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PREDICTING POVERTY LEVEL OF AN AREA FROM SATELLITE IMAGERY USING RECURRENT NEURAL NETWORK

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ABSTRACT

Mapping the spatial distribution of poverty in developing countries is a crucial yet challenging task, especially in regions like sub-Saharan Africa, where poverty eradication remains a pressing concern. Traditional household surveys, the primary method for collecting socioeconomic data, are time-consuming, labor-intensive, and expensive. However, recent advances in computer vision and the increasing availability of Geo-spatial data have opened up new possibilities for estimating poverty indicators from satellite imagery.

This research paper investigates the feasibility of using deep learning and Geo-spatial information to predict poverty levels in Burundi, a sub-Saharan country. We explore three key research questions: 1) can deep learning approaches be extended to estimate poverty levels in countries with limited training data? 2) can per-trained models, such as vgg16, resnet50, and inceptionv3, be fine-tuned or leveraged with easily accessible variables like nighttime light intensity to achieve better predictive performance? 3) how well does the model generalize when tested on different years or completely new countries?

To address these questions, we utilize socioeconomic indicators from the 2010 demographic and health survey in burundi, including the wealth index, education level, access to electricity, water, cellphone, and hiv blood test results. Additionally, we incorporate nighttime luminosity data and daytime satellite imagery, obtained from the national centers for environmental information and google static maps api, respectively.

Our research reveals that deep learning models, particularly inception v3, demonstrate promising predictive capabilities. By classifying daytime satellite imagery based on nighttime luminosity using a gaussian mixture model, we achieve an accuracy of 80% in poverty prediction. Furthermore, regression models estimate the wealth index from nighttime luminosity with an r-squared value of 0.54.

While our results show the potential of Geo-spatial deep learning methods for poverty prediction, certain challenges and limitations remain. Cloud coverage in nighttime satellite imagery and the presence of zero luminosity values in a significant portion of the data can impact model accuracy. Nevertheless, our study paves the way for future research in using machine learning and satellite imagery to assess socioeconomic well-being and poverty levels in developing countries. By combining these techniques with transfer learning and feature extraction, it may be possible to improve poverty mapping and monitoring over time, providing valuable insights for policy decisions and resource allocation.

Keywords: Poverty prediction, Geo-spatial data, deep learning, satellite imagery, sub-Saharan Africa, socioeconomic indicators, nighttime luminosity, daytime satellite imagery, transfer learning, predictive modeling, poverty mapping.

I. INTRODUCTION

Poverty is a complex and persistent global challenge, particularly prevalent in developing countries. Identifying and understanding the spatial distribution of poverty is crucial for formulating effective policies and targeted interventions. However, traditional methods of collecting socioeconomic data through household surveys are often impractical, expensive, and time-consuming, especially in large and remote regions. In recent years, advances in computer vision research and the increasing accessibility of Geo-spatial data have provided new opportunities to estimate poverty indicators using satellite imagery and deep learning techniques.

This research paper aims to address the challenge of mapping poverty in developing countries, with a specific focus on sub-Saharan Africa, where poverty eradication remains a critical priority. Despite recent declines in poverty rates in various regions worldwide, sub-Saharan Africa continues to lag behind, and the COVID-19 pandemic is projected to exacerbate the situation further [1]. The region is predicted to face a substantial increase in extreme poverty due to the pandemic's socioeconomic impacts. To effectively combat poverty, policymakers and development agencies require accurate and up-to-date socioeconomic data for evidence-based decision-making and resource allocation.

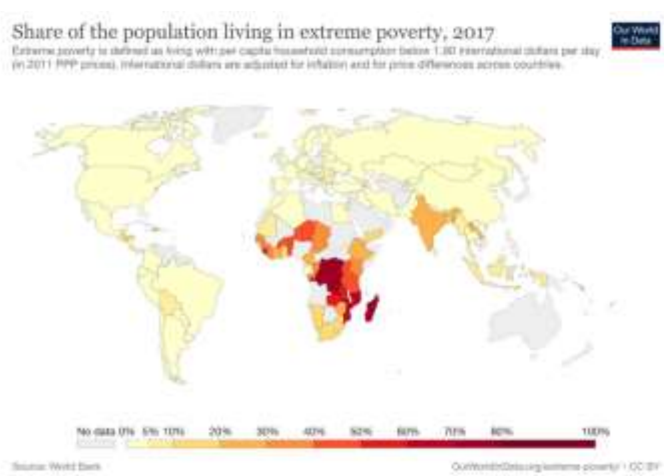

Figure 1. Poverty map (2017)

