amount of information coming from previously fitted trees when forming new trees [17]. Various algorithms can be applied to Gradient Boosted Trees to handle the missing

values in the datasets, allowing Gradient Boosted Trees to minimize loss functions and the risks of under/overfitting [18]. Because Gradient Boosted Trees' ability in "minimizing some loss function" makes it "to be more accurate than some more theoretically intensive predictive models" [17, p. 9], Gradient Boosted Trees were used in this study.

# D. Naïve Bayes

EXHIBIT 7. NAÏVE BAYES STRUCTURE

$$P(A|B_1 \cap B_2 \cap \dots \cap B_n) = \frac{P(B_1|A)P(B_2|A)\cdots P(B_n|A)P(A)}{P(B)}$$

The Naïve Bayes is a popular algorithm in machine learning because it can be used with large datasets efficiently, and it can be interpreted easily. However, as the word *naïve* suggests, Naïve Bayes assumes that the features are independent [7]. Also, special consideration is needed when using Naïve Bayes with datasets that have both numerical and categorical variables [19]. Thus, the Naïve Bayes was not used in this study, due to the limitations of the model.

# E. K-Nearest Neighbors

**EXHIBIT 8.** K-NEAREST NEIGHBORS WITH EUCLIDEAN DISTANCE STRUCTURE

$$\sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

K-Nearest Neighbors can be implemented simply because it is a non-parametric algorithm. It does not require training steps, as it does not build any models [20]. "Instead an observation is predicted to be the class of that of the largest proportion of the k nearest observations" [21, p. 251]. Because K-Nearest Neighbors is sensitive to outliers [22], it was not used in this study.

#### IV. DATA PRE-PROCESSING

# A. Cleaning and Wrangling the Dataset

As shown in **Appendix - Exhibit 9**, multiple individual variables with similar characteristics are merged into one variable. As a result, 18 new variables are formed, and they are encoded as dummy variables along with other ungrouped binary categorical variables.

The age variable is a continuous data type, with a range from 0 to 100. This variable is divided into six groups (i.e., children, adolescents, young adults, adults, middle-aged adults, and old adults). These ordinal groups are mapped with unique labels to transform them from continuous to categorical data types. Because inaccurate binning can add bias to the dataset,

numerical variables with dependent relationships to other variables remain as numerical variables.

The dataset is reorganized according to the following criteria. First, when multiple variables contain the same values under different variable names<sup>1</sup>, only one variable remains and the rest of the variables are deleted. Second, when the same property <sup>2</sup> is expressed in two different data types (i.e., categorical and numerical), and when multiple variables are similar to each other<sup>3</sup>, the variable containing more meaningful information is retained. Third, variables that contain limited information<sup>4</sup> are removed from the dataset.

Of the seven variables with missing values (i.e., v2a1, v18q1, dependency, edjefe, edjefa, meaneduc, and SQBmeaned), two (i.e., v2a1 and v18q1) were deleted from the dataset. Deleting variables can cause a loss of information and introduce bias into the model [21]; however, the proportion of missing values for both variables was too large to be replaced with statistical values (i.e., mean, median, and mode). The remaining four<sup>5</sup> variables (i.e., dependency, edjefe, edjefa, and meaneduc) were replaced with the median value of the variable. Replacing missing values with the median value is not the most accurate approach, so other techniques (e.g., predicting missing values using algorithms) can be considered in future studies.

As shown in **Appendix - Exhibit 9**, 125 variables were used to build the model after data cleaning and wrangling. Among these variables, 17 (i.e., rooms, r4h1, r4h2, r4h3, r4m1, r4m2, r4m3, r4t1, r4t2, r4t3, escolari, rez\_esc, dependency, edjefe, edjefa, meaneduc, and overcrowding) are numerical variables, either discrete or continuous data types. To examine their distribution and skewness, these variables were individually plotted, as shown in **Appendix - Exhibit 10**.

## B. Rescaling the Dataset

Normalization and standardization were performed to rescale the distribution of numerical variables. Standardization was used to rescale numerical variables, except dependency variables. Normalization was performed on dependency variables, as they had lower and upper bounds of 0% and 100%.

# EXHIBIT 11. NORMALIZATION EQUATION

$$x'_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

Normalization rescaled variables to fit within the range of 0 to 1. Max(x) indicates maximum values, and min(x) indicates minimum values [21].

<sup>&</sup>lt;sup>1</sup> For example, tamhog, tamviv, Hhsize, hogar\_total are variables representing the number of household members.

<sup>&</sup>lt;sup>2</sup> For example, mobilephone is a categorical variable representing whether the participant has a mobile phone, and Qmobiliephone is a discrete variable representing how many mobile phones the household has.

