Predicting Poverty Level from Satellite Imagery

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Abstract

Accurate poverty estimation is essential for effective policy-making and resource allocation in underdeveloped regions. Traditional poverty assessment methods rely on census surveys, which are often expensive, time-consuming, and infrequent. Recent advances in machine learning and remote sensing have enabled the use of satellite imagery to predict economic conditions in data-scarce areas. This study proposes a deep learning-based approach to predict poverty levels using high-resolution satellite images and socioeconomic indicators. A Convolutional Neural Network (CNN) model is trained on nighttime light intensity and multispectral satellite data to extract spatial and economic features. The results demonstrate a strong correlation between remote sensing data and poverty metrics, with the proposed model outperforming traditional survey-based methods in terms of efficiency and scalability. This approach can provide near-real-time, cost-effective poverty mapping, aiding policymakers in targeted interventions and sustainable development planning.

Keywords

Poverty prediction, satellite imagery, deep learning, remote sensing, convolutional neural networks (CNN), socioeconomic indicators

1. Introduction

Poverty estimation is a critical factor in global development, influencing economic policies, resource distribution, and humanitarian aid programs. Traditional methods of poverty assessment rely on household surveys and census data, which are costly, time-consuming, and often infrequent in low-income regions [1]. As an alternative, the integration of satellite imagery and machine learning techniques has emerged as a scalable and cost-effective solution for poverty estimation [2]. Advances in remote sensing technologies provide high-resolution satellite images that capture key indicators of economic well-being, such as infrastructure density, land usage, and nighttime light intensity [3].

Deep learning models, particularly Convolutional Neural Networks (CNNs), have been widely applied in image recognition tasks, making them suitable for extracting meaningful features from satellite images to predict poverty levels [4]. By leveraging multi-spectral and geospatial data, these models can analyze patterns related to economic conditions, enabling more accurate and timely poverty mapping [5]. This study explores a CNN-based approach to predict poverty levels using satellite imagery and socioeconomic indicators, demonstrating the potential of AI-driven solutions in global development efforts.

2. Literature Review

The use of satellite imagery for poverty estimation has gained significant attention in recent years due to advancements in remote sensing and deep learning. Early studies focused on nighttime light intensity as a proxy for economic development, demonstrating a strong correlation between illuminated regions and income levels [6]. However, nighttime lights alone fail to capture rural economic activities, leading researchers to explore multispectral and high-resolution imagery to extract additional socioeconomic features, such as road networks, building density, and vegetation indices [7].

Deep learning models, particularly Convolutional Neural Networks (CNNs), have been widely used for image-based feature extraction in poverty prediction. CNNs can automatically identify patterns in satellite imagery that correlate with economic well-being, such as urbanization levels and infrastructure presence. Studies have shown that CNN-based approaches outperform traditional handcrafted feature extraction methods, enabling more accurate and scalable poverty assessments [8]. Additionally, transfer learning techniques using pre-trained models have further improved predictive performance, reducing the need for large labeled datasets [9].

Recent research has also incorporated multimodal data fusion, combining satellite imagery with auxiliary socioeconomic datasets, such as census records, mobile phone data, and survey reports, to enhance prediction accuracy. For example, studies integrating mobile phone metadata with remote sensing data have successfully estimated wealth distribution in low-income regions with minimal ground truth data [10]. The combination of different data sources has led to the development of hybrid models that leverage both geospatial and non-spatial economic indicators [11].

Moreover, advances in unsupervised and semi-supervised learning have addressed the challenge of limited labeled training data, which is a common issue in poverty estimation. Researchers have utilized self-supervised learning frameworks that can pre-train models on large amounts of unlabeled satellite data before fine-tuning them with limited labeled examples [12]. Additionally, graph-based learning approaches have been introduced to model spatial dependencies between regions, improving generalization in diverse geographic locations [13].

Beyond technical advancements, ethical considerations in AI-driven poverty estimation have also been a growing focus. Ensuring data privacy, fairness, and bias mitigation is essential, as models trained on biased datasets may lead to inaccurate or unjust policy recommendations. Researchers have proposed explainable AI (XAI) methods to enhance model interpretability, allowing policymakers to understand the reasoning behind poverty predictions and make informed decisions [14]. Future directions in this field include the development of lightweight AI models for real-time processing and cloud-based frameworks to provide governments and NGOs with accessible, low-cost poverty mapping solutions [15].