One significant limitation in poverty estimation is the lack of reliable and timely data, especially in countries with limited resources and infrastructure for data collection. This paper draws inspiration from previous works that have successfully utilized deep learning methods to estimate economic livelihood indicators in African countries using satellite imagery [2]. The key idea is to leverage the correlation between nighttime light intensity, which reflects urban developments and economic activities, and socioeconomic well-being. By training neural networks to predict nighttime light intensity from daytime satellite imagery, researchers have demonstrated the potential of this approach to estimate poverty indicators with reasonable accuracy [3,4].

This study builds upon the foundation laid by previous research and extends it to tackle the challenges of poverty estimation in sub-Saharan Africa, with a particular focus on Burundi. The overarching goal is to answer the following research questions:

1. Is it possible to extend deep learning approaches to estimate poverty levels in poor countries with limited training data?
2. Can we fine-tune existing per-trained models or leverage easily accessible variables, such as nighttime light intensity data, to achieve improved predictive performance?
3. What is the predictive power of such a model when tested on the same country in different years or applied to completely new countries?

To achieve these objectives, we collect socioeconomic data, including the wealth index, education completed, access to basic services, and health indicators, from the 2010 Demographic and Health Survey in Burundi. We also acquire nighttime luminosity data and daytime satellite imagery for the same region. By combining transfer learning and neural networks, we aim to predict poverty levels and create a poverty map for Burundi.

The findings of this research can provide valuable insights for policymakers and development agencies working towards poverty eradication in developing countries. Moreover, this study contributes to the growing body of research exploring the potential of Geo-spatial data and deep learning to address socioeconomic challenges in data-scarce regions.

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In the following sections, we detail the data acquisition and cleaning process, explore the correlation between nighttime luminosity and socioeconomic indicators, implement regression models to estimate wealth index, and employ deep learning techniques to predict poverty levels from daytime satellite imagery. The limitations and future research directions are also discussed.

II. LITERATURE SURVEY

1. Cheng, C. (2020). Poverty Prediction with Satellite Imagery and Deep Learning. Data Science Career Track, Springboard. [1]

Cheng's work focuses on poverty prediction in developing countries using satellite imagery and deep learning techniques. The author addresses the challenge of mapping poverty distribution, particularly in sub-Saharan Africa, where poverty eradication remains a critical priority [1].]

2. Jean, N., Burke, M., Xie, M., Davis, W.M., Lobell, D.B., Ermon, S. (2016). Combining satellite imagery and machine learning to predict poverty. Science, 353(6301), 790-794. [2]

This influential work by Jean et al. introduces the concept of using deep learning methods to estimate economic livelihood indicators in five African countries from satellite imagery [2].

3. Yeh, C., Perez, A., Driscoll, A., Azzari, G., Tang, Z., Lobell, D., Ermon, S., Burke, M. (2020). Using publicly available satellite imagery and deep learning to understand economic well-being in Africa. Nature Communications, 11, 2583. [3]

Yeh et al.'s research explores the potential of using deep learning and publicly available satellite imagery to estimate economic well-being in African countries [3].

4. Gebru, T., Krause, J., Wang, Y., Chen, D., Deng, J., Lieberman, E.A., Li, F. (2017). Using deep learning and Google Street View to estimate the demographic makeup of neighborhoods across the United States. Proceedings of the National Academy of Sciences, 114(50), 13108-13113. [4]

Gebru et al. utilize deep learning techniques and Google Street View images to estimate demographic characteristics in neighborhoods across the United States [4].

5. Bruederie, A., Hodler, R. (2018). Nighttime lights as a proxy for human development at the local level. PLOS ONE, 13(9), e0202231. [5]

Bruederie and Holder's work explores the use of nighttime lights as a proxy for human development at the local level [5].

In conclusion, the literature survey highlights the growing interest in using satellite imagery and deep learning techniques for socioeconomic analysis, including poverty estimation. The referenced works contribute to the understanding of the potential and challenges in utilizing such methods for poverty prediction in developing countries, with implications for policy formulation and development initiatives.