<sup>&</sup>lt;sup>3</sup> For example, r4h1 is a variable representing the number of children under the age of 12 years in the household, and hogar\_nin is a variable representing the number of children between the ages of 0 and 19 in the household.

<sup>&</sup>lt;sup>4</sup> For example, Id is a variable representing survey participants' identification number.

<sup>&</sup>lt;sup>5</sup> SQBmeaned was deleted based on dataset reorganization criteria.

EXHIBIT 12. STANDARDIZATION EQUATION

$$x_i' = \frac{x_i - \bar{x}_i}{\sigma}$$

Standardization rescaled variables into a normal distribution, with means of 0 and standard deviations of 1.  $\bar{x}$  indicates the mean of the variable, and  $\sigma$  indicates the standard deviation of the variable [21].

#### C. Reducing the Dimensionality of the Dataset

After normalization and standardization, Principal Component Analysis (PCA) was performed to "reduce the dimensionality (number of variables) of the dataset but retain most of the original variability in the data" [23, p. 5]. As shown in **Exhibit 13**, the amount of explained variance above 60 principal components is very low.



#### EXHIBIT 13. EXPLAINED VARIANCE RATIO OF COMPONENTS

#### V. DATA MODELLING

Some important findings were made during exploratory analysis and data cleaning and wrangling. First, the model should be able to deal with the supervised multiclassification problem. Second, the model should be able to work with heterogeneous datasets (i.e., a mix of categorical and numerical variables). Third, the model should excel in processing outliers and missing values. Therefore, Random Forest and Gradient Boosted Trees were selected from the five previously considered models to predict the poverty status of Costa Rican households. Before building models, the study randomly split the dataset into train and test sets. The train set comprises 80% of the dataset, while the test set comprises the other 20%.

#### VI. EVALUATION

Because the dataset is imbalanced, stratified five-fold crossvalidation was performed on the train set to determine the generalized performance of the model. Stratified crossvalidation helps ensure "that the proportions between classes are the same in each fold" [24, p. 255]. The accuracy of the Random Forest model is 76.0%, while the accuracy of the Gradient Boosted Trees model is 77.6%.

To determine the models' predictive power on the test set, accuracy was calculated. The accuracy of Random Forest and Gradient Boosted Trees is 78.1% and 79.6%, respectively.

Because the models are built on an imbalanced dataset, other performance evaluation methods (i.e., F1, recall, and precision) were used to compare the performance of the model under different metrics. As shown in **Exhibit 14**, the Random Forest model achieved the highest score with 88.5%, followed by Gradient Boosted Trees with 82.4%. Random Forest performed well in the precision method, while it underperformed Gradient Boosted Trees in the recall method. Therefore, F1 was used, as this measure provides "the harmonic mean of precision and recall" [4, p. 13]. Gradient Boosted Trees achieved an F1 score of 68.4%, and Random Forest achieved a score of 64.9%.

**EXHIBIT 14**. MULTICLASSIFICATION MODELS PERFORMANCE RESULTS

Model	Accuracy	F1	Recall	Precision
Random Forest	78.1	64.9	56.9	88.5
Gradient Boosted Trees	79.6	68.4	61.7	82.4

Performance evaluation metrics do not yield the same result as data balancing. Therefore, the most accurate approach will involve equally weighting all four classes through databalancing techniques (e.g., over-sampling, under-sampling, the synthetic minority over-sampling technique (SMOTE), and class weights) during the data pre-processing. These techniques can be explored further in future studies.

# VII. FEATURE IMPORTANCE

Because Gradient Boosted Trees achieved a higher F1 score than Random Forest, feature importance analysis was performed on Gradient Boosted Trees to determine which variables had the greatest effect on the model. As shown in **Exhibit 15**, the meaneduc variable (i.e., average years of education for adults) was found to be the most impactful variable.

EXHIBIT 15. TOP THREE IMPORTANT COMPONENTS



This study has several limitations. First, although the dataset was assembled by a credible organization, the Inter-American Development Bank, some information (e.g., the data collection period and dataset creation time) is unavailable; therefore, it is difficult to understand what kinds of variance are included in the dataset. Second, Costa Rica's population in 2020 was 5,094,114 [25], but the size of the dataset used in this study is 9,557. The small sample size suggests that the population's characteristics may not be adequately represented in the dataset. However, the historical patterns of poverty among Costa Rican households and the percentage of urban populations agree with the dataset. As this dataset was originally published by the Inter-American Development Bank to develop a machine learning model to predict poverty status, this study assumes that collected samples truly reflect the population of Costa Rica. If the collected sample does not reflect the population demographics for some reason (e.g., the sample is collected from the specific regions, or the sample is collected from the specific target), the research findings would less closely reflect the population.

