# Measuring non-monetary poverty via machine learning and neutrosophic method: Review

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**Abstract**

Poverty is an emerging problem that most economies are facing today. The study is aimed at exploring research conducted on measuring non-monetary poverty via machine learning. Non-monetary poverty is identified through the following factors: demographics, population, distribution of income, climate, culture, ethnics, and availability of natural and artificial resources. Today, one of the most important aspects of non-monetary poverty measurement is using machine learning for multiple data points other than wealth or income to assess the quality of life of an individual or community. The socioeconomic factors that contribute poverty in emerging nations have also been found using machine learning algorithms. To achieve our goal neutrosophic model and machine learning algorithms were applied. Neutrosophic model used for reviewing the poverty indicators along with ML algorithms. While exploring the utility of machine learning in our study to measure poverty we will find the answers for the following questions: (1) Why it is important to take into consideration of non-monetary approaches while calculating poverty rate? (2) Which machine learning algorithms were used in poverty measurement? (3) What is the future scope of machine learning applications in poverty prediction? In finding answers for those questions, we have analyzed overall 10 papers which were collected according to exclusion and inclusion criteria and the purpose of the selection according to the content of the paper. During the survey it was found out that machine learning gives sophisticated data for identifying non-monetary reasons of poverty and this survey is first that uses machine learning to non-monetary poverty factors.

**Keywords:** Poverty; Non-monetary vs Monetary approach; Machine learning; Deep learning; Demographic and Household data; Satellite imagery; Remote sensing.

## 1. Introduction

Poverty is a multidimensional experience characterized by material deprivation, economic hardship, and a lack of fundamental consumer goods and services such as education and healthcare [1]. It is caused by changing income inequality and other social, economic, medical, and demographic dynamics in a market economy, resulting in an inability to purchase required life resources. Individual, societal, household, and geographical aspects all influence poverty. Moreover, it is defined as the inability to get adequate resources to meet a socially acceptable minimum level of living and exacerbated by factors such as a lack of resources, a poor income, and significant unemployment. Poverty is regarded as an undesirable situation that necessitates aid, and it is the focus of socioeconomic development initiatives in developing countries [2]. Various qualitative and quantitative measurements are used to identify and quantify poverty.

Poverty, nowadays, measured in two ways, and one of them considered to monetary whereas the second one is non-monetary one. Although the traditional method concentrates on financial resources (less than $2 dollar of daily income), non-financial factors like health and education are becoming increasingly important in evaluating poverty rate of population. To capture the complexity of poverty, multidimensional poverty measures that consider market

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and non-market factors have been proposed [3]. Non-monetary variables can help distinguish persons who live in poorness and shed light on the characteristics of deprivation. However, varied definitions of poverty lead to the classification of various demographic segments as poor, and there are notable distinctions between measurements of poverty that are monetary and non-monetary. It's critical to consider both strategies at the same time to prevent misspecification of objectives and performing an inaccurate assessment. To prevent misidentifying objectives and assessing policies improperly, it is crucial to take into account both approaches at the same time [4]. Furthermore, gender influences how poverty is measured, and women's poverty may be underestimated by presenting only monetary metrics. To be more accurate in reflecting women's poverty, other measures that account for power dynamics within homes have been put forth.

Machine learning is rapidly being utilized for poverty assessing. Applying machine learning techniques to remotely sensed data for poverty mapping has been the focus of recent methodological advancements [5]. By contrasting survey-based and subnational machine learning-based estimates of poverty, both methods have been proven effective. Nevertheless, it's possible that the validation processes employed in machine learning techniques don't fairly evaluate model performance. Machine-learning-based estimations have proven to be competitive with conventional poverty mapping techniques, according to alternative validation techniques. Furthermore, as a step toward sustainable development, machine learning approaches have been put out to detect, validate, and analyze poverty. The multidimensional poverty index has been estimated at the individual level using machine learning methods. [6] Large data sets, including demographic, geographic, and socioeconomic data, may be processed using machine learning algorithms to find patterns and links. These datasets can be used to train algorithms that discover complex relationships between various factors and create predictive models that identify vulnerable populations or calculate poverty rates. For example, by studying satellite imagery, machine learning can detect informal settlements or assess the condition of houses. To determine whether areas lack access to quality health care, we can review medical records. Likewise, it can look at education data to determine literacy and school attendance rates.

Combining non-monetary techniques with machine learning to account for the various dimensions of poverty that impact people's quality of life can lead to a deeper knowledge of poverty. With this strategy, organizations and politicians may more effectively customize interventions, targeting particular need areas and encouraging sustainable development to elevate impoverished communities. To develop significant and effective solutions, it's crucial to guarantee ethical concerns, data protection, and accuracy in these approaches. [7].

In our research study we consider the above-mentioned information and figure out how by non-monetary approach the poverty is measured today along with inserting machine learning to enhance correctness of data. For this purpose, we will answer the following research questions while we conduct our review paper:

1. Why it is important to take into consideration of non-monetary approaches while calculating poverty rate?
2. Which machine learning algorithms were used in poverty measurement?
3. What is the future scope of machine learning applications in poverty prediction?

The remaining part of the paper will be structured following: Section 2 will briefly outline selected review materials from investigating previous works that has been done in this sphere of poverty measurement. Section 3 will describe detailed research methodology that is going to be used in the review paper whereas Section 4 discusses the results and findings from the relevant data’s that has been extracted from the research which are under review on this study and lastly, Section 5 will conclude the outcomes and remarks future research scopes which can be continued by research scholars in similar specialty.

## 2. Related Reviews

Reviews of relevant literature are conducted in two ways. In the first path, the information provision context was largely used to study the effects of a non-monetary approach to poverty evaluation. The second section contains review articles on the application of machine learning to poverty measurement. [8] Table 1 presents general information on previously published studies and reviews on machine learning in poverty calculating.

Table 1: Surveys and Reviews Related to Machine Learning to Poverty Measurement.

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| Pape r Ref | Year | Field of Research | Contribution | Limitations |
|---|---|---|---|---|
| **[13]** | **2022** | Integration of AI and ML for Poverty Prediction | Performed integrated review using transparency, interpretability and explainability of context in poverty prediction.ML approaches combined with satellite imagery close to matching survey data. Evaluation of papers based on properties of the model and attempt to explain predictions. | Transparency is often well covered, but interpretability is not. Some papers have low quality in terms of layout, spelling, and content. Lack of explainability in some parts of the scientific process. |
| **[10]** | **2020** | Review in machine learning in applied economics and agriculture . | Identified machine learning opportunities and challenges in adapting to applied economics. Increases data flexibility and functions. Resolves challenges of complex simulation models. Provides potential solutions for large numbers of explanatory variables Discusses the role of economists in addressing limitations of machine learning | ML approaches need improvement in calibration. NNs are not greatly used in economic analysis. RNNs are not well placed to detect the place of an event. Performance of RNNs deteriorates with longer input sequences. |
| **[9]** | **2015** | Poverty targeting with machine learning | The research focuses on how machine learning can be used to improve poverty targeting tools. | Restricted scope, emphasis on particular factors, reliance on replication data instead of primary sources, possible algorithmic bias, and restricted applicability in different situations; |
| **[12]** | **2022** | Literature review for AI, ML and DL in poverty measurem ent | Provides insights on factors correlated to predictive power of welfare. Shows that hard indicators achieve better performance in predicting welfare. Combination of ML and DL significantly increases predictive power. Medium resolution satellite imagery achieves similar results as high-resolution ones. Using more datasets for training increases predictive power of welfare estimates | Limited inclusion criteria for year of publication Integrative review method instead of systematic approach Excluded papers completed prior to 2014 and not applying ML to study socioeconomic wellbeing from SI |

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| **[11]** | **2023** | Classifying poverty through machine learning along with focusing multidimensional poverty | Study combines satellite images and machine learning. It also disseminates the SIML poverty analysis paradigm to a wider audience. | Lack of welfare standardization; the negative correlation between country inclusion and predictive power, and the limited inclusion criteria. |
| **[58]** | **2023** | Impact of economic growth and fiscal policy on poverty rate | Studying the impact of economic growth and budgetary measures on poverty levels in Uzbekistan. Solving the problem of the lack of research on poverty in Uzbekistan. Using the neutrosophical AHP approach and time series models for analysis. | The number of observations is small because there is a limited amount of data accessible. The user did not provide any text. No causal link between taxes and poverty levels has been shown. Insufficient examination of individual government spending and their influence on poverty. |

In the area of machine learning approaches for poverty measurement and forecasting were published numerous scientific works and publications over the last decade. However, the early paper who have laid groundwork for the potential research field machine learning was the paper [9]. The paper analyzed targeting poverty through machine learning algorithms and presented and evidenced that machine learning can enhance the way of poverty prediction and minimized prediction errors by sampling out the performance. The survey extracted data from USAID tool of poverty demonstration and used proxy means test (PMT) as targeting tool for regression analysis in quantile forest to prioritize machine learning as an effective tool. Though paper suggested machine learning algorithm in evaluating poverty with proxy methods, increasing the number of variables that the algorithm can create the model from the start might result in even higher improvements in targeting accuracy [30].