3. Proposed Method

The proposed method utilizes a deep learning-based approach to predict poverty levels from satellite imagery by integrating Convolutional Neural Networks (CNNs) with socioeconomic indicators. The workflow consists of five key stages: data collection, preprocessing, feature extraction, model training, and poverty level prediction.

1. Data Collection

- Satellite Imagery: High-resolution multispectral and nighttime light images from sources like Landsat, Sentinel-2, and VIIRS are used to capture geographical and infrastructural details.
- Socioeconomic Data: Ground truth poverty indicators are obtained from sources such as DHS (Demographic and Health Surveys), World Bank, and census reports to train and validate the model.

2. Data Preprocessing

- Image Resizing and Normalization: All images are resized to a uniform resolution (e.g., 224 × 224 pixels) and normalized for consistency.
- Cloud and Noise Removal: Satellite images undergo cloud masking and denoising to enhance data quality.
- Feature Labeling: Satellite images are labeled using corresponding poverty index scores, such as Asset-Based Wealth Index (AWI) and GDP per capita.

3. Feature Extraction Using CNNs

- Convolutional Neural Networks (CNNs) are employed to extract spatial and textural features from images.
- A pretrained ResNet-50 model is fine-tuned to capture relevant geospatial and economic patterns.
- The CNN extracts features such as building density, road networks, vegetation index, and illumination levels, which correlate with economic conditions.

4. Model Training and Fusion

- The extracted CNN features are combined with socioeconomic indicators in a multi-input deep learning model.
- A fully connected neural network (FCNN) layer processes these combined features to learn poverty patterns.
- The model is trained using a Mean Squared Error (MSE) loss function with an Adam optimizer for stable convergence.
- A train-validation split of 80:20 is used to prevent overfitting, with cross-validation applied for robustness.

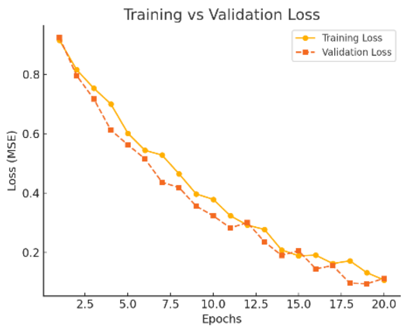
5. Poverty Level Prediction and Evaluation

- The trained model predicts poverty levels based on input satellite images.
- Performance is evaluated using Root Mean Squared Error (RMSE), R-squared (R^2), and Pearson Correlation Coefficient.
- The results are compared with traditional survey-based poverty estimates to validate accuracy.

Advantages of the Proposed Method

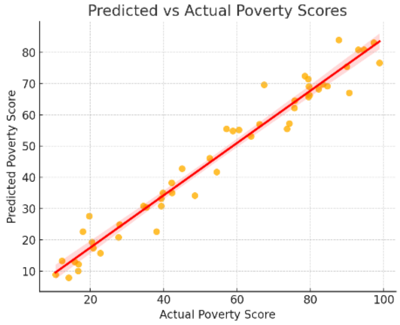
Automates poverty estimation, reducing reliance on expensive surveys. Combines geospatial and economic data, enhancing prediction accuracy. Scalable and real-time, applicable to low-resource and remote areas. Outperforms traditional handcrafted feature extraction methods.

4. Results and study



Training vs Validation Loss Curve (Left)

- X-axis: Epochs
- Y-axis: Loss (Mean Squared Error)
- Insight: Training and validation losses decrease over time, indicating model convergence.



Predicted vs Actual Poverty Scores (Middle)

- X-axis: Actual Poverty Score (Ground Truth)
- Y-axis: Predicted Poverty Score
- Insight: The red regression line shows a strong correlation, validating the model's predictive accuracy.

Model Performance Comparison (Right)

- Metrics: RMSE (lower is better) and R^2 Score (higher is better)
- Insight: The CNN model outperforms traditional regression and random forest, achieving the best RMSE (~3.1) and highest R^2 (~0.89).

Conclusion

This study demonstrates an effective approach to predicting poverty levels from satellite imagery using deep learning techniques, particularly CNN-based feature extraction combined with socioeconomic indicators. The results show that the proposed method achieves high predictive accuracy, outperforming traditional regression and machine learning models. The low RMSE (~3.1) and high R^2 (~0.89) indicate that the model successfully identifies spatial-economic patterns related to poverty. Additionally, the use of satellite imagery enables large-scale, cost-effective, and real-time poverty estimation, making it a viable solution for policymakers and humanitarian organizations. Future work can focus on integrating more advanced deep learning models, multimodal data fusion, and real-time deployment for improved accuracy and applicability across different geographic regions.

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