Along with the limitations of the dataset itself, due to resource and time constraints, several important techniques could not be performed. In future studies, these approaches can be applied to improve poverty status prediction.

# A. Handling Missing Values

In this study, two variables (i.e., v2a1 and v18q1) with a significant amount of missing values were deleted, and the missing values of four variables (i.e., dependency, edjefe, edjefa, and meaneduc) were replaced with the median value of those variables. However, these methods are not the most accurate techniques for handling missing values. Because inaccurate data cleaning and wrangling techniques can introduce bias or reduce variance in the dataset, it is important to pre-distinguish the types of missing values (e.g., missing completely at random, missing at random, and missing not at random). Another approach involves predicting the approximate value of missing values using algorithms (e.g., K-Nearest Neighbors). These more precise techniques will correct the reduction in accuracy caused by mishandling missing values.

# B. Handling Dataset Imbalance

As mentioned earlier, among the four classes, the nonvulnerable class comprises approximately 62.7% of the dataset. This indicates that the dataset is imbalanced. Therefore, the dataset has to be balanced to prevent the machine learning model from becoming biased towards the majority class. There are four methods to balance the dataset. The first method is random under-sampling. Random under-sampling will "randomly delete examples in the majority class" [26, p. 113]. The disadvantage of random under-sampling is that "this method can discard potentially useful data that could be important for the induction process" [27, p. 2]. The second method is random over-sampling. Random over-sampling will "randomly duplicate examples in the minority class" [26, p. 113]. Random over-sampling has its own disadvantages as well. Random over-sampling does not "add any new information" to the model, as it involves "duplicating examples in the minority class" [26, p. 121]. To overcome the disadvantages of random over-sampling, SMOTE was invented by researchers. SMOTE "synthesizes new examples for the minority class" [26, p. 121]. However, SMOTE can potentially add noise to the model, as synthetic minority examples are formed with different minority class examples [26]. Lastly, class weights can be used to equally weigh all four data classes. This technique places different weights on each class to emphasize the minority class [3]. All four techniques have their advantages and disadvantages; therefore, future studies can apply these techniques to the model to find the best performing databalancing method.

# C. Tuning Model Performance

As shown in **Exhibit 14**, performance varies between the four evaluation metrics. Recall and F1 underperform training accuracy, while accuracy and precision outperform training accuracy. Because the dataset is imbalanced, not all classes may be classified equally. The other possibility is that the test set may represent a localized portion of the train set, as it comprises only 20% of the dataset. However, these are just two of many possible explanations for its performance. In future studies, further examination (e.g., building separate one-versus-rest classifiers to review the performance of each class) can be conducted to clearly distinguish factors that may cause under/overfitting and to determine the generalized performance of the model.

# D. Implementing the Naïve Bayes

Other studies have proven that the Naïve Bayes works well in predicting poverty status [4]; therefore, future studies can consider implementing the Naïve Bayes. However, the Naïve Bayes performs well only when variables are independent. Social datasets contain variables that are sometimes highly correlated with each other, forming a dependent relationship. In the future studies, further feature engineering can be attempted to eliminate dependency between variables.

Assuming that independence can be established by eliminating dependency, two approaches can be considered in future studies for implementing the Naïve Bayes in predicting poverty status.

First, binning can be considered as a way to transform a heterogeneous dataset into a homogeneous dataset. Numerical variables can be binned to remove numeric attributes and transform them into categorical variables. However, variables grouped by unspecific criteria can introduce bias to the dataset; thus, binning can be conducted only when specific, objective, and clear criteria is available.

Second, if the dataset cannot be made homogenous, having a mix of categorical and continuous variables, special consideration is needed when implementing the Naïve Bayes classifier. Hsu *et al.* [19] developed the Extended Naïve Bayes (ENB) classifier, in which probabilities of categorical variables are calculated using the original method in the Naïve Bayes model, and variances of numerical variables are found using the statistical theory.

IX. CONCLUSION

In this study, a dataset collected through a proxy means test by the Inter-American Development Bank was used to predict the poverty status of Costa Rican households. Based on characteristics of the dataset (i.e., multiclassification, heterogeneous dataset, missing values, and outliers), Random Forest and Gradient Boosted Trees were selected to develop multiclassification poverty prediction models.

Before building Random Forest and Gradient Boosted Trees models, irrelevant or highly correlated variables were deleted, and missing values were replaced with the median value of the variable to simplify the dataset. Both normalization and standardization were used to rescale categorical and numerical variables. Also, PCA was performed to reduce the dimensionality of the dataset.

