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Mapping Poverty for Sustainable Development Using AI, A Review of Literature

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Abstract:- Extreme poverty is among the challenges the United Nations seeks to eradicate by the year 2030 as outlined in its Sustainable Development Goals. However, governments and other stakeholders face challenges in accurately identifying poverty in households for evidence-based implementation of SDG programs. Current strategies are slow, inaccurate and costly to efficiently support efforts to identify poverty for sustainable development. Consequently, many strategies to map out poverty for intervention measures do not succeed which could be contributing to the global decline in the rate of reducing poverty. Artificial intelligence which has become widely available and has been used in many sectors, could be leveraged to improve poverty mapping for evidence-based interventions for sustainable development. Despite living in the era of AI, it has not been fully utilized in mapping poverty. This review seeks to explore the extent of research on the adoption of AI in mapping poverty so as to find the gap for further research. It aims to establish the extent of AI-based research on identification of poverty in respect to global distribution of research studies, methods, algorithms and sources of data which have been used in studies to identify poverty. The findings will help to identify gaps for research to help in designing evidence-based strategies for intervention measures. A systematic review was done for the period 2020 to 2024 using databases and snowballing hybrid search approach. A qualitative analysis was done on the extracted data to uncover new patterns and identify research gaps.

***Keywords**:- Artificial Intelligence, Poverty Classification, Sustainable Development Goals.*

I. INTRODUCTION

Sustainable development goals (SDGs) are current development targets fronted by the United Nations (UN) to make member countries work towards satisfying human needs and improving the quality of life for the current and future generations (Anuoluwapo & Uwizeyimana, 2021). A pivotal goal among the 17 SDGs is eradication of poverty in which the UN seeks to "End poverty in all its forms everywhere" by the year 20230 such that no one survives on less than $2.15 per day as per the 2017 purchasing power parity (United Nations Department of Economic and Social Affairs, 2023). For the first time since the 1990s, the rate of poverty reduction declined from about 1% to 0.6% per annum in 2013, which declined further to 0.5% by the year 2017 (Bank, 2020).

As the target date set for achieving the goals draws nearer, there are indications that the goals might not be realized after all, especially in developing countries unless transformative measures are introduced to boost current intervention efforts (United Nations Department of Economic and Social Affairs, 2023). Subsequent effects of COVID-19, climate change and unfavorable economic conditions have reduced resources allocated for development which has sustained sluggish decline in the rate of poverty reduction.

Most governments and other stakeholders use inaccurate and costly methods of identifying poor and most deserving populations for social-economic support which leads to provision of the resources to undeserving people (Eshiotse et al., 2023). Targeting the poor is one of the techniques which is inefficient due to socio-political manipulations, while the income and consumption of households which are almost the same which makes it difficult to differentiate the poor from the poorest through targeting (Research Institute (Ifpri), 2018).

The UN recognizes Information and Communication Technology (ICT) as an enabler of development that could be adopted to boost current efforts to attain the SDGs. A trending technology that has continued to revolutionize many sectors of society which could be adopted to rekindle efforts towards achieving the SDGs is Artificial intelligence (AI). AI is the most disruptive technology of the digital generation which could be adopted to revolutionize efforts for eradication of poverty (Brynjolfsson & Mcafee, 2017) (Borges et al., 2021).

AI is a technology which enables computing machines to simulate human intelligence and perform tasks like human beings, including automation of those processes (Benbya et al., 2020). It is useful in transforming processes through automation, revelation of new information from big data, and integration of resources to solve complex problems among many other tasks (Raghavendra et al., 2022).

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AI uses different methods with different focus and application to address real-world issues. These includes machine learning (ML), deep learning, natural language processing (NLP), expert systems, computer vision, data mining and robotics among others (Mvurya, 2020). ML is a core branch concerned with learning from information and experiences, while deep learning (DL) is a sub-branch of ML suitable for learning from complex patterns and relationships to make decisions (Motlagh et al., 2023). The branch of natural Language Processing deals with processing human language while computer vision is used to manipulate and use videos and images to produce useful information. There is also a motion planning method which is used for creating models of motions from autonomous systems, and reinforcement learning where an AI agent interacts with an unknown environment which gets rewarded according to its actions (Shuford & Islam, 2024). Robotics branch deals with design, development, processing and application of robots to support humans in performing address real-world tasks (Van Bulck et al., 2023). Adoption of AI could mainly help to solve complex problems through automation and integration of resources, and generation of new insights from large datasets (Nishant et al., 2020).