In [11], 60 papers were reviewed in order to understand how effective to use AI tool and machine learning to poverty prediction. Despite of being review paper it also analyzed intersection of machine learning with satellite images. Paper provides an overview about introduction of SIML poverty analyses to audience along with quantitative synthesis of reviewed papers. Although, machine learning (ML) and deep learning (DL) models are discussed as being superior, the research lacks specific performance measures, comparisons, and benchmarking against current approaches. The comprehension of the suggested model's superiority is restricted due to the absence of a comparison examination.

The author in [12] reviews the state-of-the-art in using satellite imagery for poverty analysis. Factors correlated to predictive power include pre-processing steps, datasets used, welfare indicator targeted, and AI model choice. Studies targeting hard indicators achieve higher predictive power than those targeting soft indicators. The combination of machine learning and deep learning significantly increases predictive power compared to using either alone. Spatial resolution of satellite imagery is important but not critical to performance. No evidence of predictive performance changing over time was found. Spatial resolution of satellite imagery has a positive but insignificant effect on predictive power. Number of pre-processing methods used has a significant positive effect on predictive power. Number of datasets used has a positive and highly significant correlation with predictive power. Targeting 'hard' welfare indicators leads to higher predictive power than 'soft' indicators. Using machine learning increases predictive power compared to using deep learning. Combining machine learning and deep learning increases

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predictive power significantly. Number of countries included in a study is negatively associated with predictive power. No evidence of a statistically significant effect of predictive power improving over time.

[10] presents machine learning approaches in applied economics and it identifies limitations of econometric and simulation models. Paper explored potential solutions offered by machine learning and addressed challenges of complex simulation models. Machine learning methods are introduced from an applied economist's perspective. Limitations of econometric and simulation models in applied economics are identified and potential solutions afforded by ML are explored. Challenges of complex simulation models are highlighted. Economists have a vital role in addressing the shortcomings of ML.

[13] reviews 32 papers in the field of explainable machine learning. The transparency aspect is well-documented in many papers. Interpretability and explainability are weak in the field. Few researchers attempt to interpret their models or explain predictions. Domain knowledge is commonly used for feature selection but not in other aspects. Also, some experimental results reveal insights into interpretability and explainability. And very little effort has been spent on interpreting and explaining the transfer-learning approach. The properties of the final model should be described in an understandable way. Linear models and simpler decision trees are straightforward to describe. Saliency maps or heat maps can be used for more complicated models.

[58] the complex relationships between economic indicators, budgetary measures, and poverty rates in Uzbekistan are examined. The research examines poverty, economic growth, and fiscal factors using Neutrosophic Analytic Hierarchy Process (AHP) and standard econometric models like ARDL and VAR. The study excels at using the Neutrosophic AHP approach to explore variable correlations. Robust econometric models like ARDL and VAR improve analytical rigor. Granger causality tests illuminate poverty, economic growth, and fiscal policy links. A limited dataset limits the analysis's scope. The study wisely recommends in-depth studies of how government spending and taxes affect poverty rates. Overall, research sheds light on the complex link between economic conditions and poverty in Uzbekistan. The study provides significant insights, but fixing data issues and studying other fiscal options may improve its depth and application.

Based on the literature evaluations mentioned above, it is clear that there is a lack of thorough review publications and review articles that explore the application of machine learning algorithms for non-monetary poverty forecasting. This provided us with the motivation to close this gap and carry out a study answering Section 1's research questions.

## 3. Research Methodology

This research conducted to review poverty measurement through machine learning (ML). Thus, the structure of the research methodology (see Figure 1) was designed according to this purpose and following scientific guidelines [14]. The research methodology consists of four steps.

1. First step includes major searching activities which are: timespan, database and keyword. We have selected timespan for the research as et-the end of 2023 where our investigation started to draw out conclusion from scientific researches. While selecting papers to review we have paid attention to three criteria:
1. Source of paper (in which databases this paper is extracted from e.g., Scopus, Elsevier, Google scholar)
2. Reliability of paper (whether the paper is not extracted from copy-pasted or from internet)
3. Most recent papers (mainly for last 5 years)

For searching information, we have used keywords as: “monetary and non-monetary poverty”, “ML and AI in poverty”, “poverty and deep learning”, “and machine learning”, “non-monetary poverty” and overall, from the searches we have gathered 15 papers to our survey.

2. Second step was mainly about sorting out the papers that were collected in the first step and classified them with determined criteria’s that contains necessary information for the survey and they are followings:

- research works theoretically describing the relationship between poverty and ML were excluded
- surveys theoretically analyzing the impact of ML on poverty were excluded
- papers containing only ML in poverty without classifications of non-monetary approaches were excluded;
- conference publications were excluded;

The reason behind these criterions to analyze deep learning of poverty measurement through machine learning. Out of 15 only 5 of them remained to analyze the ML in poverty measurement and we performed remaining papers with these papers. And we discovered that first publication of ML in poverty prediction and measurement was published in 2015 and hence we took this period as our beginning period for the review.

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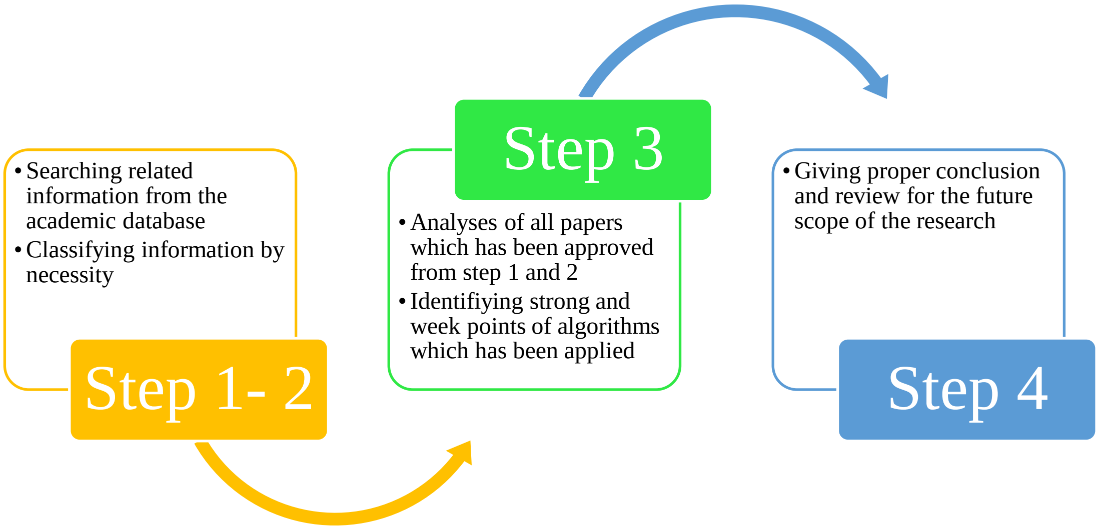


Figure 1: Process of survey

To detect the trend of publications on poverty prediction using machine learning algorithms for given time period, selected articles were divided by year of publication, and the result is shown in Figure 2. Overall, it can be observed that from 2017 to 2021, just a few publications were devoted to machine learning algorithms in poverty measurement, with the boom occurring in 2022, when five papers were released in this sector. This suggests that academics are increasingly interested in using machine learning algorithms in assessing poverty. [14]