As a result, under the assumption that the dataset reflects the characteristics of Costa Rica's population, the Random Forest model achieved a 64.9% F1 score, while the Gradient Boosted Trees model achieved a score of 68.4%. However, in terms of F1 scores, these models underperformed the Jordanian model and the average of other models found in the literature.

Further, this study found that education (i.e., meaneduc) has the greatest impact on predicting the status. Finding a causal relationship between educational attainment and poverty was not a goal of this study, so further examination of this topic was not carried out. However, many prominent scholars have revealed that additional years of education increase individual income [28].

Despite their several limitations, both Random Forest and Gradient Boosted Trees demonstrated the ability to predict poverty status among Costa Rican households. Future studies could address the limitations described in this study to improve the performance of these models. Further, the models' robustness could be measured by adding a variety of social and economic factors into the dataset. Such efforts will continue after this study to strengthen the models, as this is an area of research with development potential.

X. APPENDIX A. EXHIBIT I. ORIGINAL DATASET WITH DESCRIPTIONS OF VARIABLES

#	Variable Name	Missing Values	Variable Description	
1	Id	0	Survey participant ID	
2	v2a1	6,860	Monthly rent payment	
3	hacdor	0	=1 overcrowding by bedrooms	
4	Rooms	0	# of all rooms in the house	
5	hacapo	0	=1 overcrowding by rooms	
6	v14a	0	=1 if the household has a toilet	
7	Refrig	0	=1 if the household has a refrigerator	
8	v18q	0	=1 if the household has a tablet	
9	v18q1	7,342	# of tablets household owns	
10	r4h1	0	# of males younger than 12 years of age	
11	r4h2	0	# of males 12 years of age and older	
12	r4h3	0	# of males in the household	
13	r4m1	0	# of females younger than 12 years of age	
14	r4m2	0	# of females 12 years of age and older	
15	r4m3	0	# of females in the household	
16	r4t1	0	# of persons younger than 12 years of age	
17	r4t2	0	# of persons 12 years of age and older	
18	r4t3	0	# of persons in the household	
19	tamhog	0	Household size	
20	tamviv	0	Household size	
21	escolari	0	# of years of schooling	
22	rez_esc	0	# of years behind in school	
23	Hhsize	0	Household size	
24	paredblolad	0	=1 if predominant material on the outside wall is block or brick	
25	paredzocalo	0	=1 if predominant material on the outside wall is socket (wood, zinc, or asbestos)	
26	paredpreb	0	=1 if predominant material on the outside wall is prefabricated or cement	
27	pareddes	0	=1 if predominant material on the outside wall is waste material	
28	paredmad	0	=1 if predominant material on the outside wall is wood	
29	paredzinc	0	=1 if predominant material on the outside wall is zinc	

#	Variable Name	Missing Values	Variable Description
30	paredfibras	0	=1 if predominant material on the outside wall is natural material
31	paredother	0	=1 if predominant material on the outside wall is other
32	pisomoscer	0	=1 if predominant material on the floor is mosaic, ceramic, or terrazzo
33	pisocemento	0	=1 if predominant material on the floor is cement
34	pisoother	0	=1 if predominant material on the floor is other
35	pisonatur	0	=1 if predominant material on the floor is natural material
36	pisonotiene	0	=1 if no floor at the household
37	pisomadera	0	=1 if predominant material on the floor is wood
38	techozinc	0	=1 if predominant material on the roof is metal foil or zinc
39	techoentrepiso	0	=1 if predominant material on the roof is fiber cement or mezzanine
40	techocane	0	=1 if predominant material on the roof is natural material
41	techootro	0	=1 if predominant material on the roof is other
42	cielorazo	0	=1 if the house has a ceiling
43	abastaguadentro	0	=1 if water provision inside the dwelling
44	abastaguafuera	0	=1 if water provision outside the dwelling
45	abastaguano	0	=1 if no water provision
46	Public	0	=1 electricity from CNFL, ICE, or ESPH/JASEC
47	planpri	0	=1 electricity from private plant
48	noelec	0	=1 no electricity in the dwelling
49	coonele	0	=1 electricity from cooperative
50	sanitario1	0	=1 no toilet in the dwelling
51	sanitario?	0	=1 toilet connected to sewer or cesspool
52	sanitario3	0	=1 toilet connected to sentic tank
52	sanitario5	0	=1 toilet connected to hole or latrine
54	sanitario6	0	=1 toilet connected to other system
55	anargeoginar1	0	-1 no main source of energy used for cooking (no kitchen)
55	energeoeinar?	0	-1 moin source of energy used for eaching is clearing the
57	energeocinar3	0	-1 main source of energy used for cooking is electricity
59	energeoeinar <sup>4</sup>	0	-1 main source of energy used for cooking is gas
50	elimbogu 1	0	-1 if subhish is disposed mainly by tenker truck
59	alimbasul	0	-1 if nubbish is disposed mainly by talket nuck
60	elimbasu2	0	-1 if rubbish is disposed mainly by botan honow of buried
62	elimbasu3	0	-1 if rubbish is disposed mainly by burning
62	elimbasu4	0	-1 if rubbish is disposed mainly by throwing in an unoccupied space
64	alimbasus	0	-1 if rubbish is disposed mainly by dirowing in river, creek, or sea
04 65	ennoasuo	0	-1 if rubbish is disposed manny by other
05	epared 1	0	
00	epared2	0	=1 if wails are regular
0/	epared 5	0	=1 II walls are good
08		0	
09 70	etecho2	0	
70	etecno3	0	
/1		0	=1 if floor is bad
72	eviv2	0	=1 if floor is regular
/3	eviv3	0	
74	Dis	0	=1 if disabled person
75	Male	0	=1 it male
/6	temale	0	
77	estadocivil I	0	=1 it less than 10 years old
78	estadocivil2	0	=1 it free or coupled union
79	estadocivil3	0	=1 it married
80	estadocivil4	0	=1 if divorced
81	estadocivil5	0	=1 if separated
82	estadocivil6	0	=1 if widow/er
83	estadocivil7	0	=1 if single

