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Role of a Social Activist Towards Poverty Reduction

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ABSTRACT

Poverty rates are not a taboo subject. In actuality, it occurs in every nation on earth when governments and social activists fight to lower the poverty rate. Unfortunately, there are a number of problems with the current methods for identifying the appropriate targeted underprivileged population to whom financial aid should be given, including data openness and inaccurate, redundant, or imbalanced data. The goal of this research set out to determine the ways in which social activists in india have contributed to the decline of poverty. The following were the goals of the study: to determine the influence of social activists in enhancing livelihoods in order to forecast a decrease in poverty in india and to evaluate social activists' impact on india's efforts to reduce poverty through forecasting. Several feature engineering and data cleaning pre-processing methodologies are used in this research's machine learning approach, which is then followed by three different regression algorithms for predictive analysis. Using the costa rican household poverty dataset, the proposed machine learning model is tested. According to the experimental results, the random forest regressor outperforms the other two regression models tested in terms of r2 and rmse score, scoring 0.8355 well-fitted and 0.148 error rates, respectively.

Keywords: social activist, poverty reduction, prediction, machine learning, feature selection.

INTRODUCTION

The terms development, human rights, and humanitarian help are frequently associated with the word "non-governmental organisation" (NGO). Although there are many other kinds of NGOs, such as those that battle fires, the phrase is most commonly used to refer to developmental NGOs. These groups are acknowledged as important players in the effort to create a future that is more equal and sustainable for everybody. However, scholars including [1-3] have criticised the development aid that these organisations offer.

Up until the late 1970s, non-governmental organisations (NGOs) received very little recognition for their work implementing development programmes. The majority of these recognitions came in the form of short-term emergency and relief operations as well as service delivery [4]. As state-led approaches to development during the 1970s and 1980s mainly failed, NGOs emerged as the development industry's sweetheart. The NGOs were seen as the alternative to traditional development methods, providing creative and community-focused approaches to advocacy, service delivery, and community empowerment [5].

Poverty reduction refers to all government programmes designed to lower the incidence and prevalence of poverty in the country. The World Bank created strategies for reducing poverty in a number of nations as a development strategy that came about as a result of the combined efforts of all parties interested in ending poverty. Generally speaking, everyone who has an interest in seeing poverty and related issues reduced takes part in its planning and execution [6]. The Non-Governmental Organisation is one of these parties involved (NGO) [7].

Study [8] presents a viewpoint that accentuates this vision by depicting sustainable development as a ray of hope for an improved standard of living for everybody. This viewpoint highlights the complex interactions between these components while also highlighting how important it is to take care of basic necessities. For example, providing good work not only guarantees financial security but also gives people a feeling of purpose and dignity. Not only does having access to wholesome food sate hunger, but it also promote general health and productivity. In a similar vein, dependable energy supplies expand economic prospects and provide access to contemporary conveniences, while safe housing promotes a feeling of security and community. Together, these factors fan the flame of a higher quality of living, opening the door to the possibility of a happier, more affluent life for all people and communities.

NGOs play a vital role in mitigating poverty due to their dual role-playing capabilities. They can address social issues through two distinct approaches: top-down and bottom-up. This research investigates the function of non-governmental organisations (NGOs) in the bottom-up approach to reducing poverty. NGOs are developmental organisations that serve three key functions in developing this method: developer, service provider, and facilitator. NGOs play a vital role in reducing poverty by offering essential services like loans, relief, health services (such as counselling and check-ups), and more. NGOs take on the role of developers, adopting, planning, and carrying out programmes to teach or train the local populace on a variety of topics in an effort to help people escape poverty. NGOs play the role of a facilitator, encouraging communication between neighbours and active involvement in neighbourhood projects. Through encouraging such involvement, NGOs make sure that community needs are met and that the views of the locals are directly heard.

