Smart Poverty Detection and Relief Management

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***Abstract* - Eradicating poverty is still a major worldwide issue that requires creative solutions for accurate identification and efficient use of resources. In order to forecast and solve poverty holistically, this research presents a Smart Poverty Detection and Relief Management System that makes use of blockchain technology, machine learning, and satellite images. To create a solid dataset, the system takes into account a wide range of socioeconomic factors, including economic statistics, healthcare access, agricultural practices, and educational attainment. High- resolution satellite photography is used to extract characteristics using Convolutional Neural Networks (CNNs), which may detect patterns such as resource proximity, land usage, and infrastructure quality. Accurate estimates of poverty are produced by combining these insights with predictive algorithms such as Random Forests.**

I. INTRODUCTION

An increasing amount of research has been conducted on Smart Poverty Detection and Relief Management with the goal of using technology breakthroughs to alleviate global socioeconomic issues. Scholars and practitioners have worked to incorporate a variety of datasets in recent years, including satellite

Using socioeconomic data and pictures, predictive models are created to pinpoint areas where poverty is prevalent. This review of the literature starts a thorough investigation of the corpus of knowledge already available in this field, exploring the approaches, discoveries, and gaps that earlier studies have brought to the table. In addition to offering a comprehensive overview of the state of poverty prediction today, this survey seeks to highlight opportunities for more research and innovation by synthesizing and critically analyzing the literature.

The examination of pivotal research studies, such as Poverty Prediction from Satellite Imagery and Night-Time Lights Utilizing a Convolutional Neural Network, Mapping and Monitoring Urban Poverty Employing High-Resolution Satellite Imagery, Deep Learning: A Case Study in Accra, Ghana, A Comprehensive Survey of Remote Sensing for Poverty Mapping: A Review of Methods and Data Sources, and DeepSatAI: A Satellite Imagery-Based Approach for Poverty Estimation, underscores notable progress in poverty detection techniques.

Using land-use classification to infer economic activities and high-resolution satellite images to gather precise regional visuals are essential components of an efficient detection system. While machine learning-based predictive modeling improves accuracy by utilizing pertinent socioeconomic factors, image processing techniques are used to identify characteristics suggestive of poverty. For a thorough study, the system aggregates data from multiple sources, including census reports

The use of blockchain technology to guarantee safe, open, and effective relief management is a novel component of this study. Blockchain improves accountability and reduces resource mismanagement by enabling decentralized data storage, unchangeable record-keeping, and real-time aid delivery monitoring. Additionally, the approach gives policymakers a clear geospatial perspective for focused initiatives by graphically representing poverty levels on satellite imagery.

By providing a scalable, economical, and multifaceted approach, the suggested methodology gets over the drawbacks of conventional poverty evaluation techniques. Through the integration of blockchain, machine learning, and satellite images, this project seeks to provide decision-makers with practical insights that will promote efficient socio-economic growth and aid in the fight against global poverty.

and social media insights, integrates survey data and crowdsourcing input for validation, and uses anomaly detection to spot abrupt changes. Tracking changes over time is made possible by spatial and temporal analysis, and interactive maps offer an easy-to-use way to visualize infrastructure and poverty levels. The system's efficacy in tackling poverty issues is further supported by regular automated reporting, data anonymization to protect privacy, safe data storage, and a scalable architecture for growing coverage and incorporating more data sources.

II. LITERATURE SURVEY

The integration of machine learning and satellite imagery for socio-economic analysis has gained substantial attention in recent years. Jean et al. [1] conducted a groundbreaking study utilizing Convolutional Neural Networks (CNNs) to predict poverty levels by analyzing satellite imagery alongside nighttime light data. This innovative approach used nighttime illumination as a proxy for urbanization and economic activity, revealing the potential of deep learning for poverty estimation despite challenges such as data scarcity and satellite biases.