#	Variable Name	Missing Values	Variable Description
84	parentesco l	0	=1 if household head
85	parentesco2	0	=1 if spouse/partner
86	parentesco3	0	=1 if son/daughter
87	parentesco4	0	=1 if stepson/daughter
88	parentesco5	0	=1 if son/daughter-in-law
89	parentesco6	0	=1 if grandson/daughter
90	parentesco7	0	=1 if mother/father
91	parentesco8	0	=1 if father/mother-in-law
92	parentesco9	0	=1 if brother/sister
93	parentesco10	0	=1 if brother/sister-in-law
94	parentesco11	0	=1 if other family member
95	parentesco12	0	=1 if other non-family member
96	idhogar	0	Household level identifier
97	hogar_nin	0	# of children 0 to 19 in household
98	hogar_adul	0	# of adults in household
99	hogar_mayor	0	# of individuals 65+ in the household
100	hogar_total	0	# of total individuals in the household
101	dependency	2,192	Dependency rate
102	Edjefe	123	# of years of education of male head of household
103	Edjefa	69	# of years of education of female head of household
104	meaneduc	5	Average years of education for adults (18+)
105	instlevel1	0	=1 no level of education
106	instlevel2	0	=1 incomplete primary
107	instlevel3	0	=1 complete primary
108	instlevel4	0	=1 incomplete academic secondary level
109	instlevel5	0	=1 complete academic secondary level
110	instlevel6	0	=1 incomplete technical secondary level
111	instlevel7	0	=1 complete technical secondary level
112	instlevel8	0	=1 undergraduate and higher education
113	instlevel9	0	=1 postgraduate higher education
114	bedrooms	0	# of bedrooms
115	overcrowding	0	Persons per room
116	tipovivi1	0	=1 own and fully paid house
117	tipovivi2	0	=1 own, paying in installments
118	tipovivi3	0	=1 rented
119	tipovivi4	0	=1 precarious
120	tipovivi5	0	=1 other(assigned or borrowed)
121	computer	0	=1 if the household has a notebook or desktop computer
122	television	0	=1 if the household has a TV
123	mobilephone	0	=1 if the household has a mobile phone
124	qmobilephone	0	# of mobile phones household owns
125	lugarl	0	=1 region Central
126	lugar2	0	=1 region Chorotega
127	lugar3	0	=1 region PacÃfÂfīco <sup>6</sup> central
128	lugar4	0	=1 region Brunca
129	lugar5	0	=1 region Huetar Atl $\tilde{A}f\hat{A}_{j}$ ntica <sup>7</sup>
130	lugar6	0	=1 region Huetar Norte
131	areal	0	=1 zona urbana
132	area2	0	=2 zona rural
133	Age	0	Age in years
134	SQBescolari	0	Escolari squared

 <sup>&</sup>lt;sup>6</sup> The original dataset has a character encoding error.
<sup>7</sup> The original dataset has a character encoding error.