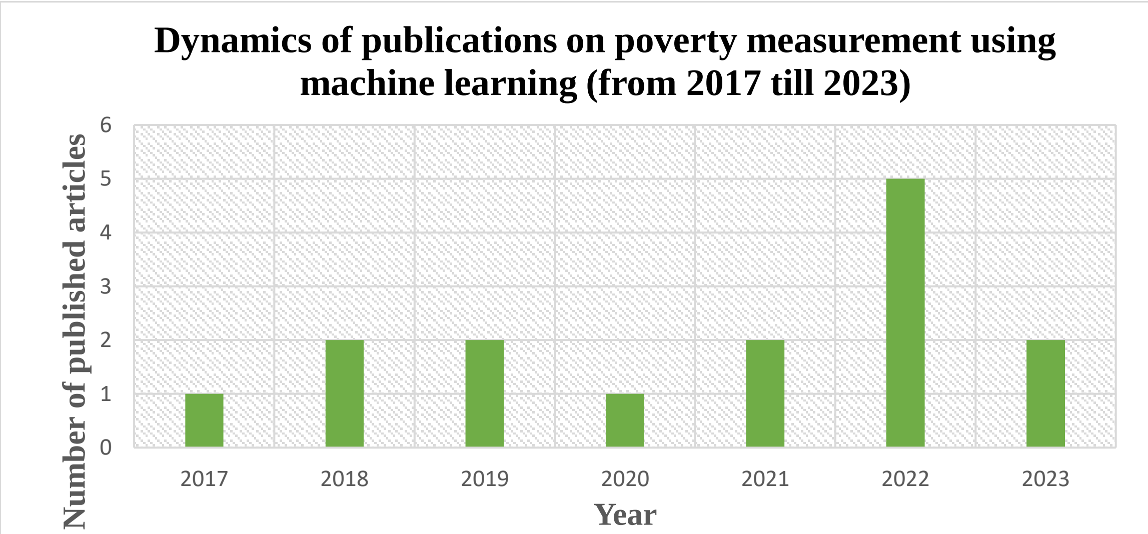


Figure 2: Papers published using ML and AI in poverty reduction

### 3.1 Neutrosophic Theory

Neutrosophic theory is a mathematical paradigm that addresses the difficulty of working with ambiguous, incomplete, and inconsistent data. It has been used in a variety of domains, including supply chain management, diabetes diagnosis, group theory, civil engineering, and classroom assessment. It has been suggested that a risk assessment technique based on neutrosophic numbers may be utilized to deal with ambiguous and partial information in supply chain management [36].
Poverty measurement and predictions are unpredictable. And for this neutrosophical theory, which might solve such challenges, is examined in various fields. This section addresses neutrosophical theory, methods, and poverty measurement applications. To handle uncertainties and imperfections, fuzzy sets (FS) were invented in 1965 [37]. Smarandash's neutrosophical sets (NS) contain basic and intuitionistic fundamental sets. The true membership (TM) degree of a component in a set is provided by FS, IFS, and NS. Unlike FS, IFS's FM function is independent of the TM function [38]. NS allows degrees of true membership (TM), false membership (FM), and indeterminate

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membership (IM). NS has distinct TM, IM, and FM functionalities. Smarandash compared NS to numerous FS extensions. NS example SVNS was invented by Smarandash. SVNS was introduced at an international conference in Salt Lake City by its developer, Haibin Wang. NS and SVNS have been presented at seminars, conferences, and articles to attract researchers [39].

The neutrosophic model may be broken down into many stages: constructing pairwise comparison matrices, calculating the total values for each column, determining normalized values, and getting the criteria weight. The first step is mathematically represented as follows [40]:

<[$T11\ L$, $T11\ U$ ], [$I11\ L$ , $I11\ U$ ] [$F11\ L$ , $F11\ U$ ]> … <[$TmL\ 1$, $TmU1$], [$ImL\ 1$, $ImU1$] [$FmL\ 1$, $FmU1$]> <[$TmL\ 1$, $TmU1$], [$ImL\ 1$, $ImU1$] [$FmL\ 1$, $FmU1$]> … <[$Tmm\ L$ , $Tmm\ U$ ], [$Imm\ L$ , $Imm\ U$ ] [$Fmm\ L$ , $Fmm\ U$ ]>
where:
T- a degree of truth
I – a degree of indeterminacy
F- a degree of falsity
i= 1,2, …, m criteria
The second phase may be shown as follows [40]:
$Sum\ ij$ = ([$\sum m\ k$=1 $Tkj\ L$, $\sum m\ k$=1 $Tkj\ U$], [$\sum m\ k$=1 $Ikj\ L$, $\sum m\ k$=1 $Ikj\ U$], [$\sum m\ k$=1 $Fkj\ L$, $\sum m\ k$=1 $Fkj\ U$]
The third stage may be represented by the formula [40]:
$Nor\ ij$ = ([$\sum m\ k$=$T1kj\ L\ Tkj\ L$, $\sum m\ k$=$T1kj\ U\ Tkj\ U$], [$\sum m\ k$=$Ikj\ 1L\ Ikj\ L$, $\sum m\ k$=$Ikj\ 1U\ Ikj\ U$], [$\sum m\ k$=$F1kj\ L\ Fkj\ L$, $\sum m\ k$=$F1kj\ U\ Fkj\ U$]
And the last step may be expressed as follows [40]:
$Wj$ = [$\sum m\ k$=1 $Tkj\ L$ $\sum m\ k$=1 $Tkj\ L$, $\sum m\ k$=1 $\sum m\ k$=$T1kj\ U\ Tkj\ U$] $m$,
[$\sum m\ k$=1 $Ikj\ L$ $\sum m\ k$=1 $Ikj\ L$, $\sum m\ k$=1 $\sum m\ k$=$Ikj\ 1U\ Ikj\ U$] $m$,
[$\sum m\ k$=1 $Fkj\ L$$\sum m\ k$=1 $Fkj\ L$, $\sum m\ k$=1 $\sum m\ k$=$F1kj\ U\ Fkj\ U$] $m$

## 4. Findings about Machine Learning Algorithms in Poverty Measurement

This section of our research devoted for illustrating main findings that we came across while conducting this survey paper. Here we outline each work that we took into consideration separately and find answers for our research questions which we have set up for the survey in this section.

*4.1. Monetary and non-monetary poverty in urban slums in Accra: Combining geospatial data and machine learning to study urban poverty (CGDMLUP)*

This paper's goal was to conduct survey in urban areas to identify main drivers of poverty result. They have analyzed data from Ghana Statistical Service (GSS) and Accra Metropolitan Assembly (AMA) who provide them with household data and census. Also, they have analyzed how slum population growing every year and aimed to review urgent polices in state which are providing slum population with housing, connecting them to jobs and improve infrastructure.

Contribution of the paper were followings: to discuss and identify of slum population, using data drive from geospatial to estimate rural area poverty. In order to study poverty in slums, it is vital to define and identify slums. However, this has proven difficult since objective metrics of slums are lacking and general definitions of slums do not necessarily apply to local circumstances. This study uses cutting-edge techniques, such as machine learning and geospatial data, to close this knowledge gap and improve slum research methodology. [15]

First step in this research was to collect data from proper sources as geospatial data, household surveys and population registration data. They conducted research based on The Ghana Living Standards Survey Round Six (GLSS 6) and collected 2,402 enumeration areas (EAs) in AMA. It was used as bases of estimating poverty rate. Then, they took pictures from Geospatial data using Quickbird-2 multispectral (Blue, Green, Red, and Near-Infrared) mosaic images. Spatial and spectral characteristics were computed from this imagery. Overall, they have calculated 7 spectrum conditions Line Support Regions (LSR), Histogram of Oriented Gradients (HOG), Linear Binary Pattern Moments (LBPM), Pan Tex, Fourier Transform (FT), the normalized difference vegetation index (NDVI), and the mean of the four original bands (Blue, Green, Red, and Near Infrared).and the initial Bands (Blue, Green, Red and Near-Infrared). One to four output layers are returned by each feature. One layer is returned by each of the four local averages of the original multispectral channels. For every adviser under the AMA, the mean, standard deviation, total, and other descriptive statistics were computed for each output of a spatial and spectral characteristic.

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After proper collection of data authors started to analyze the poverty starting with slum index. And for this they have chosen machine learning algorithm (Random Forest) which is currently popular in predicting and measuring poverty and used variables of UN-habitant. [16] The three most crucial factors in determining the slum index are elevation, population density, and the number of people living in each dwelling.

The degree of poverty was evaluated at the neighborhood level in the second phase. The sixth wave of the Ghana Living Standards Survey (GLSS 6) and data from the 2010 Population and Housing Census were combined with geographical characteristics and population density to estimate poverty. Four levels of the research region were often represented by the variables: household, census tract, neighborhood, and GIS. In the process of choosing the models, two steps were taken. Initially, the LASSO estimator with Bayesian reduction was used for feature selection, resulting in the selection of 15 variables. The final model was then chosen via a stepwise process, with the p-value serving as one of the selection factors. They also made a map of poverty [14].

And at the last stage, authors combined above results and analysis and surveyed monetary and non-monetary poverty measurement using both slum index and regression analyses. Results for monetary analyses give clear picture that slum index is highly tied to poverty rates and moreover regression analyses also highlighted lower elevation causes higher poverty rate. And it has been evidenced that 0.75 slum heads were living in slums since birth, but interestingly this population were considered to have lower poverty rate than in poorer slums. Ethnic ties were also key factors in evaluating poverty among them which is non-monetary driver of poverty as well as region.

The study discovered strong correlations between living in Accra's slums and elements including higher female fertility rates, more financial destitution, and less school attendance. Furthermore, there was a concentration of the poor in areas that were low lying, perhaps because they were more vulnerable to floods. Region, ethnicity, and religion have also been shown to be significant determinants of long-term poverty. While minorities and new immigrants worked in wholesale commerce in poorer slum neighborhoods, ethnic majority tended to be employed in manufacturing. These results illustrate a range of economic prospects in the setting of impoverished neighborhoods [15].

*4.2. Machine Learning Approach for Bottom 40 Percent Households (B40) Poverty Classification*

The paper focuses on how households in the Bottom 40 Percent (B40) are classified as poor in Malaysia. Their poverty threshold known as PLI (poverty line index) and identified by EPU (economic performing unit). They have divided poverty index as following: Top 20 with high income, Middle 40s and bottom 40. And they have plan to recover this B40 line into M40. During this survey they have come across different results.