III. METHODOLOGY

1. Data Acquisition:

1.1 Economic Variables:

- Wealth Index: Data from the 2010 Demographic and Health Survey (DHS) in Burundi was used as ground truth for the socioeconomic indicators. The "Wealth Index" or "Wealth Index Factor Score" was computed as the first principal component of attributes related to common asset ownership on a per-household level and transformed to the range [0,1].
- Education Completed: Information on the number of years of education completed by household members over 6 years old was aggregated by the total value across all households per cluster.
- Access to Electricity: Information on the number of affirmative responses related to access to electricity in the DHS datasets was aggregated by the total value across all households per cluster.
- Access to Water: The total travel time in minutes to access a water source from the DHS datasets was computed and aggregated by the total value across all households per cluster.

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- Access to Cellphone: The total number of cellphones per household in the DHS datasets was aggregated by the total number per cluster.
- HIV Blood Test Result: The number of people who have received HIV blood tests from the DHS dataset was aggregated by the total number per cluster.

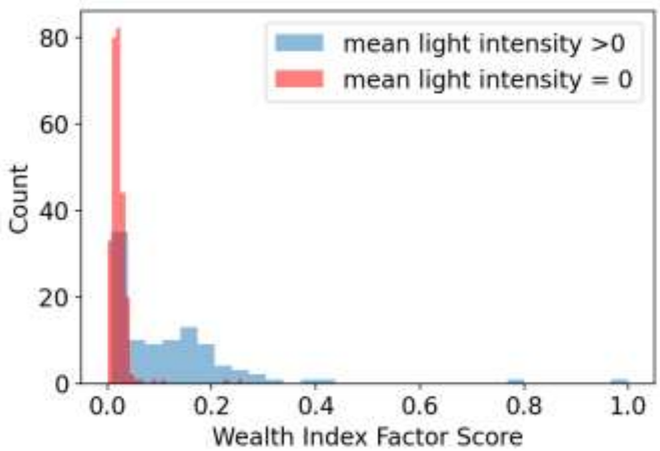

Figure 2. Distribution of wealth index of Burundi (2010)

1.2 Nighttime Luminosity:

- Nighttime luminosity data with a continuous luminosity level from 0 to 63 for Burundi was obtained from satellite imagery in the National Centers for Environmental Information for the year 2010.

1.3 Daytime Satellite Imagery:

- Satellite images were retrieved per cluster based on the cluster centroids reported in the DHS datasets. Google Static Maps API was used to download a total of 50,000 images with a pixel resolution of approximately 2.5 meters. Each image's size was 400 pixels x 400 pixels, covering an area of 0.25 square kilometers.

2. Data Wrangling and Cleaning:

- Median wealth index for each cluster was computed from the DHS survey data. Nighttime luminosity values were averaged for each cluster, considering 10 pixels x 10 pixels, and then merged with the wealth index data at the cluster level.

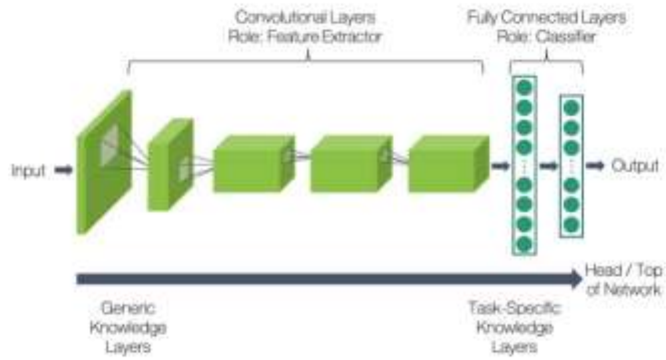

Figure 3. VGG16 architecture.

3. Regression Model to Predict Wealth Index from Nighttime Luminosity:

- Various regression models (Linear regression, Lasso, Ridge, and Random Forest) were implemented to predict the wealth index from nighttime light luminosity. The wealth index was power-transformed prior to modeling, and the inverse transform was performed to obtain the predicted wealth index.