AI has become widely available and its adoption has positively transformed many sectors such as healthcare, education, telecommunication, agriculture, construction and transportation (Motlagh et al., 2023). In education, AI has been used to decentralize education systems, develop smart learning environment and delivery techniques, and provided systems for student feedback, adaptive learning and reasoning (Zhai et al., 2021). Over 65% of universities in the United States (US) have integrated AI in education and regard it as the future of any development (Kuleto et al., 2021). It has been used to develop recommendation, matching, classification and automated administrative systems which have enhanced learning. It has been used to predict student dropouts, answer enquiries and build interactive teaching assistants thereby showing its capability to perform intelligent tasks for sustainable development. In agriculture, data mining has been used to predict crop yield by analyzing data on climate and various factors of production(Mvurya, 2020). AI is also pivotal in the manufacturing where it has been used in optimizing, controlling and troubleshooting systems, and is key in the development of systems the next industrial generation known as Industry 4.0 (Wuest et al., 2016).

Recent research studies on application of AI to identify poor people for socio-economic support have shown very high levels of accuracy (Maruejols et al., 2023) (Agyemang et al., 2023) (Zamzuri et al., 2023) (Nzelibe, 2024). Despite the quickly growing adoption of this technology, the rate of poverty reduction has continued to decline globally leading to a sluggish sustainable development(Bank, 2020). The objective of this review was to identify studies which have been done using AI to identify poverty, the sources of data, and the methods and techniques which were used. The findings will help to establish the status of on application of AI to identify poverty to support research. The next sections describe related literature, methodology, results, discussion and conclusion of the literature review.

II. RELATED STUDIES

This section analyzes related studies to provide an overview of the status of research that leveraged AI to map poverty in regards to methods, algorithms and data sources. A study focusing on AI methods and survey data sources reviewed 15 papers found random forest (RF) to be the most frequently used algorithm (Isnin et al., 2020). Survey data was again found to be the most preferred source of data followed by satellite and call data. It was noted that stored survey data and satellite data were becoming popular choices for machine learning. The study also found out that only 5 out of 15 papers selected their algorithms through comparison which helped to improve accuracy while others used other reasons to select an algorithm for reviewed 15 papers and only 5 of them did experimentation to select the best algorithm. The findings confirmed that artificial intelligence approached could improve the accuracy and speed of predicting poverty, and advanced studies have resulted from the use of diverse datasets.

A related study that found that the use of AI approaches in prediction of poverty could help to improve the identification process by enhancing the efficiency in terms of speed, accuracy and the general process(Usmanova et al., 2022). The study which reviewed 20 papers for the period 2018-2022 found that government data was the most frequently used source of data at 35%, followed by household survey (20%) and night time light imagery captured via satellite which was quickly become popular. The studies used machine learning method and found out that random forest (RF) algorithm was the most frequently used algorithm as it was adopted in 55% of the papers reviewed. RF is an ensemble algorithm popular for its simplicity to implement and is not sensitive to overfitting and noise challenges. The studies show that there was a general rise in the number of publications on AI and identification of poverty reflecting a rise of interest in the field.

Table 1: Analysis of Publications from Related Studies

Author	No. Publications	AI Method Used	Most Used Data Sources	Algorithm
Isnin et al., 2020).	15	Machine learning	survey	RF
(Usmanova et al., 2022)	20	Machine learning	government survey	RF

III. METHODOLOGY

A. Research process

This section describes the methodology used for the review. A systematic review approach was adopted which entails planning, conducting the review and reporting in line with the research objectives (Hossain et al., 2022).