Authors collected data from sources as: eKasih NDBP (national poverty databank) in Malaysia and total number of households intaking were 99,546 from 3 different states: Johor, Pahang and Terengganu. All in all, 15 attributes were taken to analyse (see figure 3)

| Attribute | Type | Description |
|---|---|---|
| State | Nominal | State |
| Area | Nominal | District |
| Strata | Nominal | Strata (urban or rural) |
| Ethnic | Categorical | Ethnic |
| Marital status | Categorical | Marital status |
| Age | Continuous | Age |
| Sex | Nominal | Gender (female or male) |
| Jobs | Categorical | Occupation |
| Education | Categorical | Education level |
| Type of ownership | Categorical | Ownership type of the house |
| Household number | Discrete | Total number of household |
| Total income | Continuous | Total income of the household for the past 12 months |
| Income per capita | Continuous | Per capita income |
| Date of record | Nominal | Registration date |
| Poor status | Categorical | Poverty status for the household (Poor, Hardcore Poor, Excluded) |

Figure 3: Variables from “eKasih” dataset

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Machine learning methods were applied, such as k-Nearest Neighbors, Decision Tree, and Naive Bayes. For training data, sampling techniques and data pre-processing operations are carried out. These operations included several techniques of data processing as data cleaning, normalisation, feature engineering and selection and sampling methods. [17] In data cleaning process they have uploaded all dataset into WEKA (Waikato Environment for Knowledge Analysis) and identified that it contains missing values. After altering them manually they have come to another hinder that the datasets created. The thing was database did not contain information for B40 category and they overcome this problem manually by dividing total income to 12 in order to find average income. Next, a manually formed pre-labelled class for B40 is created using each state threshold. In normalization stages they have categorized data from 0 to 1 for following attributes: Age, Number of Households, Total Income, Average Monthly Income and Per Capita Income. [18,19] After they have used 3 ranking methods (Correlation, Information Gain and Symmetrical Uncertainty) in future selection processing.

For every approach, the following eight fundamental characteristics are identified: state, area, ethnicity, number of households, total income, average monthly income, per capita income, and enumeration date. The classification accuracy increased from 93.35% to 95.76% and the Kappa score from 0.82 to 0.87 when these top features were used.

***Outcome of Analysis:***

Naive Bayes Classifier: Using the sample parameter improved accuracy from 91.52% to 97.27%.

The decision tree classifier (J48) was designed to attain a high accuracy of 99.27%. The ideal values of the confidence coefficient (0.4) and the minimal number of objects (2) were found.

The Manhattan distance function with a k value of 1 are found to have the greatest accuracy of 96.80% for the k-Nearest Neighbors (IBk) classifier.

The 10-fold cross-validation approach is used to compare the performance of Naive Bayes, J48, and IBk classifiers. With the greatest accuracy of 99.27% and the highest Kappa statistic agreement of 0.98, the J48 classifier performed best.

Tests of statistics: To find statistically significant differences between classifiers, a paired adjusted t-test was used. With an accuracy of 99.27%, the J48 classifier surpassed the Naive Bayes and IBk classifiers statistically.

Using the eKasih dataset, Decision Tree (J48) was shown to be the best classifier for categorizing B40 households. It is emphasized how crucial feature selection, parameter adjustment, and preprocessing methods are to enhancing classifier performance.

Using the eKasih dataset, the effectiveness of three classification techniques: Naïve Bayes, Decision Tree (J48), and k-Nearest Neighbor (IBk) was evaluated for the categorization of B40 households. Before the performance comparison, preprocessing methods including data cleaning, feature engineering, feature selection, sampling, and parameter tweaking were carried out. The Decision Tree model performed better than the other classifiers and produced statistically significant results. Decision Tree models work well with datasets like eKasih because they are less susceptible to outliers and missing values. Pruning reduces the complexity of the tree structure, which lowers the likelihood of overfitting and increases the accuracy of the B40 classification. Consequently, it is advised to use the Decision Tree (J48) model for B40 Classification utilizing the eKasih dataset.

*4.3 Poverty Classification Using Machine Learning: The Case of Jordan (PCML)*

Paper focuses on multidimensional poverty problem in Jordan. Machine learning approach proposed to assess and monitor poverty status. Approach considers household expenditure and income surveys since early 2000s. Light GBM algorithm achieves best performance with 81% F1-Score. Machine learning can revolutionize poverty identification and tracking [20].

The study's objective is to create a machine learning-based system for evaluating and tracking Jordanian family poverty. It makes use of information from many nationwide surveys on household income and spending that the Department of Statistics (DoS) carried out between 2002 and 2017. By utilizing a dataset including 63,211 households and 47 attributes, comprising 17 categorical variables, the research emphasizes the disparity between the impoverished (13.9%) and affluent (86.1%) groups. Preprocessing methods including one-hot encoding, normalization, and standardization have been applied to address this issue.

Evaluations were conducted on sixteen machine learning methods (Logistic Regression; Ridge Regression; Stochastic Gradient Descent; Passive Aggressive; k-Nearest Neighbors; Decision Tree; Extra Tree; Support Vector Machine; Naive Bayes; AdaBoost; Bagged Decision Trees; Random Forest; Extra Trees; Gradient Boosting Machine; Light GBM; Scalable Tree Boosting System). Compared to other models, Light GBM and packed decision trees had the highest F1 scores, almost 80%. The study also looked at class weights, SMOTE, random oversampling,

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and random under sampling as solutions to the imbalanced dataset issue. It's interesting to note that the model performances for the situations with balanced and unbalanced data differed slightly. Interestingly, Light GBM obtained the greatest F1 score (81%), using random resampling; decision trees with batches fared better (80%) when class weight balancing (grid search) was used.

Consequently, the study shows how different machine learning algorithms may be used to anticipate poverty in Jordan. It indicates that resolving data inconsistencies has little effect on model performance and emphasizes the appropriateness of Light GBM and packed decision trees for poverty modeling. This study provides important information to groups and officials working to lower poverty in Jordan and establishes the groundwork for future efforts in poverty forecasting.

### *4.4 Small area estimation of non-monetary poverty with geospatial data (SAENMPGD)*

The paper evaluates the benefits of combining household surveys with satellite and geospatial data to produce estimates of non-monetary poverty in small areas. [21] The use of geospatial data can improve the precision and accuracy of non-monetary poverty estimates. Geospatial data are well suited for assessing small areas because they are geographically complete and not subject to selection bias [22].

Data description included four methodologies such as constructing non-monetary measures of poverty, constructing synthetic household survey, remote sensing data and geographical structure. Comparing to monetary poverty non-monetary poverty can be easily identified from census data of a country and they have extracted from Sri Lankan and Tanzanian censuses in 2012. For each household they identified set of assets in households (TV, computer, housing equipment's) and demographic identities (gender, education, working area, size of family) for welfare and weighted each of them. Each welfare indicator's loading factor was estimated using principal component analysis, with the first principal component being kept. Households falling below these levels were defined as non-monetarily poor. Poverty thresholds were established based on the 20th percentile in Tanzania and the 4th percentile of non-monetary wellbeing in Sri Lanka. After the analyses that has been done with census authors draw synthetic survey for each country. The researchers combined household budget surveys with census data at the village level in Sri Lanka (GN Division) and at the village level in Tanzania to construct the synthetic survey. The village in Tanzania is the smallest administrative unit, whereas the GN Division is the administrative division in Sri Lanka. The researchers kept the villages and GN Divisions that were included in the household survey after combining the data. To match the number of households in each administrative unit for each survey, census households were randomly picked from the matching administrative units. By using a random selection process, the NSO can make sure that the synthetic survey accurately reflects the features of the real survey. The auxiliary data for small area estimation were obtained from various publicly available sources, including satellite imagery, climate data, population estimates, and crop yield estimates. For the geographic structure of Sri Lanka and Tanzania, authors collected number of villages, areas, and regions in each country.

Three main techniques are used in the Small Area Estimation (SAE) of poverty rates: The Empirical Best Linear Unbiased Predictor (EBP) model at the household level, the Fay-Herriot area-level model, and direct survey estimates. The Fay-Herriot model uses direct survey estimates as benchmarks, whereas the EBP model functions at the household level. When measuring poverty rates with more accuracy through the integration of satellite data, each technique has pros and cons [21]. The Fay-Herriot model, which is widely employed in small area estimates, may eliminate variance at lower levels by aggregating supplementary data to small area levels. Its shortcomings include underestimating prediction variance, ignoring within-cluster variation, and presenting difficulties when applied to non-poverty regions [23].