The goal of this research is to forecast the degree of poverty by analysis using several regression models on data related to household characteristics. Instead of concentrating only on income level, elements including household consumption, the cost of living, and other characteristics of living conditions should be taken into account while analysing the causes of poverty. Additionally, survey data may be skewed and contain redundant information. Due to numerous data flaws, including missing values, skewed, and redundant data, it could result in inaccurate predictions. Several data handling techniques are used to reduce errors and guarantee the machine learning model's accuracy.

2. LITERATURE REVIEW

2.1. Concept of Poverty

Because poverty is multidimensional, it requires a wide variety of social, political, economic, and societal reforms to be mitigated. Global collaboration is required to address global concerns such as the decrease and eventual eradication of poverty. Over 1 billion people are estimated to still live in poverty by the World Bank. Poverty is a condition that is seen throughout the world. This is an intolerable state of things considering the resources and technology that are available today [9].

Poverty has gained a lot of attention and sparked debates in international development forums across the globe. According to the European Anti-Poverty Network, poverty is mostly caused by the way resources are distributed and how society is structured. Although the causes and levels of poverty vary by region and population, its negative, if not disastrous, effects on the affected groups are negligible to nonexistent. According to studies, an additional 100 million people could become severely poor as a result of the current global financial crisis [10]. The origins and effects of poverty are frequently confused. Some of the outcomes of poverty include increased crime rates, adolescent pregnancies, food insecurity, school dropouts, social isolation, homelessness, subpar living conditions, severe health issues, and inadequate welfare. Both industrialised and developing nations experience poverty, but the incidence is higher in the latter [11].

Non-governmental organisations are crucial in empowering marginalized individuals by providing them with self-sufficiency through programmes like vocational training, socioeconomic projects, and other initiatives of a similar nature. Non-governmental organisations (NGOs) address the needs of women, support their socio-economic advancement, health consciousness, and general sensitization through work, education, and other opportunities. Their functions encompass more than just providing for women's basic needs; they also empower women and foster the growth of their families. Research indicates that NGO initiatives have a favourable impact on women's empowerment [12].

2.2. Poverty Prediction

By using a machine learning technique to estimate the level of poverty, the authors in [13] evaluated the variables that are important in determining poverty. They made use of data from two sources: the Poverty Possibility Index, which provides data on individual cases, and the Oxford Poverty & Human Development Initiative, which provides the poverty index for different countries. The authors conducted a statistical analysis to obtain an understanding of the correlations among several variables that could influence the probability of poverty. The studies examined a range of machine learning approaches, such as neural networks, decision trees, random forests, gradient boosting, and linear regression, to see which model would be most effective for categorising and forecasting poverty. Based on the significant score, this study identifies the variables that influence poverty. The authors came to the conclusion that, in terms of complexity, accuracy, and dependability, the gradient boosting classifier is the best. One of the most important elements in poverty is one's level of education, followed by the nation in which one resides. As opposed to [13], which looks at the vast population across nations, the writers of [14] and [15] investigated particular nations for their studies on poverty, such as China and Jordan, respectively.

In [16], the task of predicting poverty in metropolitan environments in North and South America was examined through the use of satellite pictures and household income. The investigation was motivated by the labor-intensive and expensive way of collecting socioeconomic data [17]. It then turns to remote sensing data, which is more appropriate for large-scale poverty estimation, such as high-resolution satellite photos. A descriptive urban environment is created by combining actual satellite data with crowd sourced OpenStreetMap (OSM) data, which may be utilised to identify the urban zones within each metropolis.

2.3. NGOs and methods for reducing poverty

NGOs are significant non-state actors that collaborate closely with a variety of entities, such as the public and corporate sectors, governments, academia, think tanks, and local communities. NGOs assist people around the globe by working on a variety of topics. NGOs employ the market model to implement two different ways to decreasing or alleviating poverty: both the demand-side and supply-side strategies [18]. The supply-side technique refers to NGOs providing basic social services and focusing on the people, while the demand-side method focuses on a bigger picture as NGOs play an indirect role and work with other agencies to modify legislation and enact policies to help the poor. NGOs serve a demand-side function as an articulator of the people's voice, working to mobilise and explain the public's demand for services from the market and the government, in order to assist the public in realising their development objectives [19]. This essay made an effort to limit its attention to NGOs using the bottom-up and supply-side strategies.