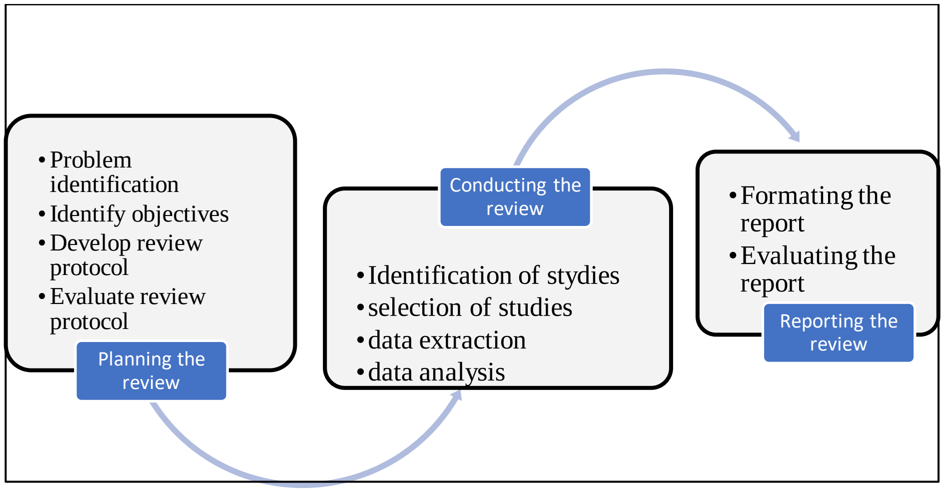

Fig.1: Stages of the Systematic Literature Review (Isnin et al., 2020)

B. Search Strategy

A hybrid search approach recommended for systematic literature review was done to get target articles (Wohlin et al., 2022). In this case a preliminary search was done with Google scholar followed by snowballing using articles from the preliminary search. Keywords were generated from a pre-survey of electronic publications related to use of AI in identification of poverty and sustainable development for conducting the search. The following search string was built using the keywords and wildcards to search for articles from Google Scholar:

("Artificial intelligence" OR "AI" OR "machine learning" OR "data analytics" OR "Deep Learning" OR "Computer Vision" OR "Natural Language Processing" OR "NLP") AND ("identification of poverty" OR "Classification of Poverty" OR "Poverty Detection" OR "Poverty Assessment" OR "Poverty Identification" OR "map poverty")

Snowballing was subsequently used to search for additional articles from various digital data sources.

C. Inclusion and Exclusion Criteria

Studies were extracted for the period 2020 to 2024. The articles included were those done specifically to identify poor people using AI for sustainable development and their full article was accessible to the researchers. The papers included must also have been from primary studies, written in English and peer-reviewed.

D. Data Extraction and Reporting

This study's objective was to find out the extent of research on utilization of AI to identify poverty by identifying the methods and techniques used, and the findings of the studies. To extract data for answering this question, a table consisting the key variables of the research namely methods, techniques and accuracy (finding) was created for capturing the data. Other complementary variables namely author, year of publication, region, technique and features used were added to the table to help in analyzing the data. The selected articles were read and required data extracted to the table. The PRISMA approach was followed in conducting and reporting the review study (Hossain et al., 2022).

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IV. RESULTS

This section describes the results of article selection, data extraction and reporting.

A. Selection of publications

This study used a hybrid search method for relevant articles which involved a preliminary database search and snowballing as recommended for getting publications from different sources (Wohlin et al., 2022). Articles selection process and reporting was guided by the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) (Davis et al., 2014). A total of 1480 articles were extracted with Google scholar search engine for the period 2020 to 2024. Some 1467 articles were removed on application of the exclusion criteria leaving thirteen eligible articles for inclusion. Another seven eligible articles were selected through snowballing and added to the list of eligible records which increased the eligible and finally selected articles to 20 as shown in the PRISMA diagram in figure 2.