In contrast, the household-level EBP model functions at the individual household level, leveraging information on welfare variability and regional variables. Conditional random effects regression, which is a feature of the EBP model, provides efficiency advantages by conditioning on sample values and using simulated welfare to improve forecast accuracy [24] [25]. The premise of normalcy is central to the EBP paradigm, requiring welfare modifications. In order to improve estimates and conform to model assumptions, monotonic adjustments such as ordered quantile normalization seek to bring the welfare distribution closer to normal. Model selection is still very important, and the least absolute shrinkage and selection operator (LASSO) is becoming more and more well-liked because of its data-driven methodology and ability to prevent overfitting. In order to preserve consistency with official statistics, benchmarking processes seek to calibrate small area estimates with direct sample estimates.
Evaluation criteria include a range of summary statistics that evaluate the effectiveness and accuracy of SAE approaches, such as coverage rates of confidence ranges, poverty rates, Mean Squared Error, and Relative Bias. All in all, these techniques, although displaying clear benefits, have certain constraints. With evaluation criteria directing

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the assessment of their performance, their integration provides a thorough framework for accurate poverty rate calculation at local area levels [26], [21].

Authors used a mixed empirical best forecast (EB) model at the household level to combine survey data with geospatial data. The model estimates household wealth projections based on survey data and uses the estimated parameters to model census wealth. Census data is linked to auxiliary geospatial and remote sensing data at the village level to overcome the problems associated with using outdated census data. The paper reports that combining survey data with geospatial data significantly improves the accuracy and reliability of non-monetary poverty estimates. The EB forecast model moderately underestimates standard errors of point estimates but has a level of coverage similar to survey-based standard errors. Fay-Herriot's estimates, prior to comparative analysis, underestimate poverty levels in both Tanzania and Sri Lanka.

### *4.5 A machine learning approach to targeting humanitarian assistance among forcibly displaced populations (MLTHAFDP)*

The research paper examines poverty assessment methodologies in Lebanon in detail, focusing on multidimensional poverty and household expenditure. Through rigorous analysis using the Multidimensional Poverty Index (MPI) and the Proxy Means Test (PMT), the study examines the classification of households into poor and non-poor categories based on these different measurement approaches. The comparison reveals the subtleties of understanding the accuracy and limitations of poverty projections, especially when exposing exclusion errors. Data is extracted from Vulnerability Assessment of Syrian Refugees (VASyR) which subsequently joined with UNHCR, WFP, and UNICEF from 2018 till 2021. It had detailed information of non- monetary poverty factors such as: (1) demographics (individuals and households, working conditions); (2) shelter, utility, sanitation, settlement conditions; (3) income, assets and liabilities of refugees; (4) consumption and dietary demands of refugees; (5) health and safety and (6) and surviving strategies. Partitioning and testing models using remaining partition were used in analysing method along with modeling and cross validation using R Package Caret. Calibration to identify best model for predicting PMT scores with five accuracy metrics used to evaluate model performance. Use of ROC curves to define optimal poverty cutoffs.

Machine learning techniques applied to geospatial and survey data. Comprehensive framework for targeting humanitarian assistance among forcibly displaced populations. Importance of capturing multiple poverty dimensions and geographical heterogeneities. Insights for improving targeting strategies in the context of shrinking humanitarian funding. The results indicate a significant correspondence between expenditures and measures of multidimensional poverty, highlighting the consistency in identifying poor households. However, there are discrepancies between predicted values and actual poverty status, highlighting the challenges inherent in accurate forecasting models.
Authors identified influential determinants that affects poverty categorization, including educational attainment, household composition, coping mechanisms, and access to basic services. In addition, the study delves into geographic patterns of poverty, examining differences in poverty rates across areas and over time. Using various indicators such as food consumption, housing conditions, educational attainment and financial aid received, the study provides a comprehensive view of poverty. Geographic factors such as vegetation indicators, night light intensity and population density are considered to assess the vulnerability of Syrian refugees living in Lebanon.

### *4.6 Quarterly Multidimensional Poverty Predictions in Mexico using Machine Learning Algorithms (QMPPMLA)*

This paper describes how efficient is machine learning in particular country for time intervals and as equally importance for the government as well as organizations such as World Bank, OECD, IDB because it is as important to identifying poverty as fighting against it. [30] In order to assess machine learning (ML) algorithms for classifying poverty, this article looks at performance metrics other than accuracy. Examining these models' out-of-sample robustness and effectiveness in predicting poverty status is the primary goal. Accuracy is only one performance indicator; thus, the study explores other metrics that may be obtained from the confusion matrix in order to give a more complete framework for evaluation.

To forecast poverty levels, the scientists employed a dataset that included satellite images and socioeconomic factors. Support vector machines (SVMs), random forests, and convolutional neural networks (CNNs) are just a few of the machine learning methods that are employed. Income, education, and work status are examples of socioeconomic indicators, while geography and infrastructural data may be obtained from satellite images. Accuracy, memory, specificity, precision, negative predictive value (NPV), F1 score, and kappa are confusion matrix-based metrics that the researchers used to preprocess the data, perform feature engineering, and assess the models.

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The study's conclusions about the shortcomings of accuracy as a lone metric are convincing. Although accuracy serves as a gauge for accurate predictions, it is insufficient to offer a thorough assessment of a model's performance. Model behavior is explained in detail by metrics like as recall, specificity, accuracy, and net present value (NPV) that are obtained from the confusion matrix. This makes the F1 score the harmonic mean of accuracy and recall a more trustworthy metric, particularly when assessing models that forecast a person's poverty level. The study does, however, draw attention to the inherent trade-offs in these strategies. For instance, maximizing one measure might force a compromise on another. The thorough examination of machine learning models using a variety of measures, which offers a deeper knowledge of model performance, is one of the research's most noteworthy qualities. He stresses that it's important to take into account a variety of indicators instead of depending just on accuracy. However, because the study's conclusions can be based on a particular data collection or skewed toward certain socioeconomic or geographic situations, it might be difficult to generalize the findings. Moreover, practitioners who are not experienced with these evaluation approaches may encounter difficulties due to the intricacy of the measurements.
To sum up, this article suggests going beyond the use of accuracy alone and instead evaluating machine learning models for poverty categorization in greater detail. He draws attention to the subtleties of model evaluation by using metrics that are obtained from a confusion matrix. The study highlights the importance of using multiple metrics to evaluate different aspects of model performance, thereby offering valuable information for future research and practical applications in poverty classification using machine learning algorithms.

*4.7 Program targeting with machine learning and mobile phone data: Evidence from an anti-poverty intervention in Afghanistan (PTMLMPD)*

In the pursuit of successful poverty reduction, assisting the ultra-poor remains a significant problem. This study investigates a novel technique for identifying ultra-poor families in Afghanistan's most impoverished districts using machine learning (ML) algorithms and mobile-phone data. Traditional techniques frequently rely on asset or consumption-based indicators, but this study investigates how mobile phone data might increase targeted precision and efficiency.

Data in this article includes survey data as targeting ultra-poor population (TUP) in Afghanistan population by World Bank taking 6 regions between 2015 and 2018.TUP program had an eligibility criterion like geographic which included community wealth ranking (CWR) and a follow-up in-person survey. Besides meeting those criteria to be considered as Ultra Poor it should meet 6 more non-monetary measurements as school-age children, non-beneficial assets, women under age 50, living in a cave, begging and no adult men in incomes. The survey comprised 535 households in Afghanistan's impoverished neighborhoods, the majority of which were filled by people who had cellphones. Machine learning algorithms are used to forecast family income by analyzing call detailed data (CDR) from mobile providers. The utility and efficacy of ML-based targeting are demonstrated by contrasting methodologies such as telephone data, survey data, and traditional asset-based approaches.

The study's findings indicate that the future looks bright. Machine learning algorithms based on telephone data have been demonstrated to be almost as accurate in detecting extremely poor families as classic asset- or consumption-based models. Surprisingly, integrating survey data with CDR resulted in enhanced target accuracy. However, limits occurred. Low phone ownership decreases the efficacy of CDR-based targeting, emphasizing the need of prioritizing homes without phones before adopting CDR algorithms.

The advantage is obvious: machine learning-based targeting saves substantially more time and money than testing or consumption-based strategies. The increased cost of screening using CDR is modest, making it a cost-effective choice. However, these challenges are impossible to avoid. Access to CDR for the entire population is required for maximum targeting precision. Furthermore, moral concerns regarding data privacy and the possibility of purposeful underreporting of phone ownership are legitimate considerations.

Thus, this study emphasizes the expanding possibility for employing machine learning-based mobile phone data to reach extremely poor people in underdeveloped countries like Afghanistan. The increasing usage of mobile phones in developing nations, together with gains in productivity and relative accuracy, demonstrates the promise of this method. However, you should use caution. Ethical issues, access to extensive knowledge, and the danger of strategic conduct need deliberate decision making. This research serves as a guide for demonstrating the potential of novel approaches in the battle against poverty, and it advocates for a balanced strategy that incorporates efficiency, ethics, and inclusivity in the implementation of such interventions.