NGOs have also embraced an integrated multi-sectorial approach, which integrates social services like family planning, safe drinking water, healthcare, and education with physical and technical investments for small-scale agricultural projects [20]. While NGOs' projects are smaller than government or large macroeconomic policy initiatives, they are more successful in reaching the underprivileged members of the society. Compared to other organisations working to reduce poverty, NGOs are more successful in reaching the poor, albeit not the poorest among them [21].

When NGOs strive to improve participatory development, they also play the role of facilitators. They are able to interact with the populace more personally, maintaining their connections, boosting civic involvement, and encouraging community involvement. As easterly noted, the small-scale nature of their programmes allows them to foster relationships locally and find solutions from insiders rather than outsiders. NGOs are community-based and prioritise the needs of the people [22].

3. METHODOLOGY

3.1. Proposed Framework

There are multiple steps in the suggested machine learning model. The dataset is first cleaned up and the categorical variables are encoded as part of the prep and pre-processing step. This is done to make sure that unprocessed data from outside sources is converted or encoded in a fashion that makes sense for predictions made by modelling. The engineering of features comes next. The BorutaPy Feature Selection algorithm is used for feature selection, ordinal variable feature fusion, and redundant feature removal. The Synthetic Minority Over-sampling Technique (SMOTE) technique [23] was used to alleviate the problem of imbalanced target class distribution, which occurs when one or more classes predominate over the others and impacts the precision of models and prediction assignments, before models were applied to the dataset. Finally, K-fold cross-validation with k=3 is used to train and test the dataset in linear regression, decision trees, and random forests. The performance measures employed in this research analysis are Root Mean Square Error (RMSE), R-Square (R2) and Mean Square Error (MSE). After that, the average score for each metric across all repetitions will be determined and closely scrutinised. The goal is to identify the characteristics that most strongly lead to poverty and estimate the amount of poverty using one of the four measures.

3.2. Regression Model

Various regression models are employed in this work for the purpose of analysis.

- **Decision Tree Regressor (DTR)**

A component of the Decision Tree method used in predictive analysis is the Decision Tree Regressor. It uses a tree structure as its shape, including nodes, branches, and leaves. The technique uses a top-down, greedy search strategy to divide the provided data into smaller subtrees while gradually creating a decision tree that goes along with it. The algorithm divides the data into distinct branches starting at the root node and continuing until it reaches a leaf node. A forecast derived from the computed mean or average value is called a leaf node. The decision tree uses the data-to-output mapping that occurs during the training phase to determine how to branch out. As per [24], the sample data and its true value are utilised to fit the model during the training process. It also discovers how the data and the target variable relate to one another. When forecasting, the model constructs a tree that is identical to the one it was trained on employing the train data.

- **Random Forest Regressor (RFR)**

Employing the bagging, or bootstrap and aggregation, technique, many decision trees are used in the Random Forest Regressor, an ensemble application. Using a separate data sample, each decision tree is trained using this technique. Instead of using a single decision tree, numerous decision trees are joined to try and determine the final outcome. Regression output is derived from the mean value of each tree's forecast. It is thought that the more trees utilised, the more effective the model will be. The best course of action is to experiment to see how the model functions.

- **Linear Regression (LR)**

Linear regression is among the most fundamental regression techniques for generating predictions. The link between the independent variables, X, and the estimated dependent variables, Y, is represented as a straight line using a linear approach. This model takes into account the equation Y = bX + C, where b is the line's slope or regression coefficient and is the intercept, or constant. In order to forecast a given value, the algorithm searches for the best values to fit the best regression line during training. It can be used to ascertain which components are important to the outcome variable and how well the variables predict the variable.