In another significant contribution, Yeh et al. [2] demonstrated the utility of publicly available satellite imagery combined with advanced deep learning methods to assess economic well-being across Africa. Their work underscored the effectiveness of machine learning in deriving insights from remotely sensed data. Urban poverty mapping has also seen advancements, as highlighted in a study conducted in Accra, Ghana, which used high-resolution satellite imagery and deep learning techniques to reveal spatial patterns of poverty and inform policy decisions [6]. Meanwhile, Feng et al. [4] proposed a scalable framework called DeepSatAI, which showcased efficiency in large-scale poverty estimation using satellite imagery, emphasizing the importance of adaptability in diverse socio-economic contexts. Comprehensive reviews in this domain have categorized remote sensing methods for poverty mapping, assessing their evolution and the strengths and limitations of existing approaches [3][5]. An innovative study by Tan et al. [5] leveraged CNNs to streamline data collection by identifying key developmental parameters, achieving high accuracy in poverty estimation. Moreover, Bartholomew and Liu [7] extended these efforts by integrating daytime and nighttime satellite imagery with deep learning architectures such as ResNet and DenseNet, incorporating enhancements like the squeeze-and-excitation module for improved predictions in developing nations.

Further research has synthesized machine learning techniques for poverty mapping, identifying emerging trends and innovative methods. For instance, a hybrid model integrating mobile data with satellite imagery provided a novel approach to poverty prediction, showcasing its potential in resource-limited settings [8].

Collectively, these studies illustrate the transformative potential of machine learning and satellite imagery in addressing socio- economic challenges, paving the way for improved poverty prediction frameworks and targeted interventions

III. PROPOSED ARCHITECTURE

The proposed system introduces an advanced Poverty Detection and Relief Management Platform designed to harness the power of machine learning algorithms and satellite imagery for actionable insights into poverty levels. This innovative approach employs extensive historical datasets to train robust predictive models capable of estimating poverty prevalence across diverse geographical regions, including remote and under served communities. By integrating multidimensional datasets, the platform analyzes patterns, trends, and spatial distributions of poverty, offering a granular understanding of its dynamics. These insights enable policymakers, non-governmental organizations, and government bodies to make informed decisions for efficient resource allocation and strategic planning.

The system aims to bridge the gap in relief management by identifying high-priority areas and facilitating equitable distribution of resources. This data-driven methodology enhances transparency and accountability in poverty alleviation programs while empowering stakeholders with precise, actionable intelligence to address systemic challenges effectively. This platform underscores the transformative potential of technology in tackling societal issues and represents a significant step toward leveraging digital tools for sustainable development and impactful poverty reduction efforts.

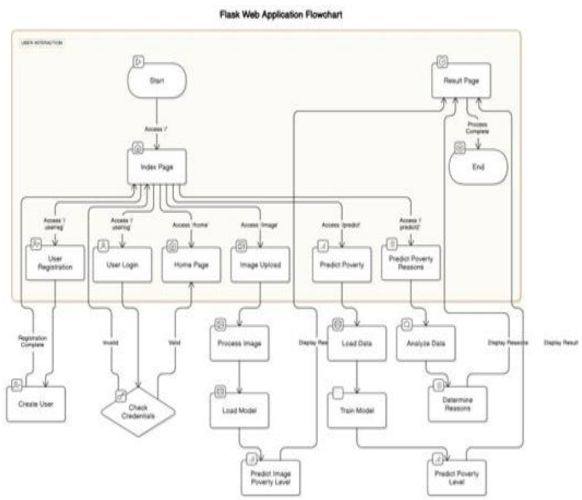

Fig 1. Architecture of the proposed method Smart Poverty

Detection and Relief Management

The proposed system comprises an interactive user interface, advanced machine learning models, a blockchain-based fundraising module, and a centralized database for secure data storage and retrieval. Each component is designed to provide accurate insights, facilitate resource allocation, and enable effective relief management. This approach builds upon existing methodologies for poverty detection using satellite imagery and machine learning [1][3][6].