*4.8 A comparison of machine learning approaches for identifying high-poverty counties: robust features of DMSP/OLS night-time light imagery (CMLAIHPC)*

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In this research, the authors look at how machine learning may be used to detect high-poverty regions using nighttime light footage. The study examines 96 high-poverty counties and 96 low-poverty counties in China in 2010, utilizing 15 statistical and geographical parameters taken from DMSP/OLS night light data for categorization. It discusses a wide range of approaches, strategies, and empirical research used to investigate poverty from a multidimensional standpoint. The emphasis is on the use of remote sensing data, namely night-time satellite images and other spatial data sources, to detect, quantify, and analyze poverty levels in various geographic areas.
Data for this study were acquired using nighttime light images received from the Department of Defense Meteorological Satellite Program/Operational Linescan System. Since 2010, the focus has been on 96 Chinese counties with high poverty rates and 96 nations without poverty. The dataset was supplemented with 15 statistical and geographical variables, resulting in a strong training set for machine learning algorithms. Nightlight imaging has proven to be a vital resource, delivering reliable and distinct spatial data. The study emphasized the adaptability of machine learning in recognizing poverty, providing a new viewpoint when compared to standard data gathering methods.

The authors utilize seven machine learning algorithms and five feature significance criteria to provide a thorough evaluation of their performance. The results demonstrate strong performance: user accuracy exceeds 63%, producer accuracy exceeds 66%, and total accuracy exceeds 82% for poor county identification (poverty probability greater than 0.6). This demonstrates the efficiency of machine learning techniques, despite variances between them.
One significant component is the identification of nine consistent, trustworthy indicators for detecting poverty at the county level, which includes both geographical and statistical aspects. This conclusion calls into question past research that have largely employed nightlight pictures to investigate poverty, urging a more detailed approach.
In terms of strengths, comprehensive assessment of machine learning algorithms, feature significance measures, and robust feature identification all contribute significantly to the discipline. A thorough strategy is emphasized that encompasses both geographical and statistical aspects, resulting in a novel way for picking variables for determining poverty. However, a more thorough explanation of the constraints and difficulties faced during the study process would have enhanced the paper. Additionally, reducing any biases and uncertainties in machine learning models will increase the confidence in the findings.
Looking ahead, further research might investigate the variables causing the disparities between machine learning algorithms identified in this study. Investigating the transferability of the found resilient traits to diverse geographic and socioeconomic situations may help broaden the scope of the suggested strategy. Furthermore, examining the temporal dynamics of poverty using time series of night-time light data might shed information on the changing nature of poverty.

*4.9 Estimating city-level poverty rate based on e-commerce data with machine learning (ECLPRBECDWML)*
Current paper that was reviewed is about to investigate city-level poverty with a help of machine learning and e-commerce data. The aim was to demonstrate city level poverty rates estimation via machine learning algorithms like support vector regression (SVR) and deep neural network (DNN). This study presents a strong framework that combines machine learning algorithms with e-commerce data to accurately and dynamically estimate poverty at the municipal level and it highlights the potential of e-commerce datasets as useful proxies for predicting poverty rates by utilizing Support Vector Regression (SVR) and Deep Neural Networks (DNN) in conjunction with astute feature selection.

The research identifies several strengths of the proposed framework, starting with the models' improved prediction skills compared to SVR, with DNN displaying exceptional performance with feature selection. This demonstrates the potential of deep learning to uncover intricate patterns in e-commerce datasets. Another notable strength is the incorporation of feature selection procedures that offer a more in-depth understanding of the factors driving poverty rates.

Furthermore, the study treats e-commerce data as a supplement to existing datasets, providing new insights into economic situations that traditional datasets may overlook. However, the report acknowledges certain limitations. Data accessibility and confidentiality issues restrict the widespread use of e-commerce data. Obtaining complete datasets remains a significant challenge, particularly in communities with low economic status. In addition, the low transaction volume in underdeveloped areas increases the likelihood of inaccurate projections, so caution should be exercised when interpreting the results.

In conclusion, incorporating e-commerce data with cutting-edge machine learning algorithms presents a viable approach for estimating poverty at the municipal level. The study's key advantages include the usefulness of the prediction models, the careful feature selection, and the complementary nature of the e-commerce data. Despite the

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challenges associated with data accessibility and transaction volume restrictions, the framework demonstrates its potential to supplement existing poverty estimation methodologies.

Future research could explore the scalability of the proposed framework across multiple administrative levels to gain a more comprehensive understanding of poverty dynamics. Employing time series and panel data analysis could strengthen the framework's temporal resilience and provide more detailed insights into poverty's evolution. Enhancing the framework's applicability and pinpointing potential areas for improvement may involve envisioning ensemble learning techniques and conducting comparison assessments with alternative methodologies.

*4.10 Identifying Urban Poverty Using High-Resolution Satellite Imagery and Machine Learning Approaches: Implications for Housing Inequality (IUPUHRSIMLA)*

This article investigates urban poverty with a help of high-resolution satellite imagery along with machine learning in Chinese community dividing it into levels. Depending on communities' poverty level it varied based on monetary and non-monetary factors such as housing, income distribution and wealth distribution. In order to find out urban poverty with a help of those factors' authors used 4 machine learning techniques and 25 variables. Data was collected regarding the case study from the Jiangxia and Huangpi suburbs of Wuhan. Satellite pictures of Jiangxia, being a significant location within the Wuhan metropolitan area and boasting a strategic geographical position, has seen a surge in population and urbanization rates. The results demonstrated that urban poverty measured with best models and the results are viable to be adapted by policy makers for sustainable society in economics.

Authors collected data from following sources: first, a collection of Google Earth images from 2016, which includes 3 band multispectral (R: red, G: green, and B: blue) stacks with a resolution of 4.09 meters per pixel. This picture was created by combining satellite, aerial, and Street View photographs after they were processed. Satellite imagery utilized includes Quick Bird, Landsat, and World View, while aerial data is mostly derived from commercial firms. Second, the local government submitted a land cover dataset and administrative boundary data from 2016. Finally, the local agency sent the 2016 population census and poverty information to neighborhood and village committees. Since each dataset has a geographic coordinate component, combining them for a geographical analysis is feasible. Poverty incidence (PI), or the percentage of impoverished people in the entire region, was used as the indicator for urban poverty in this study. PI is commonly used as one of the parameters to characterize regional poverty. [56]

Coming to calculation process they have calculated images for their geometric features, shape and texture features to explore significance in differentiating poverty in China with help of four regression analyses via machine learning algorithms as random forest (RF), support vector regression (SPV), Gaussian process regression (GPR) and neural network (NN). Machine learning approaches have received a lot of attention for their capacity to anticipate complicated and nonlinear connections, as seen by their success metrics. These approaches, which maximize predictions based on previous experiences or example data, are commonly utilized to help decision-making processes. [34]

Results were classified as the best model performance for every machine learning algorithm in R set software adjusting the performance and sampling the numbers in set called "set. seed" and summarized in table 2. Based on the results SPV (support vector machine) with R2 values of 0.5341 and 0.5324 respectively shown best results as the characteristics of remote sensing images can accurately identify urban poverty in Jiangxia and Huangpi, accounting for about 53% of the variance. The least accuracy shown among the four models for Huanpi it was GPR which indicated 0.4231 whereas for Jiangxia was NN (neural network) even less accuracy with showing 0.3492.

**Table 2.** Model performance of each machine learning model of Jiangxia and Huangpi.

| | RF | GPR | SVR | NN |
|---|---|---|---|---|
| Jiangxia | 0.3581 | 0.3653 | 0.5341 | 0.3492 |
| Huangpi | 0.5082 | 0.4231 | 0.5324 | 0.4937 |

The variable significance indicators demonstrated that F18, F17, F7, and F6 were consistently important in identifying urban poverty. The models were evaluated with LISA and revealed a strong match between the projected poverty index and the survey-based PI. The study emphasizes the potential of machine learning in recognizing urban poverty, focusing on the significance of certain structural traits.

Finally, the study revealed the ability of machine learning regression models, notably SVR, in employing remote sensing image data to identify urban poverty in China. The persistent importance of some factors emphasizes the significance of structural parameters such as GLCM and HoG in identifying residential regions with varying levels of poverty.

## 5. Discussion

This study focuses on the need to enhance traditional methods to poverty assessment with the more advanced capabilities provided by machine learning (ML) techniques. When it comes to understanding the complex and

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diversified nature of poverty, standard methodologies focused simply on monetary indicators might be inadequate. The goal of this research is to apply machine learning to overcome these limits and provide a better and more comprehensive understanding of the dynamics of poverty.

There is a clear link between the present popularity of machine learning and technological advancements, as well as the unprecedented data multiplication that occurred during this time. As data sets grow and complexity, traditional statistical approaches struggle to extract usable insights. Algorithms for machine learning designed to handle large and complex data sets have become critical in many areas of research. Machine learning is popular because of its ability to recognize complex patterns, deal with non-linear relationships, and extract insights from multidimensional data pieces. These qualities are intrinsically linked to the complex structure of poverty and the circumstances that contribute to it.

The application of machine learning to measure poverty represents a paradigm shift from one-dimensional, money-focused appraisal to multidimensional analysis. This study takes a scientific approach to exploring a broad range of machine learning approaches like Support Vector Machines, Random Forests, and Neural Networks, and et., (see Figure 4) shows how different algorithms may capture the many causes of poverty. Machine learning algorithms contribute to a more sophisticated understanding of poverty by including non-monetary variables such as education, living conditions, and access to necessities. This helps to depict the complex reality that disadvantaged people face.