3.3. Details of the Dataset

The type of walls, roof, floor, and ceiling in the family's home, as well as the items they own such computers and tablets, can be used to predict the family's poverty level. This information is included in the Costa Rican household dataset [25]. Four levels of poverty are distinguished by the 143 variables in the dataset: non-vulnerable households, vulnerable homes, and extreme poverty. The "Target" column contains the values corresponding to the poverty level. A distinct identifier known as "idhogar" is used to identify each individual in a row and determine whether or not they are members of the same household. The dataset's attributes list the house's exterior characteristics, such as the roof, walls, and flooring; the options for disposing of waste from the home's sewerage connection; the assets owned (such as computers, televisions, and tablets); the level of education attained; the availability of dependency care; and other demographic details about the household.

3.4. Feature Selection and Feature Engineering

There are three characteristics in the dataset that have a sizable percentage of missing values: "years_behind_school," "num_tablets," and "monthly_rent." The dataset does not contain duplicate rows. These attributes are no longer included in the dataset. To facilitate processing, some non-numerical facts are encoded into numerical values. Examples of this data include the values from the columns "dependency," "eduyears1," and "eduyears2." Following missing data handling and pre-processing, the data is cleansed. We then carry out feature engineering. Squared-variable variables like "SQBmeaned," "SQBschooling_years," "agesq," "SQBage," and so on are included in the dataset.

The Boruta Feature Selector is used to choose key features while making predictions in order to minimise the amount of input variables. With regard to the "Target" column, all the noteworthy and intriguing qualities are automatically selected by an algorithm. The values of the poverty level for each row are listed in this column, and they are helpful throughout the training and testing phases. Out of the 118 remaining characteristics, 15 features are finally selected during the course of the model's 100 iterations. Table 1 displays the 15 traits that were chosen. Reducing the amount of features is required for several reasons, including to limit the computational cost of modelling and, occasionally, to enhance the performance of the models.

Table 1: Features chosen for the poverty prediction method

Serial Number	Chosen Features
1	Wall
2	Roof
3	Floor
4	Rooms
5	Males_13_younger
6	Males_13_old
7	Females_13_younger
8	Females_13_old
9	Person_13_younger
10	Person_13_older
11	Tablet
12	Eduyears 1
13	ceiling
14	Overcrowding
15	qmobilephone

3.5. Measures of Performance

A model is considered well-fitting if there is minimal variation between the predicted and actual values. The machine learning metrics used in this study to assess the models' performance are R^2, MSE, and RMSE. Prediction error is the measure of the discrepancy among the model's fitted line and the expected data points. The MSE calculates the separations among the data points and the regression line. The formula displayed below is the basis for calculating the inaccuracy.

$$MSE = \frac{1}{n}\sum_{j=1}^{n}(Xi - \hat{X}i)^2 \qquad (1)$$

The two values are divided to yield the residual error value, which needs to be squared to eliminate any negative signs. It also acts as a gauge for the difference among what is actually and what is expected. The result is a collection of errors, or the average of the squared disparities among each data point's actual and anticipated values, summed squared. The square of error serves as the basis for this metric, whose value ranges from 0 to infinity. In other words, the closer the value is to finding the best line fit, the better the model performs.

Furthermore, [26] says that the RMSE is calculated using the square root of the average squared variation between the actual and predicted values. The response variable, or target value to be predicted, has the same unit order, as demonstrated by Equation 2, which is repeatedly square rooted from the MSE. Furthermore, RMSE is favored over MSE as the superior error measure in the event of big error values because it gives the squared difference among actual and expected values more weight.

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(Xi - \hat{X}i)^2} \qquad (2)$$

Finally, a coefficient of determination is R^2. It provides an indicator of how well the regression model line reproduces the real results. Its value, which ranges from 0 to 1, is determined by the entire variance of the forecast that the algorithm is able to explain. Better model performance is indicated by a number closer to 1, and worse model performance is indicated by a value closer to 0.

