Does Artificial Intelligence Prevail in Poverty Measurement?

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Abstract. Artificial Intelligence (AI) has been used widely by many domains in academic research to explore and learn much ambiguity information from small to large dataset. It is also tremendously implemented in daily lives especially in late 20 centuries in diverse formation to enhance business scalability and improving business operation for better services and performances. This trend is also seen to evolve in the field of socioeconomic studies, with an individual or household economic and social status relative to the rest of society. Is this technology present in the field of socioeconomic especially in poverty measurement? What is the form of problem solved? Therefore, the authors try to answers these question through systematic review method from the existence of poverty measurement research until the beginning of 2019. A systematic literature search was performed in the Web of Science and Scopus to identify all potential relevant studies using Kitchenham, 2007 guideline. Of the 53 article documents, 15 papers were selected after subsequent title/abstract and full text screening related to poverty measurement. The findings show that Linear Regression is a popular method chosen and closely followed by Random Forest and Deep Learning. Most studies diversify the use of data sources to predict poverty more accurately. The tendency to use satellites data can be seen more significantly than other types of data. Overall from 2007 to early 2019, the potential for using AI in the socioeconomic remains open.

1. Introduction
Artificial Intelligence (AI) is the machine simulation of the process of human intelligence. Since 1956, it has been a fairly established research area that attempted to solve complex computer device problems [1]. In recent years, there have been increasing interesting research attempts to use AI such as machine learning (ML) [2-4,11-13], image recognition [14–23], speech recognition [24–27], natural language generation [28–31], sentiment analysis [32–37], neural networks [19,29] and deep learning [38–40] in many disciplines such as security [41–48], health care [49–51], medical [52–56], e-commerce [57], management [57], smart cities [58], big data [41,43,47,58–60] and such. Artificial intelligence slowly embarks in socioeconomic domain including measuring poverty.

Poverty was a problem that faced by many developing countries. Poverty must first be identified and calculated to eradicate it. This is achieved using indices of poverty that fall into two main categories: monetary indices of poverty and non-monetary indices of poverty [61]. Monetary indexes are based on local or foreign currency monetary income indicators and include the different national poverty lines. In the meantime, non-monetary indices depend on wealth proxies and estimate the severity of deprivation by depriving one of the proxies mentioned. One such non-monetary index is the multidimensional poverty index (MPI) developed at the University of Oxford. These indices however mostly use statistical method since then. In many ways, the evolution of Industrial Revolution (IR 4.0) also provides an opportunity for inequality to use it as an irradiated to define poverty levels differently. How far this evolution has been benefited by poverty area? This study will reveal the past studies by using Systematic Literature Review (SLR).
A SLR is an evaluation of a clearly stated issue using formal and explicit methods to identify, select and review relevant research and collect and analyse data from studies included in the report. Statistical methods may or may not be used to analyse and summarize the findings of the studies included. [62] The authors' assertions of rigor in their work can be supported by a systematic review, which makes it possible to identify shortcomings and priorities for future research.

This study sets to achieve three objectives namely i. Review and identify research related to poverty tracking using AI methodology ii. Identify machine learning algorithm used for poverty measurement iii. Identify type of data has been used and what kind of task relevant has been used to achieve poverty identification. The next section describes the method of review using SLR while the findings are highlighted in the next section. A summary proceeds with the results of the SLR focused on proof synthesis. Finally, with conclusion, the last section ends.

2. Methodology

The review processes for this SLR used the guidelines proposed by [63,64]. According to [63], SLR is active in three main phases; review preparation, evaluation and reporting. The process stages summary as in Figure 1.

2.1 The Need of Review

The purpose of this SLR is to address some of the stated objectives of assessing how far and how artificial intelligence has been used in the field of poverty to quantify, define and forecast poverty for a country or region in order to overcome the technological gap in identifying the poverty of a nation.