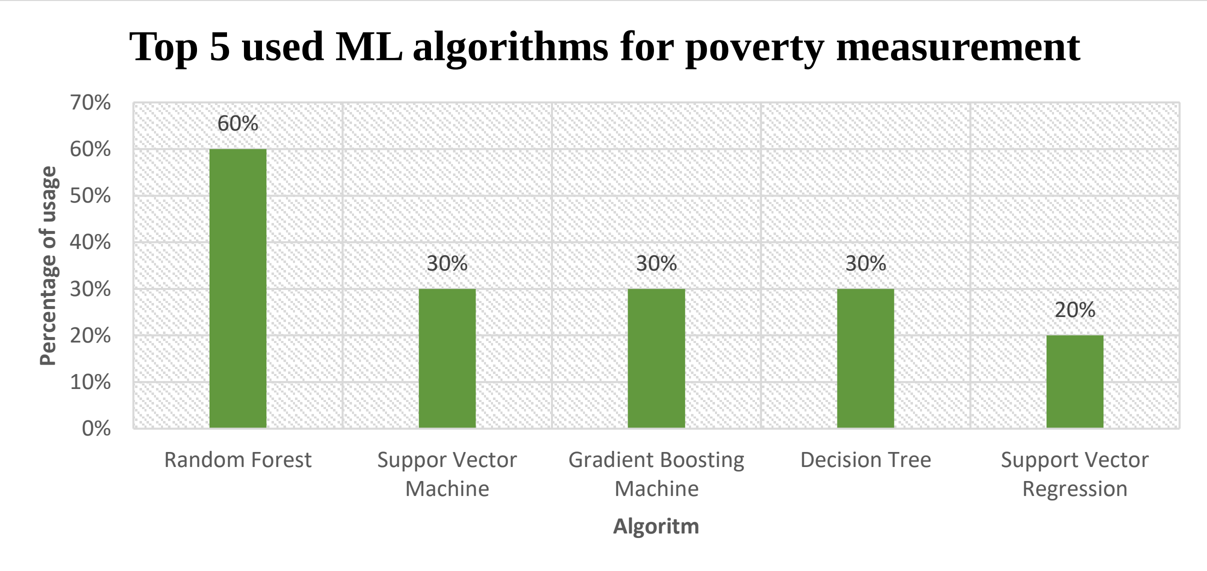


Figure 4: Most popular machine learning algorithms in papers discussed above.

Using machine learning to measure poverty involves a variety of challenges, despite its enormous promise. The study looks at these issues, highlighting critical elements such as a lack of data and the resource-intensive nature of machine learning algorithms. The ethical implications of algorithmic decision-making and the risk of bias are seriously considered, with a focus on the need of ethically deploying machine learning models that require careful interpretation. The findings of empirical research conducted in a range of locales, including Mexico, Afghanistan, China, and Indonesia, give a clear grasp of the effectiveness of machine learning algorithms in a variety of socioeconomic settings. In addition to identifying important standards for future implementation, the research discusses the benefits and drawbacks of machine learning models in terms of their capacity to anticipate poverty in specific geographical areas.

This study investigates the intricacies of machine learning measurements and demonstrates that holistic evaluation extends beyond accuracy. The constraints of relying only on accuracy are highlighted via the evaluation of measures such as recall, specificity, precision, F1 score, and kappa. This complex examination of machine learning models, which uses several variables, provides a more in-depth understanding of model performance. This understanding will help to guide future research and practical applications in the subject of poverty classification.
Finally, this study gives insight on the mutually beneficial relationship between machine learning and poverty assessment, which may be regarded a significant contribution to the ongoing conversation on poverty measurement. As the science of machine learning advances, it is critical to develop both algorithms and ethics. To fully address the multifaceted nature of poverty, the research demonstrates the need of a balanced combination of technological innovation, scientific discoveries, and ethical considerations. This establishes a foundation for future study and

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emphasizes the need of addressing its multifaceted character. The introduction of machine learning into the poverty measurement process will not only improve prediction accuracy but will also give a more thorough understanding of the many factors that lead to poverty. This will eventually result in more effective policy interventions and resource allocation strategies.

For a comprehensive review of the analyzed articles, Table 3 was developed to highlight and summarize the main aspects of ML algorithms used in poverty measurement. The table has an information column for the analyzed work and a second column indicating the year of publication. The analyzed articles in the column "Country" contain information about the countries that are the subject of poverty prediction. The "Data" column contains information about the dataset used, while the "Method" column lists the names of the ML algorithms used. The last two columns describe the advantages and disadvantages of the models created.

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Table 3: Poverty prediction in applying ML algorithms.

| Ref. | Year | Country | Data | Method | Advantages | Disadvantages |
|---|---|---|---|---|---|---|
| [15] | 2017 | Africa (Albania, Ethiopia, Malawi, Rwanda, Tanzania, and Uganda) | Three types of data used: population census, household data (in the Accra Metropolitan Assembly (AMA), 2,402 enumeration areas (EAs) were used to get the data.), geospatial data. Datasets have location information and can be combined spatially. | Machine learning and geospatial data are used to define slums objectively. Household survey data and census data are combined with satellite imagery and other geospatial data. Poverty rates are estimated at the neighborhood level. | 1.The paper employs innovative methods to advance the methodology in slum research.<br>2.Providing systematic bibliometric literature reviews.<br>3.Analyzing the content of collected papers.<br>4.Identifying the data used for poverty prediction via AI.<br>5.Evaluating the advantages and disadvantages of AI models for poverty prediction.<br>6.Discussing the future scope of AI applications in poverty prediction. | 1. GLSS 6 data contains only 852 observations in AMA.<br>2.Limited number of variables can be included in the final model.<br>3.Use of a very conservative model selection procedure.<br>4.Use of Lasso estimator and stepwise procedure for model selection. |
| [27] | 2018 | Malaysia (Johor, Pahang and Terengganu) | eKasih dataset has been used | Naïve bayes; Decision Tree (J48); and kNearest Neighbors | 1. A feature selection algorithm experiment was carried out utilizing multiple ranking approaches.<br>2. For each of the three ranking algorithms, eight key attributes are defined.<br>3. Detection of missing values and outliers in a data collection. | 1. Attributes such as marital status, education, and property type have missing data.<br>2. The dataset's misfits.<br>3. A monetary-based poverty criterion could not account for all facets of poverty. |
| [20] | 2021 | Jordan | Jordanian household expenditures and income levels were taken since 2000s | Machine Learning Algorithms: Logistic Regression; Ridge Regression; Stochastic Gradient Descent; Passive Aggressive; k-Nearest Neighbors; Decision Tree; Extra Tree; Support Vector Machine; Naive Bayes; AdaBoost; | 1.Machine learning-based categorization of poverty in Jordan: summary of resources and techniques | 1.Data limitations (only national household expenditures and income surveys were taken)<br>2.Modeling limitations (performance evaluation (limited up to F-1 scores) and algorithm choices |



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| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | Bagged Decision Trees; Random Forest; Extra Trees; Gradient Boosting Machine; Light GBM; Scalable Tree Boosting System | | (does not includes deep learning)); 3.Socio-economic factors (e.g., cultural changes, social policies, external influences) |
| **[28]** | 2022 | Tanzania and Sri Lanka | Household data of Sri Lanka and Tanzania, National Household Budgets for 206 and 2018 respectively, remote sensing data and lastly, geographic structure of both countries. | Methodology outlined the three approaches that are evaluated: Estimates from direct surveys, the Fay-Herriot area-level model, and the household-level EBP model | 1. Assesses the advantages of integrating geographical data with household surveys. 2. It has been discovered that data aggregation increases the precision of poverty estimations. | 1. It is anticipated that a subset of coefficients will not change over time. 2. A lack of census data to determine accuracy and dependability. |



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|---|---|---|---|---|---|---|
| **[26]** | 2023 | Lebanon (Syrian Refugees) | Geographical data is utilized in humanitarian relief and anti-poverty initiatives.<br>Studies on poverty targeting make use of mobile phone data.<br>Chi et al. estimated poverty using ML algorithms and geographical indicators.<br>For their poverty cutoffs, Verme and Gigliarano employed ROC curves and PMT.<br>Food security was one of the non-monetary metrics that Chaaban et al. considered. | Distance approach was used one of the methodologies for this paper; and the other one was machine learning in poverty prediction; | 1.Multidimensional poverty analyses (it gives analyses which is beyond just monetary factors as education, food, electricity, sanitation, etc.)<br>2.Comparative analyses using machine learning algorithms as PMT (proxy means test) and MD-PMT (Multidimensional Proxy Means Test) | 1. Inability to do thorough geospatial analysis;<br>2. Lack of access to administrative data and certain algorithms utilized by humanitarian groups<br>3.Difficulty in validating and optimizing models for precise forecasts<br>4. Dependency on PMT scores depending on spending<br>5. Exposure to changes in inflation and pricing<br>6. Capturing non-financial dimensions of poverty is limited. |