#	Variable Name	Missing Values	Variable Description
135	SQBage	0	Age squared
136	SQBhogar_total	0	Hogar_total squared
137	SQBedjefe	0	Edjefe squared
138	SQBhogar_nin	0	Hogar_nin squared
139	SQBovercrowding	0	Overcrowding squared
140	SQBdependency	0	Dependency squared
141	SQBmeaned	5	Meaneduc squared
142	Agesq	0	Age squared
143	Target	0	Poverty level

# B. EXHIBIT 9. DATASET AFTER PRE-PROCESSING

#	Variable Name	Variable Type	Variable Description	
1	Rooms	Discrete	# of all rooms in the house	
2	Refrig	Categorical	=1 if the household has a refrigerator	
3	v18q	Categorical	=1 if the household has a tablet	
4	r4h1	Discrete	# of males younger than 12 years of age	
5	r4h2	Discrete	# of males 12 years of age and older	
6	r4h3	Discrete	#of males in the household	
7	r4m1	Discrete	# of females younger than 12 years of age	
8	r4m2	Discrete	# of females 12 years of age and older	
9	r4m3	Discrete	# of females in the household	
10	r4t1	Discrete	# of persons younger than 12 years of age	
11	r4t2	Discrete	# of persons 12 years of age and older	
12	r4t3	Discrete	# of persons in the household	
13	escolari	Discrete	# of years of schooling	
14	rez_esc	Discrete	# of years behind in school	
	paredblolad		=1 if predominant material on the outside wall is block or brick	
	paredzocalo		=1 if predominant material on the outside wall is socket (wood, zinc, or asbestos)	
	paredpreb		=1 if predominant material on the outside wall is prefabricated or cement	
1.5	pareddes	G / 1	=1 if predominant material on the outside wall is waste material	
15	paredmad	Categorical	=1 if predominant material on the outside wall is wood	
	paredzinc		=1 if predominant material on the outside wall is zinc	
	paredfibras		=1 if predominant material on the outside wall is natural material	
	paredother		=1 if predominant material on the outside wall is other	
	pisomoscer		=1 if predominant material on the floor is mosaic, ceramic, or terrazzo	
	pisocemento		=1 if predominant material on the floor is cement	
16	pisoother	Coto o mino 1	=1 if predominant material on the floor is other	
10	pisonatur	Categorical	=1 if predominant material on the floor is natural material	
	pisonotiene		=1 if no floor at the household	
	pisomadera		=1 if predominant material on the floor is wood	
	techozinc		=1 if predominant material on the roof is metal foil or zinc	
1 78	techoentrepiso	Coto o mino 1	=1 if predominant material on the roof is fiber cement, or mezzanine	
17°	techocane	Categorical	=1 if predominant material on the roof is natural material	
	techootro	_	=1 if predominant material on the roof is other	
18	cielorazo	Categorical	=1 if the house has a ceiling	
19	abastaguadentro		=1 if water provision inside the dwelling	
	abastaguafuera	Categorical	=1 if water provision outside the dwelling	
	abastaguano	1	=1 if no water provision	
20 <sup>9</sup>	Public	Categorical	=1 electricity from CNFL, ICE, or ESPH/JASEC	
	planpri		=1 electricity from private plant	

 <sup>&</sup>lt;sup>8</sup> Variables in this row are grouped together based on a characteristic (i.e., roof materials) to encode to dummy variables; however, the study determined that 66 observations are not applicable to any of the four variables in the group. These observations were deleted in this study.
<sup>9</sup> Variables in this row are grouped together based on a characteristic (i.e., electricity type) to encode to dummy variables; however, the study determined that 15 observations are not applicable to any of the four variables in the group. These observations were deleted in this study.