4. Empirical Results

There are 15 feature columns and 8446 observation rows in the final dataset. The dataset's unequal class distribution of poverty level raises the possibility of bias in the forecast. SMOTE is applied to the dataset to resolve this problem. Before applying SMOTE, the distribution of the "Target" column fluctuates, and each class's distribution is balanced based on the highest number—4885 from Target 4: non-vulnerable—after SMOTE has been applied to the dataset. After that, the dataset is prepared for K-Fold Cross-Validation training and testing.

The performance metrics for the first regression model, linear regression, are depicted in Table 2. The average RMSE score of 0.8952 indicates the average error rate of the model. The degree to which the data fits the model is indicated by the R2 score of 0.2306.

Table 2: Outcome of linear regression performance metrics

Replication	MSE	RMSE	R^2
K1	.7032	.8913	.2393
K2	.7350	.8987	.2219
K3	.7112	.8957	.2305
Mean	.7164	.8952	.2306

Figure 1 shows the graphical representation of the Linear Regression performance metrics outcomes.

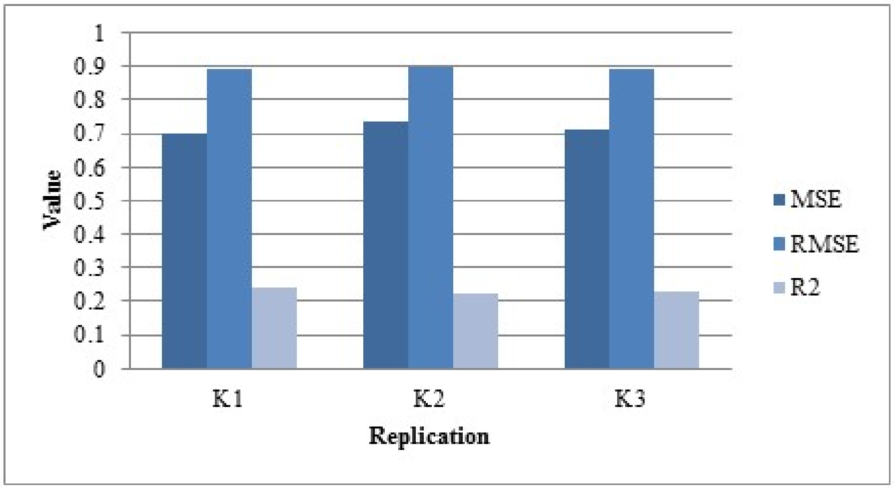

Figure 1: Linear Regression performance metrics outcomes

Table 3 shows the Decision Tree Regressor's performance metrics result. R2 is 0.7965 and the average RMSE score is 0.3414.

Table 3: Outcome of Decision Tree Regressor's performance metrics

Replication	MSE	RMSE	R^2
K1	.1203	.3521	.7848
K2	.1120	.3355	.8024
K3	.1128	.3366	.8024
Mean	.1150	.3414	.7965

Figure 2 shows the graphical representation of the Decision Tree Regressor performance metrics outcomes.