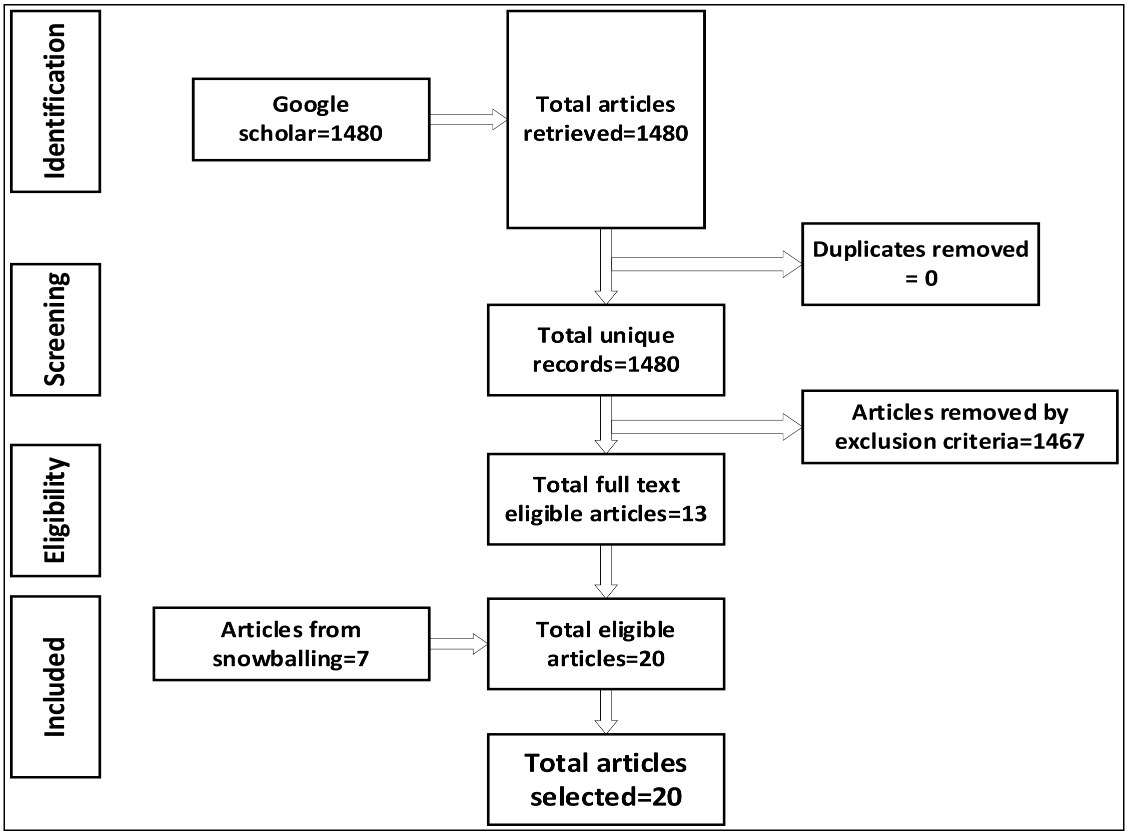

Fig. 2: Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Diagram Showing the Selection Process of the Research Articles.

The selected articles were read and required data for the target variables was extracted and recorded for analysis as shown in table 2. The variables used include author, year of publication, region, data source, AI method, technique, features used and accuracy achieved.

Table 2: Extracted Data for Selected Publications

Author	Publication Year	Region	Data Source	AI Method	Algorithm Used	Features used	Accuracy (%ge)
Alsharkawi et al., (2021)	2021	Jordan	Historical surveys	ML	LightGBM	Full set	81
Yinet al., (2021)	2021	China	satellite platform	ML	random forest	Nighttime lights	95
(Hu et al., 2022)	2022	China	National Census data, land use map, satellite imagery and geospatial data	ML	Random forest	Access to facilities / services, agricultural production conditions, village construction, spatial distribution of village settlements	72
(Zhang et al., 2022)	2022	China	Survey	DL	Explainable artificial intelligence (XAI)	Household income, disability, village attributes, lack of funds, labor force, disease, and number of household members	73.3
ALSHARKAWI et al., (2022)	2022	Jordan	Government surveys	ML	Light gradient-boosting machine (LightGBM)	size of a household, total household income, total household expenditure	83
(Alsharkawi et al., 2021)	2021	Jordan	National household expenditure and income surveys	ML	Light gradient-boosting machine (LightGBM)	Not given	81
(Maruejols et al., 2023)	2023	China	Historical Survey data	ML	Random forest	low income, low endowment (land, consumption assets), unusual large expenditure (medical, gifts)	85.29%
(Agyemang et al., 2023)	2023	Pakistan	satellite	DL	CNN	Not given	81
(Zamzuri et al., 2023)	2023	Malaysia	Online dataset	ML	XGBoost and random forest	Monthly Income, Age, Occupation, and Status.	100
(Nzelibe, 2024)	2024	Africa	Geological Survey	ML	Support Vector Machine (SVM)		80.6
(Alfawzan, 2022)	2022	Saudi Arabia	satellite imagery	ML	SVM	Average family income, family size, and the percentage of small houses	80.6
(Fisker & Mdadila, 2022)	2024	Tanzania	survey and spatial data	ML	Extreme Gradient Boosting (XGB)	Primary roads, residential roads	87
(Alfawzan, 2022)	2022	SAUDI ARABIA	satellite	ML	Support Vector	Average family income, family	80.6