2.2 Research Question

Research question is the vital part in systematic review. The research question for this SLR comprise five components using the PICOC (Population, Intervention, Comparison, Outcome, Context) were proposed by [65]. Table 1 shows the criteria and scope of research questions.

| Criteria      | Research Question                                                                 |
|---------------|-----------------------------------------------------------------------------------|
| Population    | R1: How many research articles related to poverty tracking in all year till 2019? |
| Intervention  | R2: What are the artificial intelligence methods used for poverty tracking?        |
|               | R3: What is data has been used?                                                   |
Comparison R4: Did research run comparison method?

2.3 Data Sources
Two main journal repositories—Scopus and Web of Science (WoS)—were used in the study. WoS is a robust database of > 33,000 newspapers covering more than 256 disciplines including topics related to environmental studies, interdisciplinary social sciences, social issues and development and planning. This includes more than 100 years of detailed backfile and citation records, produced by Clarivate Analytics and ranks them by three separate measures: citations, papers, and citations per-paper. Scopus is the second database used in the review. Of > 22,800 publications from 5,000 publishers worldwide, it is one of the largest abstract and citation databases of peer-reviewed literature. Scopus is made up of a variety of subject areas such as environmental sciences, social sciences, agriculture and biology.

2.4 Search Strategy
The search strategy is crucial to determine either the collective article reliable to research question has been listed. To formulate the search query for this SLR, the following steps were taken:
- Derivation keywords from the research question.
- Identifying synonyms of major terms.
- Identifying keywords in relevant papers or books.
- Synonyms term generated for this search is based on author keyword and index keyword in the databases. Author has been established library for keyword search for each crucial words
- Using Boolean OR for the alternatives synonyms or variants of each keyword.
- Using Boolean AND to link major terms.

The result for search string after attempting a few numbers of search string described as in Table 2: Keywords and Searching Strategy.

| Databases       | Search string/query string                                                                 |
|-----------------|---------------------------------------------------------------------------------------------|
| Scopus          | TITLE-ABS-KEY ( "poverty classification" OR "poverty clustering" OR "poverty status" OR "poverty level" OR "poverty analysis" OR "poverty cut off" OR "poverty determinant" OR "poverty evaluation" OR "poverty identification indicator" OR "poverty index" OR "poverty indicator" OR "poverty indices" OR "poverty line" OR "poverty mapping" OR "poverty measure" OR "poverty status" OR "poverty type" OR "poverty assessment" OR "poverty prediction" OR "predict poverty" OR "target poverty" OR "socioeconomic indices" OR "monetary poverty" OR "multidimensional poverty measure" ) AND ( "machine learning" OR "artificial intelligence" OR "data mining" OR "expert system" OR "intelligent retrieval" ) ) AND ( LIMIT-TO ( LANGUAGE , "English" ) ) |
| Web of Science  | TS=( "poverty classification" OR "poverty clustering" OR "poverty status" OR "poverty level" OR "poverty analysis" OR "poverty cut off" OR "poverty determinant" OR "poverty evaluation" OR "poverty identification indicator" OR "poverty index" OR "poverty indicator" OR "poverty indices" OR "poverty line" OR "poverty mapping" OR "poverty measure" OR "poverty status" OR "poverty type" OR "poverty assessment" OR "poverty prediction" OR "predict poverty" OR "target poverty" OR "socioeconomic indices" OR "monetary poverty" OR "multidimensional poverty measure" ) AND ( "machine learning" OR "artificial intelligence" OR "data mining" OR "expert system" OR "intelligent retrieval" ) ) Refined by: LANGUAGES: ( ENGLISH ) Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI. |
2.5 Study Selection
Selection of the sample in this review involves selection of online databases and identification of search strings, and applies inclusion and exclusion as described in the early stage. The goal at this point is to ensure that the paper collection for this research is thorough.