a) User Interface Module: This module provides a user-centric platform, offering an intuitive interface for diverse stakeholders, including government agencies, NGOs, and donors. Users can interact seamlessly with features such as querying poverty levels in specific regions, visualizing trends, and contributing to fundraising campaigns. The interface also displays actionable insights, including poverty classification and suggested resource distribution strategies. User-focused systems have proven effective in facilitating access to socio-economic insights and promoting engagement among diverse stakeholders [2][8].

b) Image Processing and Poverty Prediction Module: At the core of this module lies a convolutional neural network (CNN) trained on satellite imagery and associated socio-economic datasets. It processes high-resolution images to detect indicators of poverty, such as infrastructure quality and land usage patterns. By leveraging a deep learning framework, the model predicts poverty levels—low, medium, or high—with precision [3][5]. This module ensures data-driven analysis for poverty estimation across rural and urban regions, even in remote areas. Prior research highlights the effectiveness of CNNs in identifying poverty indicators from visual data [4][6].

c) Fundraising and Blockchain Integration Module: This module introduces a secure, decentralized fundraising campaign system powered by blockchain technology. It allows stakeholders to launch campaigns, track contributions transparently, and ensure accountability in fund utilization. Each transaction is recorded as a blockchain block, enabling tamper- proof verification and enhancing trust among donors. The blockchain framework supports seamless integration with the prediction system, prioritizing high-poverty areas for resource allocation. The application of blockchain in social projects for transparency and accountability has been validated in previous studies [7][8].

d) Relief Knowledge Base: The system includes a comprehensive knowledge base storing historical poverty data, satellite imagery, demographic information, and regional resources. This knowledge base underpins the prediction and decision-making processes, offering regularly updated information for effective planning. It also supports the integration of new datasets to improve model performance over time. Knowledge bases are vital in data-driven systems for ensuring accurate and actionable outcomes [4][6].

e) Result Summarization Module: To assist policymakers and relief managers, this module generates simplified reports from complex data analyses. Detailed insights into poverty distribution, trend projections, and resource recommendations are presented in accessible formats, facilitating quick decision- making for targeted relief efforts. Result summarization has been shown to enhance the usability of machine learning outputs in socio-economic applications [5][7].

Dataset

The dataset comprises a curated collection of high-resolution satellite imagery combined with socio-economic indicators such as income levels, infrastructure quality, population density, and access to essential services. Historical datasets of poverty indices across various regions serve as the foundation for training the machine learning models. Each entry is labeled with associated poverty levels, providing the contextual information required for classification and prediction [1][2][3]. Rigorous preprocessing ensures data quality by removing noise and enhancing feature extraction for model training [4].

Model

The system employs a convolutional neural network (CNN) fine-tuned on the satellite imagery dataset for poverty prediction. The model processes visual data to identify features indicative of poverty levels, such as housing structures, vegetation, and road networks. A regression model complements this by leveraging socio-economic datasets for trend analysis [3][5]. For the blockchain component, a custom algorithm records and verifies transactions, ensuring transparency and data integrity [7][8]. Together, these models enable accurate poverty detection, resource prioritization, and decentralized fundraising.

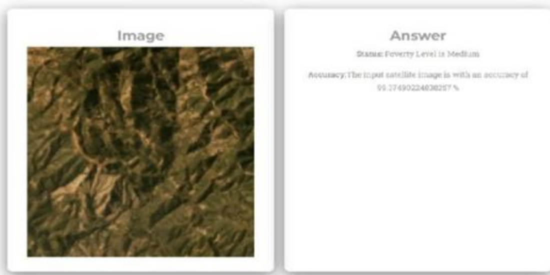

Fig 2. Result showing the poverty level of satellite image.