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					Machine (SVM)	size, and the percentage of small houses	
(Hersh et al., 2021)	2021	Belize, Central America	open satellite and survey	ML	Xtreme Gradient Boosted Trees	Satellite derived features	
(Zhang et al., 2022)	2022	China	Survey	ML	Explainable artificial intelligence (XAI)	Household income, disability, village attributes, lack of funds, labor force, disease, and number of household members,	0.733
(Ferreira et al., 2021)	2021	Portugal.	Secondary data	ML	Support Vector Machine	low-income households, low credit control households, crisis-affected households	89.5
(Hofer et al., 2020)	2020	Philippines and Thailand	satellite imagery, household surveys, and census data	computer vision	Random forest		90.06
(Gao et al., 2020)	2020	Afghanistan	household survey	ML	Decision tree model and a random forest	Income and expenditure items, household size, farm-related measures; access to particular resources, and short-term shocks, long-term household characteristics	80
(Nigus & Shashirekha, 2022)	2022	Ethiopia	survey data of Ethiopia	DL	Artificial Neural Network (ANN)	Zone, Household serial number, Household size, Ecology, Household-head age, Household-head marital status, Weight, Year, and Net calorie.	99.15%.
(Jiang, 2022)	2022	China		ML	XGBoost		98.2

Key:
ANN - Artificial Neural Network
CNN - Convolutional Neural Networks
NLP - Natural Language Processing.
ML - Machine learning
DL - Deep learning
XAI - explainable artificial intelligence
LightGBM - Light gradient-boosting machine

B. Regional Distribution of Studies Used

The regional distribution of the publications by region are presented in table 3 showing that 6 of the articles were from China, 2 from Jordan and another 2 from Saudi Arabia. Other regions namely Central America, Africa, Malaysia, Pakistan, Portugal, Thailand and Afghanistan had 1 article each. China had the largest contributions with 30%, followed by Jordan and Saudi Arabia with 10% each while the rest of the regions had 5% each.

Table 3: Analysis of Publication Distribution by Region

Region	No. of Articles	Percentage
China	6	30
Central America	1	5
Jordan	2	10
Saudi Arabia	2	10
Africa	3	15
Malaysia	1	5
Pakistan	1	5
Portugal	1	5
Philippine/Thailand	1	5
Afghanistan	1	5
Total	20	100

C. Sources of Data

The sources of data used in the studies were analyzed and organized into three categories. Surveys and satellite were the most frequently used sources at 45% each, and online/historical data sources at 10% as shown in table 4.

Table 4: Analysis of the Sources of Data Used

Source	No of Studies	Percentage %
Survey	9	45
Satellite	9	45
Online / historical data	2	10
TOTAL	20	100

E. AI Methods and Algorithms Used

➢ *AI Methods*

A total of three AI methods were used in the studies which included machine learning, deep learning and computer vision. Machine learning was used in 80% of the studies, deep learning in 15% while computer vision in 5% as shown in table 5. Machine learning was the most frequently used method of AI.

Table 5: Analysis of AI Methods Used to Identify Poverty

AI Method Used	Number of Publications	Percentage %
Machine learning	16	80
Deep learning	3	15
Computer vision	1	5
Total	20	100

➢ *Algorithms Used*

A total of 8 algorithms were selected by experimentation and comparison or based on other factors. These included LightGBM (15%), Random Forest (25%), Explainable artificial intelligence (XAI) (10%), CNN (5%) and an ensemble of XGBoost and random forest (5%). Other algorithms used were Support vector machine (20%), XGBoost (15% and ANN (5%). About 65% of the algorithms used were ensemble learning algorithms while 35% were non-ensemble learning algorithms as shown in table 6.