#	Variable Name	Variable Type	Variable Description
	noelec		=1 no electricity in the dwelling
	coopele		=1 electricity from cooperative
21	sanitario1	Categorical	=1 no toilet in the dwelling
	sanitario2		=1 toilet connected to sewer or cesspool
	sanitario3		=1 toilet connected to septic tank
	sanitario5		=1 toilet connected to hole or latrine
	sanitario6		=1 toilet connected to other system
	energcocinar1		=1 no main source of energy used for cooking (no kitchen)
22	energcocinar2		=1 main source of energy used for cooking is electricity
22	energcocinar3	Categorical	=1 main source of energy used for cooking is gas
	energcocinar4		=1 main source of energy used for cooking is wood charcoal
	elimbasu1		=1 if rubbish is disposed mainly by tanker truck
	elimbasu2		=1 if rubbish is disposed mainly by botan hollow or buried
22	elimbasu3		=1 if rubbish is disposed mainly by burning
23	elimbasu4	Categorical	=1 if rubbish is disposed mainly by throwing in an unoccupied space
	elimbasu5		=1 if rubbish is disposed mainly by throwing in river, creek, or sea
	elimbasu6		=1 if rubbish is disposed mainly by other
	epared1		=1 if walls are bad
24	epared2	Categorical	=1 if walls are regular
	epared3		=1 if walls are good
	etecho1		=1 if roof is bad
25	etecho2	Categorical	=1 if roof is regular
	etecho3		=1 if roof is good
	eviv1		=1 if floor is bad
26	eviv2	Categorical	=1 if floor is regular
	eviv3		=1 if floor is good
27	Dis	Categorical	=1 if disabled person
-	Male	6	=1 if male
28	female	Categorical	=1 if female
-	Estadocivil1	-	=1 if less than 10 years old
	estadocivil2		=1 if free or coupled union
	estadocivil3	-	=1 if married
29	estadocivil4	Categorical	=1 if divorced
	estadocivil5	5	=1 if separated
	estadocivil6	-	=1 if widow/er
	estadocivil7	-	=1 if single
	parentesco1		=1 if household head
	parentesco2	-	=1 if spouse/partner
	parentesco3		=1 if son/daughter
	parentesco4		=1 if stepson/daughter
	parentesco5		=1 if son/daughter-in-law
	parentesco6		=1 if grandson/daughter
30	parentesco7	Categorical	=1 if mother/father
	parentesco8		=1 if father/mother-in-law
	parentesco9		=1 if brother/sister
	parentesco10		=1 if brother/sister-in-law
	parentesco11	-	=1 if other family member
	parentesco12		=1 if other non-family member
31	dependencv	Continuous	Dependency rate
32	Ediefe	Discrete	# of years of education of male head of household
33	Ediefa	Discrete	# of years of education of female head of household
34	meaneduc	Continuous	Average years of education for adults (18+)
	instlevel1	- 511114546	=1 no level of education
	instlevel2	Categorical	=1 incomplete primary
		1	Furner?

#	Variable Name	Variable Type	Variable Description
35 <sup>10</sup>	instlevel3		=1 complete primary
	instlevel4		=1 incomplete academic secondary level
	instlevel5		=1 complete academic secondary level
	instlevel6		=1 incomplete technical secondary level
	instlevel7		=1 complete technical secondary level
	instlevel8		=1 undergraduate and higher education
	instlevel9		=1 postgraduate higher education
36	overcrowding	Continuous	Persons per room
	tipovivi1		=1 own and fully paid house
37	tipovivi2		=1 own, paying in installments
	tipovivi3	Categorical	=1 rented
	tipovivi4		=1 precarious
	tipovivi5		=1 other(assigned or borrowed)
38	computer	Categorical	=1 if the household has a notebook or desktop computer
39	television	Categorical	=1 if the household has a TV
40	mobilephone	Categorical	=1 if the household has a mobile phone
	lugar1		=1 region Central
	lugar2		=1 region Chorotega
41	lugar3	Catagoriaal	=1 region Pac $\tilde{A}f\hat{A}fico^{11}$ central
41	lugar4	Categorical	=1 region Brunca
	lugar5		=1 region Huetar AtlÃfÂintica <sup>12</sup>
	lugar6		=1 region Huetar Norte
12	area1	Catagoriaal	=1 zona urbana
42	area2	Categorical	=2 zona rural
43	Age	Categorical	Age in years
44	Target	Dependent	Poverty level

# C. EXHIBIT 10. DISTRIBUTION OF NUMERICAL VARIABLES



<sup>&</sup>lt;sup>10</sup> Variables in this row are grouped together based on a characteristic (i.e., education level) to encode to dummy variables; however, the study determined that three observations are not applicable to any of the nine variables in the group. These observations were deleted in this study. <sup>11</sup> The original dataset has a character encoding error.

<sup>&</sup>lt;sup>12</sup> The original dataset has a character encoding error.