2.6 Inclusion and Exclusion Criteria
The inclusion and exclusion criteria for this SLR were based on the research questions. Table 3 shows the summary of inclusion and exclusion criteria for review.

| Criteria                      | Inclusion                                      | Exclusion                                      |
|-------------------------------|------------------------------------------------|------------------------------------------------|
| Document type                 | All                                            | None                                           |
| Timeline                      | Published in all time until April 2019          | None                                           |
| Language                      | All papers must be published in English         | Papers that are not published in English        |
| Keyword Search                | All papers must focus on poverty tracking using artificial intelligence as their main contribution. | Papers that only use poverty as factor, correlation, association to other research objective or survey. |

2.7 Data Extraction and Quality Assessment
For this review, the quality evaluation covered quantitative and qualitative studies because experimental design is not limited. A checklist of the quality assurance report is used to ensure that the method of data extraction follows the quality requirements. The quality assessment checklist has been designed following guidelines proposed by [3]. Table 4 shows a list of general questions to measure the quality of selected studies. Three scale are coded for the quality assessment checklist and given a score; Yes =1; Partially = 0.5; No = 0. Based on the item checklist, each article ranged from 0 (very poor) to 5 (very good).

| No   | Item                                                                 | Answer                          |
|------|----------------------------------------------------------------------|---------------------------------|
| SQ 1 | Are the aims and objectives of the research clearly stated?          | Yes/No                          |
| SQ 2 | Is the research design clearly specified?                            | Yes/No/Partially                |
| SQ 3 | Have the researcher(s) properly carried out the process of data preparation? | Yes/No/Partially                |
| SQ 4 | Have the researcher(s) given enough data to support their results and conclusions? | Yes/No/Partially                |
| SQ 5 | Is there involved comparison of other technique in the experiment?   | Yes/No                          |

3. Research Interest Analysis
The researcher has found 53 papers using the established search terms from the first stage of the search process. Just 15 were potentially relevant after the review of titles and abstracts. Each of the papers was filtered for referring inclusion and exclusion criteria before being accepted for the synthesis of evidence. At this stage, irrelevant studies and duplicate studies were eliminated. If the titles and abstracts were not adequate to categorize the paper applicable to the research area, the researcher read the full papers. Ultimately, fifteen experiments were chosen to answer the research questions that were formulated. Figure 2 shows results of the search and selection papers process.
Figure 2. Search and Selection Paper Stage

3.1 Quality of Factors
Table 5 indicates the quality assessment scores for final identified papers consisting of 15 studies. 1 studies (6.66%) are poor, 3 studies (20%) are fair, 7 studies (46.67%) are good and 4 studies (26.67%) are very good quality. None of the paper rated as poor quality. Therefore, all selected papers were included in the next phase for further analysis.

| Quality Scale | Very poor (<=20%) | Poor (>=40%) | Fair (>=50%) | Good (>=80%) | Very Good (>=100%) | Total |
|---------------|------------------|-------------|-------------|-------------|------------------|-------|
| Number of studies | 1 | 3 | 7 | 4 | 15 |
| Percentage (%) | 6.66% | 20% | 46.67% | 26.67% | 100% |

4. Discussion
In this section, the study results are based on the research questions developed in Table 1.

R1: How many research articles related to poverty tracking in each year using artificial intelligence method?
Research in the field of poverty tracking using the artificial intelligence method only started in 2007 with only 1 issue. This research has only begun to increase in 2016 by 5 issues and slightly decreased to 4 publications in 2017. However, in recent years only 2 publications in 2018 and just started 1 publication in early 2019. This results justify poverty tracking using artificial intelligence research still lack in study. Figure 3 shows a graph of tracking poverty publication by year.
R2: What are the artificial intelligence methods used for poverty tracking? and R5: What is data mining task relevant used?

Since 2007, there are 15 artificial intelligence methods used to track poverty. It consists of feature extraction, feature selection and modelling either in the form of classification or clustering. Random Forest is seen as a frequently used method in past publications of 4 times. However, the linear regression method is still a choice of researchers based on the popularity of this methods in the economic domain ever since followed by ensemble method. Table 6 and Table 7 shows the frequency of methods used in all studies.