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|---|---|---|---|---|---|---|
| **[29]** | 2019 | Mexico | Biannual National Survey<br>of Household Income and Spending from 2008 to 2016 as training data | Linear Discriminant Analysis (LDA), Random Forest (RF), and Support Vector Machines (SVM), | 1.Random Forest (RF) algorithm shows the best performance with a mean error rate of 5.1%. RF exhibits the best Mean Rank according to seven supplementary assessment metrics.<br>2.Logistic regression (Logit) is used as a benchmark model. It allows making inference about how predictors affect poverty probability.<br>Logit model's predicted poverty rate is closer to the official rate than labor poverty and optimal cutoff for classification is chosen via cross-validation.<br>Logit model's out-of-sample error rate is 14.6% on average.<br>3.LDA's predictions during 2016 and 2018 are not as accurate as other ML models. | 1.LDA's predictions during 2016 and 2018 were not accurate.<br>2.LDA has the highest cross-validation error rate (19.4%) on average.<br>3.RF shows the best performance with a mean error rate of 5.1%. |



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|---|---|---|---|---|---|---|
| **[31]** | 2022 | Afghanistan | The study focuses on program targeting using machine learning and mobile phone data. It examines the accuracy of machine learning methods in identifying ultra-poor households. The study combines survey-based measures with mobile phone data for improved classifications. The study evaluates the effectiveness of using mobile phone data for program targeting. | CDR-based targeting method Asset-based targeting method Consumption-based targeting method Gradient boosting model (machine learning algorithm) Machine-learned asset predictor (for ultra-poverty outcome) | 1.Evaluates the use of non-traditional administrative data(non-monetary) for program targeting. 2.Assesses the accuracy of three counterfactual targeting approaches. 3.Discusses ethical and logistical considerations for using CDR methods in targeting efforts. | 1.Mismatch between survey respondent and phone owner in the TUP survey. 2.Limited to the poorest villages of a single province in Afghanistan. 3.Evaluation of poverty estimates for real-world policy applications not conducted. |



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| **[32]** | 2019 | China | Night-time light imagery; County boundary data. | Gaussian process, Random forest, Support Vector Machine, Stochastic Gradient boosting, Rotation forest, Least Squares Regression, Neutral network | 1.Demonstrates the use of machine learning approaches for identifying high-poverty counties.<br>Identifies robust features for poverty identification using night-time light imagery.<br>2.Describes the selection and acquisition of statistical and spatial features from night-time light imagery.<br>3.Discusses different machine learning approaches used for poverty identification.<br>4.Introduces feature importance measures for different classification approaches. | 1.Differences exist among the seven machine learning approaches used.<br>2.Differences in feature importance measures between the two categories.<br>3.Some features are identified as comparatively important rather than indispensable.<br>4.The study does not consider the characteristics of each approach.<br>5.Extensive and comprehensive feature selection is relatively important. |



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| **[33]** | 2022 | Indonesia | Proposed framework for poverty rate estimation based on e-commerce data. Data pre-processing, feature selection, learning algorithms, and performance measure. Aggregation based on city/district to calculate statistical features. Four metrics used for performance measurement: RMSE, bias factor, accuracy factor, R-squared. | Two machine learning algorithms, deep neural network (DNN) and support vector regression (SVR), are utilized. Statistical feature extraction, filter-based feature selection, and normalization are performed. | 1. E-commerce data can be used to estimate city-level poverty rates.<br>2. E-commerce data provides aspects such as selling price, number of items sold, number of viewers, and number of buyers for further analysis.<br>3. E-commerce data can be used as a proxy for poverty rate prediction to complement official data.<br>4.The method presented in this research can be replicated and scaled up for all cities in Indonesia.<br>5.The performance of the model can potentially be improved using other approaches. | 1. Inability to gather information on poverty rate between surveys.<br>2. Requirement of certain resources to conduct surveys. |



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| **[34]** | 2021 | China (Jiangxia and Huangpi suburbs in Wuhan) | Google Earth (GE) imagery(R: red wavelength, G: green wavelength, and B: blue wavelength); Dataset from GIM by local department of Wuhan; Population census and poor population statistics from local department. | Four machine learning approaches: Random Forest (RF), Gaussian Process Regression (GPR), Support Vector Regression (SVR), and Neural Network (NN) and 25 variables used; Coefficient of determination (R2) used to quantify model performance; | 1.Empirical evidence on the utility of image features and machine learning approaches for identifying urban poverty in China.<br>2. Identification of important variables for identifying urban poverty.<br>3. Application of findings for addressing housing inequality and urban planning. | 1. Some differences exist among the approaches and study areas.<br>2. The importance of each variable differs for each approach and study area.<br>3. The model performance is general but acceptable for policy makers. |



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## 6. Conclusion and Recommendations

Our objective was to provide a thorough examination of the use of machine learning for the evaluation of poverty. We have analysed and combined the incorporation of non-monetary methods, namely machine learning (ML), with the ground-breaking neutrosophic theory of poverty assessment. Considering this, we emphasised the significance of crucial benefits, such as the capability to objectively analyse poverty via the use of novel approaches and the incorporation of a variety of data sets, including household surveys and satellite pictures. When non-monetary multidimensional components other than monetary restrictions were taken into consideration, this combination produced a more complete picture of poverty.

In the research we have examined and evaluated 10 influential publications that elucidate the amalgamation of artificial intelligence (AI) and machine learning (ML) for the purpose of poverty forecasting. During the survey we encompassed a range of domains, including applied economics, agriculture, and specific strategies aimed at reducing poverty. Also, we have emphasized the significance of using machine learning methods in conjunction with satellite images, underscoring the efficacy of objective indicators for enhancing forecasting precision.

An in-depth examination of the findings reveals a significant increase in scholarly attention towards machine learning algorithms for poverty assessment, particularly prominent over the period from 2017 to 2023. We draw attention to the deficiency in the existing body of research on the use of machine learning in predicting non-monetary poverty, thereby elucidating a well-defined study aiming to tackle this deficiency.

With, our research does have several severe drawbacks. The creation of accurate models is made more difficult by the presence of data limits, such as a limited number of observations or variables in some bodies of study. Additionally, the inclusiveness of variables is affected by a variety of model selection techniques with varying characteristics. The difficulty in evaluating and updating models to create accurate projections is one of the significant limitations. Another significant problem is the dependence on specific poverty classification metrics.

Furthermore, it seems that there is a good scope for additional study in this subject. The elimination of data constraints via the enhancement of the inclusivity and quality of data sets would result in a significant improvement in their accuracy. There is a possibility that more advanced machine learning algorithms, which can use deep learning methods, might simultaneously yield more complete assessments of poverty. In addition, the development of methods that consider the non-monetary aspects of poverty, as well as the resolution of verification and optimisation concerns using models, will be vital to the implementation of integrated evaluations.

In conclusion, even though the current research marks a significant progress in the utilisation of sophisticated ways to assess poverty, there is still a great deal of room for improvement. Ultimately, our research not only encourages discussion on how to measure poverty by suggesting the inclusion of non-monetary approaches, but also offers a plan for further investigation in this significant field. The integration of machine learning and neutrosophic theory is becoming a potent method for enhancing the complexity and precision of poverty estimations.

Based on the analysis of the paper, it is evident that information fusion has the potential to mitigate digital monopoly in the digital economy. The paper highlights that information fusion can enable the creation of new market structures, promote competition and innovation, and reduce information asymmetry. These benefits can help ensure that the benefits of the digital economy are shared more widely and equitably.

One of the main findings of the paper is that information fusion can enable the creation of new market structures. By combining information from different sources, new market opportunities can be identified and exploited. This can create new business models and opportunities for competition, which can help to reduce the power of dominant players in the market.

Another key benefit of information fusion is its ability to promote competition and innovation. By combining information from different sources, firms can develop new products and services that are better tailored to customer needs. This can create a more competitive market, which can stimulate innovation and reduce the power of dominant players.

Finally, information fusion can help to reduce information asymmetry in the digital economy. By combining information from different sources, firms can gain a more complete understanding of m arket conditions, customer needs, and competitor behavior. This can help to level the playing field, enabling smaller firms to compete more effectively with larger, dominant players.

In conclusion, this paper has demonstrated the potential of information fusion in mitigating digital monopoly in the digital economy. By enabling the creation of new market structures, promoting competition and innovation, and reducing information asymmetry, information fusion can help ensure that the benefits of the digital economy are shared more widely and equitably. The findings suggest that policy makers and industry leaders should pay attention



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to the importance of information fusion and its role in ensuring a fair and competitive digital economy. However, there is a need for further research in this area. Future studies could focus on the practical implementation of information fusion techniques and their effectiveness in different contexts. Moreover, more research is needed on the potential risks and challenges associated with the use of information fusion, such as privacy concerns, data security, and the potential for algorithmic bias. Overall, the findings of this paper have important implications for policymakers, business leaders, and researchers interested in ensuring a fair and competitive digital economy.

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