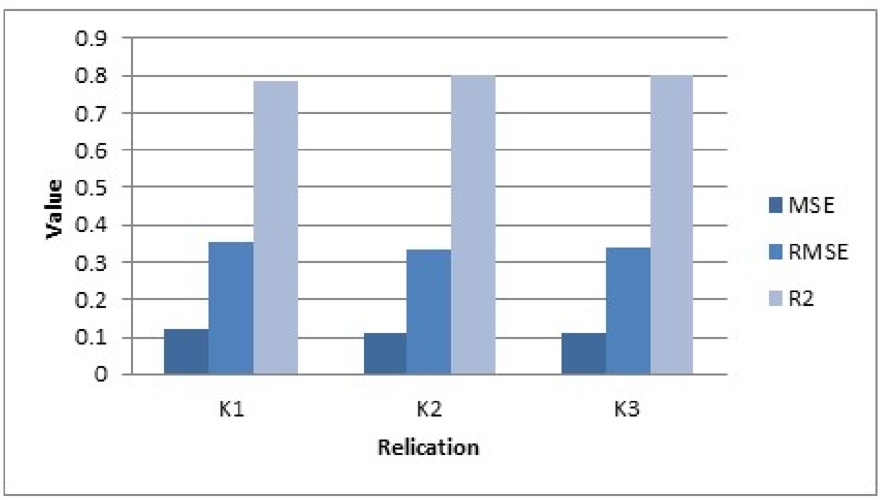

Figure 2: Decision Tree Regressor performance metrics outcomes

Table 4 displays the outcome of the model performance evaluation metrics, which are followed by the Random Forest Regressor. It has an average R2 score of 0.8355 and an average RMSE score of 0.148.

Table 4: Outcome of Random Forest Regressor performance metrics

Replication	MSE	RMSE	R^2
K1	.0635	.1621	.8305
K2	.0523	.1408	.8383
K3	.0525	.1411	.8376
Mean	.0561	.148	.8355

Figure 3 shows the graphical representation of the Random Forest Regressor performance metrics outcomes.

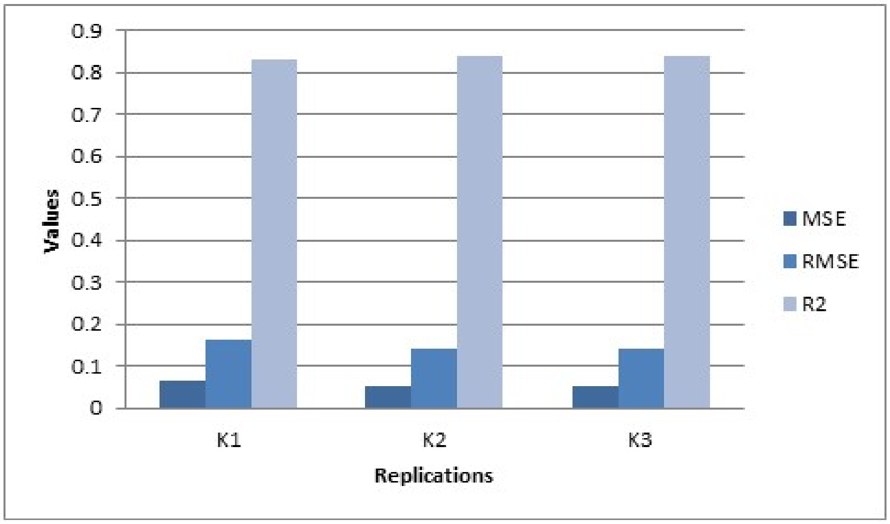

Figure 3: Random Forest Regressor performance metrics outcomes

The RMSE score, also known as the model's error rate, can be used to assess the prediction ability of the models based on Table 5. Linear regression has the highest average error rate (.8952), followed by RFR (.148) and DTR (.3414). The RFR model performed the best out of the three regression models. It more closely resembles the regression model line and has the lowest average RMSE or error rate score. By building numerous trees, generating observations using samples substituted (a technique called bootstrapping), and dividing the nodes in accordance with the best split among a chosen random selection of features at each tree node, it lessens overfitting.

Table 5: An overview of the measurements used in performance evaluation

Methods	MSE	RMSE	R^2
Linear regression (LR)	.7164	.8952	.2306
Random Forest Regressor (RFR)	.0561	.148	.8355
Decision Tree Regressor (DTR)	.1150	.3414	.7965

The decision tree system only learns from one choice path, in contrast to a single decision tree, which has a large variation. Therefore, predicting based on newly collected data is typically inaccurate.

The average R2 score shows how well the data is fitted to the model when making predictions based on features. The RFR from Figure 4 scored the highest at.8355, followed by the DTR at.7965. LR has the lowest score, at.2306. The analysis's findings make it abundantly evident that the RFR is the superior model to take into account when making predictions, as opposed to Linear Regression.