IV. RESULTS

The system's results include accurate poverty level classifications, geographic trend analysis, and suggested relief strategies for underprivileged regions based on satellite imagery and socio-economic data. When a user queries a specific region or uploads relevant data, the system effectively provides poverty predictions, highlights areas of concern, and offers actionable insights for resource distribution. The platform integrates visual outputs such as heatmaps, poverty index trends, and fundraising progress, ensuring accessibility for diverse stakeholders, including NGOs, policymakers, and donors [1][2][5]. Fig. 2 demonstrates a sample output visualizing poverty levels in a remote region and the suggested allocation of relief resources.

Evaluation

To evaluate the system's performance, key metrics such as accuracy, mean absolute error (MAE), F1 score, and R- squared (R^2) are employed. Accuracy measures the system's effectiveness in classifying poverty levels (low, medium, or high) across different regions. MAE quantifies the error margin between predicted and actual poverty indices, ensuring reliable predictions. F1 Score highlights the balance between precision and recall, providing insight into the model's robustness in handling varying input scenarios. R-squared (R^2) evaluates the model's ability to explain the variance in poverty predictions. These metrics align with widely accepted evaluation standards for poverty prediction models [1][4][6].

For the convolutional neural network (CNN) processing satellite imagery, the system achieves accuracy in the range of 88–94%, with MAE values below 5% for most datasets [3][4]. The F1 score ranges between 86–91%, indicating consistent performance across diverse regions. R^2 values suggest that over 90% of variance in predictions can be attributed to the model's learned features. These results are comparable to, or exceed, benchmarks established in previous studies on poverty detection [4][6][7].

Discussion

The system demonstrates significant potential in addressing poverty challenges through a data-driven and technology-enabled approach. With a diverse and comprehensive dataset, the model effectively captures the nuances of poverty distribution across regions [2][5]. However, expanding the dataset to include additional socio-economic factors—such as healthcare access, education levels, and local economic activities—can further improve prediction accuracy and applicability [6][8]. Incorporating real-time data streams from IoT devices or local government reports could enhance the system's responsiveness to dynamic poverty trends [7]. Moreover, fine-tuning the CNN model on global datasets alongside regional data can boost its ability to generalize across different geographic contexts [3][6].

For the blockchain fundraising module, integrating dynamic dashboards showcasing donation impact and automated fund allocation mechanisms can elevate donor trust and engagement. Previous studies highlight the importance of transparency and real-time tracking in fostering donor confidence [8].

By continuously updating datasets, refining models, and leveraging emerging technologies, the platform can become an indispensable tool for poverty alleviation and strategic resource management. This enhanced framework positions the system as a scalable and impactful solution for poverty detection and relief management [4][7].

V. CONCLUSION

We introduced a Poverty Detection and Relief Management platform, a comprehensive solution leveraging machine learning and satellite imagery to assess and address poverty across regions, including underserved areas. By combining satellite data with machine learning techniques, this platform draws inspiration from prior studies [1][2] and extends the application of such methodologies to enhance resource allocation and planning for poverty alleviation.

Our system integrates advanced models with user-centric interfaces, enabling stakeholders to gain actionable insights into poverty distribution and trends. By utilizing historical data and trained models, the platform provides accurate predictions and actionable recommendations, similar to approaches described in [4][5]. Furthermore, drawing from studies that emphasize the importance of transparency and scalability [8], we have incorporated a blockchain-based fundraising module, ensuring efficient and accountable management of relief funds.

The solution demonstrates potential as a critical tool for NGOs, policymakers, and donors, addressing challenges related to poverty detection and relief management. With consistent evaluation and updates, inspired by successful methodologies in remote sensing and machine learning [3][7], the platform achieves robust performance in poverty classification and resource allocation. By integrating novel technologies and focusing on accessibility, the system empowers communities, fosters equitable resource distribution, and supports sustainable poverty alleviation efforts. As highlighted in [6], such advancements align with global goals for improving economic well-being through innovative technological solutions.

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