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#### REFERENCES

- The World Bank, (06, October. 2021). The World Bank Costa Rica [Online]. Available: https://www.worldbank.org/en/country/costarica/overview#1.
- [2] UNDP, "Jordan poverty reduction strategy," United Nations Development Program, New York, NY, USA, 2013.
- [3] A. Alsharkawi, N. Al-Fetyani, M. Dawas, H. Saadeh, M. Alyaman, "Poverty classification using machine learning: the case of Jordan," *Multidisciplinary digital publishing institute*, vol. 13, no. 3, p. 1412, 2021.
- [4] J. A. Talingdan, "Performance comparison of different classification algorithms for household poverty classification," in 2019 ICISE, China, 2019 pp. 11-15
- [5] O. Maimon, L. Rokach, *Data mining and knowledge discovery handbook*, Boston, MA, USA: Springer, 2005.
- [6] O. Günlük, J. Kalagnanam, M. Li, M. Menickelly, K. Scheinberg, "Optimal decision trees for categorical data via integer programming," *Journal of global optimization*, vol. 81, pp. 233-260, 2021.
- [7] G. Shobha, S. Rangaswamy, *Handbook of statistics*, Amsterdam, Netherlands: Elesevier, 2018.
- [8] V. Kotu, B. Deshpande, *Data science concepts and practice*, Burlington, MA, USA: Morgan Kaufmann, 2019.
- [9] F. Pedregosa et al, "Scikit-learn: machine learning in python," Journal of machine learning research, vol. 12, pp. 2825-2830, 2011.
- [10] J. M. Rudd, H. "Gene" Ray, "An empirical study of downstream analysis effects of model pre-processing choices," *Open journal of statistics*, vol. 10, no. 5, pp. 735-809, 2020.
- [11] A. Cutler, D. R. Cutler, J. R Stevens, Ensemble machine learning: methods and applications, Boston, MA, USA: Springer, 2011.
- [12] F. Tang, H. Ishwaran, "Random forest missing data algorithms," *Statistical analysis and data mining: the ASA data science journal*, vol. 10, no. 6, pp. 363-377, 2017.
- [13] Y. Zhang, S. Wei, L. Zhang, C. Liu, "Comparing the performance of random forest, SVM and their variants for ECG quality assessment combined with nonlinear features," *Journal of medical and biological engineering*, vol. 39, pp. 381-392, 2019.
- [14] Y. Wang, G. Ma, J. Mei, Y. Zou, D. Zhang, W. Zhou, X. Cao, "Machine learning reveals the influences of grain morphology on grain crushing strength," *Acta Geotechnica*, vol. 16, no. 2, p. 3617–3630, 2021.
- [15] J. H. Friedman, "Greedy function approximation: A Gradient Boosting Machine," In *institute of mathematical statistics*, 2001.
- [16] G. Ke, et al, "LightGBM: a highly efficient gradient boosting," advances in neural information processing systems, vol. 30, pp. 3146-3154, 2017.
- [17] SAS. (2019). Exploration of missing data imputation methods [online]. Available: <u>https://www.sas.com/content/dam/sas/support/en/sas-global-forum-proceedings/2019/3643-2019.pdf.</u>
- [18] T. Chen, C. Guestrin, "XGBoost: a scalable tree boosting system," in KDD '16: the 22nd ACM SIGKDD international conference on knowledge discovery and data mining, San Francisco, CA, USA, 2016.
- [19] C. Hsu, Y. Huang, K. Chang, "Extended naive bayes classifier for mixed data," *Expert systems with applications*, vol. 35, no. 3, pp. 1080-1083, 2008.
- [20] J. Wang, J. Zucker, "Solving the multiple-instance problem: a lazy learning approach," in *International Conference on Machine Learning*, Stanford, CA, USA, 2000.
- [21] C. Albon, Python machine learning cookbook : Practical solutions from preprocessing to deep learning, Sebastopol, CA, USA: O"reilly, 2018.
- [22] G. H. Chen, D. Shah, "Explaining the Success of Nearest Neighbor Methods in Prediction, Boston, MA, USA: Now. 2018.
- [23] Y. Bouzida, F. Cuppens, N. Cuppens-boulahia, S. Gombault, "Efficient intrusion detection using principal component analysis," in 3éme conférence sur la sécurité et architectures réseaux (sar), La Londe, France, 2004.
- [24] A. C. Müller, S. Guido, Introduction to machine learning with Python : a guide for data scientists, Sebastopol, CA, USA: O'reilly, 2017.
- [25] The World Bank, Population, total-Costa Rica, [Online]. Available: <u>https://data.worldbank.org/indicator/sp.pop.totl?locations=cr.</u>

- [26] J. Brownlee, Imbalanced classification with Python: better metrics, balance skewed classes, cost-sensitive learning, Vermont, Australia: Machine learning mastery, 2020.
- [27] S. Kotsiantis, D. Kanellopoulos, P. Pintelas, "Handling imbalanced datasets: a review," gests international transactions on computer science and engineering, vol. 30, pp. 25-36, 2005.
- [28] J. J. Heckman, J. E. Humphries, G. Veramendi, "Returns to education: the causal effects of education on earnings, health and smoking," *Journal of political economy*, vol. 126, no. S1, pp. S197-s246, 2018.