Table 6. Frequency of Method Selected in Poverty Tracking Research

| Method                                      | Frequency |
|---------------------------------------------|-----------|
| Random Forest                               | 4         |
| Least Absolute Shrinkage and Selection Operator (LASSO) | 2         |
| Ordinary Least Squares (OLS) Regression     | 2         |
| Decision-Tree Algorithm                     | 2         |
| Naïve Bayes algorithm                       | 2         |
| Convolutional Neural Networks (CNN)         | 2         |
| Others                                      | 2         |
| Ridge Regression                            | 1         |
| Backwards Stepwise Regression               | 1         |
| Penalized Regression                        | 1         |
| Spearman's Rank Correlation Coefficient     | 1         |
| Quantile Regression Forest                  | 1         |
| Gradient Boost Regressor                    | 1         |
| K-Means                                     | 1         |
| Agglomerative Hierarchical                  | 1         |
| k-Nearest Neighbours (kNN)                  | 1         |
Table 7. Frequency of Learning Type in Poverty Tracking Research

| Learning Type   | Frequency |
|-----------------|-----------|
| Linear Regression | 8         |
| Ensemble        | 6         |
| Clustering      | 2         |
| Tree            | 2         |
| Bayesian        | 1         |
| Instances Based | 1         |
| Deep Learning   | 2         |

R3: What data has been used?
Various types of data have been used in past research. This diversity of data has motivated researchers to conduct research using artificial intelligence methods. Additionally, the availability of large data today allows researchers to make poverty predictions more easily and indirectly reduces the cost of policy makers’ operations. The collection of survey data stored matched with satellite data has become a trend in this field of research. In fact, it has proven to improve prediction accuracy. Table 8 shows the types of data used in the research.

Table 8. Types of Data Used in Poverty Tracking Research

| Data Type | Survey | Satellite | Call Record (CDR) | Financial Transaction |
|-----------|--------|-----------|-------------------|-----------------------|
| Frequency | 10     | 4         | 1                 | 1                     |

R4: How many publications did comparison method?
Comparing methods is one of the approach to ensure the best method selection for a prediction model. It not only improves the accuracy of prediction but also allows researchers to customize the best solution for business analysis. However, out of 15 studies, only 5 studies have done comparisons. These five studies meet more than 80% selection criteria of research required by the author such as in Table 5. The method selected to compare either has the same task relevant characteristics, used previously by researchers, has a better performance evaluation or has a different algorithm behaviour. Table 9 below shows a summary of publications that run a comparison of methods.

Table 9. Summary of Publication Undergo Comparison Method

| Comparison Method | Non Comparison Method |
|-------------------|-----------------------|
| Publication       | [66][67][68][69][70]  |
| Total             | 5                     |
|                   | [71][72][73][74][75][39][76][77][78] |
|                   | 10                    |

5. Conclusion
The purpose of this SLR was to identify the status of research on AI in poverty tracking. The study in this SLR is based on the research question constructed. Table 9 summarise finding for this SLR. A total of 15 primary studies have been identified and analyzed. The purpose of this SLR can be used to identify areas where poverty monitoring strategies can be enhanced. The techniques used in the 15 papers reviewed are summarized in Table 10. This finding indicates that there is still plenty of room for scientific work to track poverty using AI technology.

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Table 10. Summary of 15 Publication Analyses

| Article | Data Source Type | Artificial Intelligence Method |
|---------|-----------------|-------------------------------|
|         | Survey | Satellite Image | Call Data Record (CDR) | Financial Transaction | LASSO | Ridge Regression | Backwards Stepwise Regression | OLS Regression | Penalized Regression | Spearman’s rank correlation | Random Forest | Quantile Regression Forest | Gradient Boost Regressor | k-Means | Agglomerative Hierarchical Decision Tree Algorithm | Naive Bayes algorithm | k-Nearest Neighbours (KNN) | Deep Learning | Others |
| P 1: [71] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P 2: [72] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P 3: [73] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P 4: [79] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P 5: [74] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P 6: [75] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P 7: [66] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P 8: [67] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P 9: [39] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P10: [76] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P11: [68] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P12: [69] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P13: [70] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P14: [77] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| P15: [78] | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
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