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Table 6: Summary of AI Algorithms Used

Algorithm	No. of Publications	Type: Ensemble or Non-Ensemble	Percentage %
LightGBM	3	Ensemble	15
Random forest	5	Ensemble	25
Explainable artificial intelligence (XAI)	2	Ensemble	10
CNN	1	Non-ensemble	5
XGBoost and random forest	1	Ensemble	5
Support vector machine	4	non-Ensemble	20
XGBoost	3	Ensemble	15
ANN	1	non-Ensemble	5
Total	20		100

V. DISCUSSION

A. Regional Distribution of Publications

The synthesized data on distribution of the reviewed publications by region showed that 6 articles were from China, 2 from Jordan and 2 from Saudi Arabia while all the other regions including Africa had 1 publication each. A statistical analysis of this distribution found that about 75% of the studies were skewed towards Asia and the middle East region, 15% were from Africa while the entire of America and Europe had 5% each as shown in table 2 in figure 3. Africa being a developing nation had only 15% of the publications. This study aims to fill this gap.

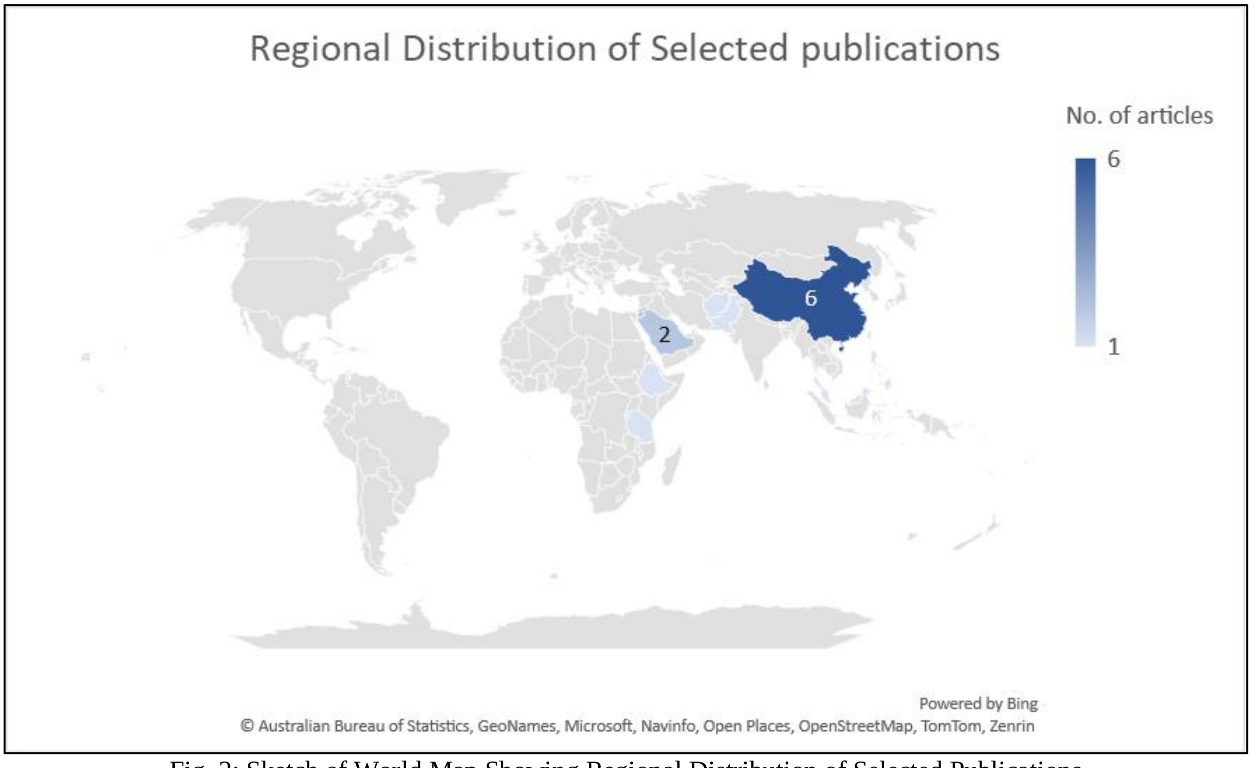

Fig. 2: Sketch of World Map Showing Regional Distribution of Selected Publications