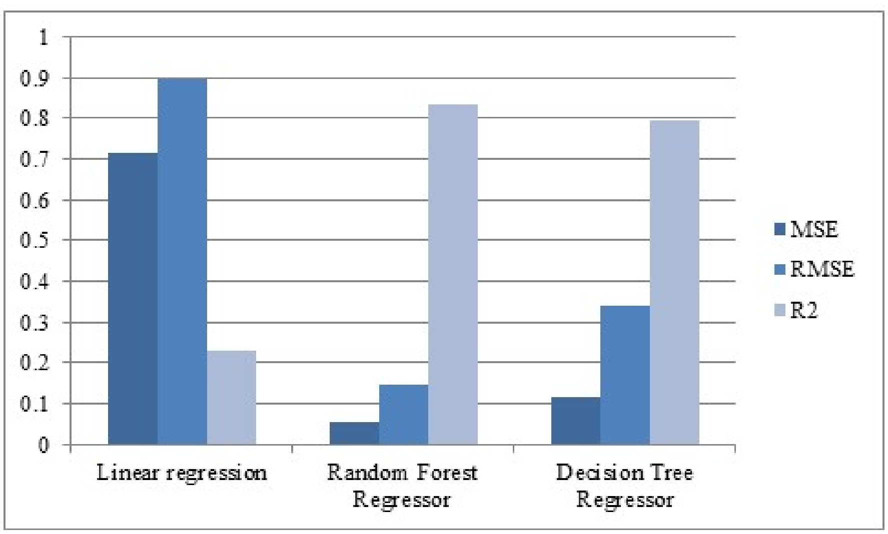

Figure 4: Performance evaluation of Models

Table 6 presents a comparison between the proposed methodologies and the previous studies. Only two studies have previously been published that predicted poverty using the same Costa Rican household information. Common machine learning models such Logistic Regression, Decision Trees, KNN, Navies Bayes, Gradient Boosting Classifier and Support Vector Machine were utilised in the first study [27]. Similar regression techniques, including decision trees, gradient boosting classifiers, and multinomial logistic regression, were also used in the second paper [28]. Thus, we limited our comparison to the models that outperformed our suggested model. Table 6 shows that our model performs marginally better than the others, with the lowest mean-squared error and the greatest R squared values.

Table 6: A comparison between our suggested and current approaches

Models	MSE	RMSE	R^2
Proposed model	.0561	.148	.8355
[27]	0.075	.2743	.9396
[28]	0.1224	.3498	.9462

5. CONCLUSION

Although poverty is a basic and universal social issue, India has one of the highest rates of poverty in the world. In order to combat poverty, social activists are a necessary addition to the government's inability to provide for the basic requirements of the populace. Various social activists have conducted extensive research to determine the most appropriate method of measuring poverty in light of the conditions in order to guarantee that their citizens would receive adequate financial assistance. However, because certain survey results are not very trustworthy, the information gathered may result in decisions being made based on preconceptions and in neglecting other individuals who are extremely poor but are unable to disclose their status. Therefore, this work uses a machine learning model to predict the household's poverty status based on data collected (comfort level in the home, average education level, house condition, etc.), identifying the characteristics that are highly contributing to poverty. The techniques employed include standard data pre-processing and preparation procedures including feature engineering, feature selection, data cleaning, addressing missing values, and categorical variable encoding.

The study findings of the regression models show that the RFR, with an RMSE performance cap of 0.148, and the Decision Tree Regressor, with a cap of 0.3414, has the lowest error rates. The highest value is obtained via Linear Regression, with an RMSE of 0.8952. Furthermore, the Random Forest Regressor and Decision Tree Regressor's R2 scores of.7965 and 0.8355, respectively, show that their models are well-fitted to generate predictions. On the other hand, with an R2 of 0.2306, Linear Regression had the lowest score. Our suggested methods performed better than other state-of-the-art methods when compared to earlier studies using the same dataset because of our efficient feature engineering and data handling techniques.

To make poverty reduction programmes more effective, especially in terms of reaching and involving marginalised populations, social activists should adopt a more integrative approach that augments the existing focus on service delivery with a more robust emphasis on poverty prediction.

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