B. Methods and Algorithms Used

Different AI methods and algorithms were used based on application and focus of the study. Machine learning was found to be the most popular method of AI as it was used in 80% of the publications. Deep learning and computer vision which were not reported in past review studies emerged as alternative AI methods of identifying poverty with 15% and 5% of the publications respectively (Isnin et al., 2020), (Usmanova et al., 2022).

Whereas machine learning produced the best performance when used with a combination of two ensemble algorithms with 100% accuracy, deep learning method which is suitable for manipulating complex patterns also produced an equally good result (99.15%) when used with Artificial Neural

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Network (ANN) which is a non-ensemble algorithm (Nigus & Shashirekha, 2022). The other AI method which emerged was computer vision which also performed very well. It produced an accuracy of 90.06% when used with random forest which is an ensemble algorithm using data from satellite sources(Hofer et al., 2020). This was better than other studies using machine learning which produced much lower results though with the acceptable performance (Eshiotse et al., 2023), (Fisker & Mdadila, 2022),(Gao et al., 2020). Application of deep learning, computer vision is likely to rise while other alternative AI methods are likely to emerge to be used alongside machine learning in studies to identify poverty for sustainable development. More studies are therefore needed to experiment the rising and emerging AI methods for comparison.

The 20 studies selected a total of 8 algorithms out of a wide range available algorithms in the field. The algorithms were selected through experimentation and comparison or some other factors which helped to select the best choices. A combination of XGBoost and random forest algorithms which is an ensemble of two ensemble algorithms produced an accuracy of 100% which demonstrated that a combination of ensemble algorithms could produce very accurate results (Zamzuri et al., 2023). Artificial Neural Network (ANN) and CNN which are non-ensemble algorithms used in deep learning produced an accuracy of 99.15% and 81% respectively which also demonstrated which could be used to identify poverty (Nigus & Shashirekha, 2022), (Agyemang et al., 2023). The results points to the need for studies with more algorithms for comparison and selection of the best choice in the emerging AI methods.

C. Data sources

The studies used various sources of data which were grouped into survey, satellite and online / historical data reflecting a diversity of the sources available. Data from surveys and satellite sources had the highest percentage of utilization at 45% each while online/historical data had a paltry 10%. There was a rise in the use of satellite sources which were not reported in previous studies where survey was the source of data (Isnin et al., 2020; Usmanova et al., 2022). The emergence of satellite sources could be due to the convenience, lower costs and accuracy associated with acquiring the data which was also more quickly accessed compared to the survey data (Zamzuri et al., 2023). Satellite sources use a wide range of images which are acquired automatically over a wide region making it a convenient source of data. Satellite data are also more accurate compared to data from manual surveys since they are automatically acquired by the satellite. Satellite as a source of data for research in AI is likely to continue rising in popularity based on the advantages associated with it which could improve the identification of poverty for sustainable development. Experiments are needed to test satellite sources with emerging AI methods for comparison.

VI. CONCLUSION

This literature review was done to establish the status of research on leveraging AI to map poverty for sustainable development. The focus of this review was to establish the number of studies done, AI methods and algorithms used and the sources of data utilized in the studies. The study identified 20 primary studies and their regional distribution, the AI methods, algorithms and the sources of data used in the studies. The research gaps identified are (i) lack of studies in regions with high levels of poverty such as Africa including Kenya where more than 40% of the population live in extreme poverty (ii) lack of studies using other AI methods and limited studies using deep learning and computer vision, (iii) limited or lack of studies using algorithms focusing deep learning and computer vision. This study has therefore given an overview on the status of research on leveraging AI to identify poverty for sustainable development.

Contribution: the study has established the status of research on leveraging AI to identify poverty for sustainable development in regards to (i) number and regional distribution of publications, (ii) methods which have been used in studies to identify poverty and their performance, (iii) identification of algorithms which could be used for identification of poverty.

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