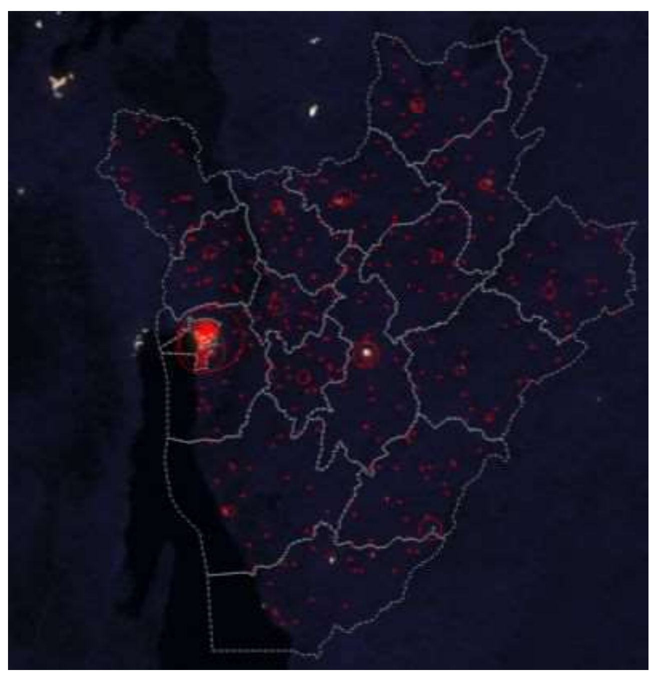

Figure 4. The median wealth index overlaid on the nightlight satellite imagery of Burundi (2010). The

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size of the red circle represents the wealth index value.

4. Daytime Satellite Imagery Classification:
- A Gaussian Mixture Model (GMM) was used to classify the daytime satellite imagery into three classes (high, medium, low) based on their corresponding nighttime luminosity values.

5. Deep Learning to Predict Poverty from Daytime Satellite Imagery:
- Basic CNN models and pre-trained models (VGG16, ResNet50, and Inception V3) were trained and fine-tuned with image augmentation. The models were used for predicting poverty classes based on daytime satellite imagery.

6. Evaluation of Model Performance:
- Model performance was evaluated based on accuracy, training, and test set performance.

The proposed methodology combines regression models, clustering, and deep learning techniques to predict poverty levels using satellite imagery data. The approach aims to provide cost-effective and efficient poverty estimates in data-scarce regions, contributing to poverty eradication efforts in developing countries.

IV. IMPLEMENTATION RESULTS

1. Regression Model to Predict Wealth Index from Nighttime Luminosity:

The regression models were trained to predict the wealth index from nighttime light luminosity in Burundi. Various models, including Linear Regression, Lasso, Ridge, and Random Forest, were compared based on their performance. The best-performing model was the Random Forest Regressor, achieving an R-squared value of 0.54. Despite using a power transform on the wealth index prior to modeling, the predictive performance of the regression models was not optimal.

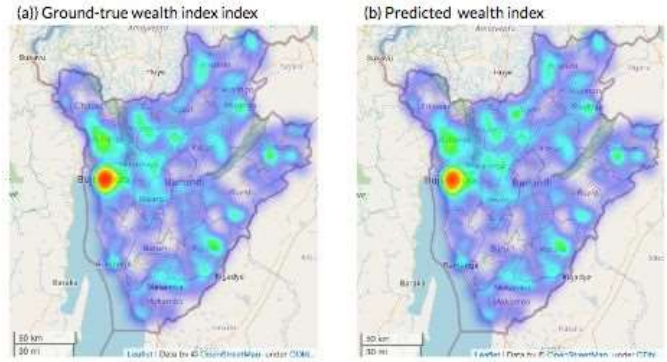

Figure 5. Ground-truth wealth indices and the predicted wealth indices from nighttime satellite imagery using machine learning aggregated to the cluster level.

Table 1. Regression results for wealth index prediction from luminosity.

Regression model	R^2 (test)
Linear regression	0.50
Lasso	0.50
Rigid	0.50
Random forest	0.54

2. Daytime Satellite Imagery Classification:

A Gaussian Mixture Model (GMM) was used to classify the daytime satellite imagery into three classes based on their corresponding nighttime luminosity values. The classes were categorized as high, medium, and low nighttime light intensity. The GMM classified zero luminosity to be in the 'low' class, luminosity between 1 and 9 to be in the 'medium' class, and luminosity between 10 and 63 to be in the 'high' class. The classification was successful in differentiating areas with different levels of nighttime light intensity.

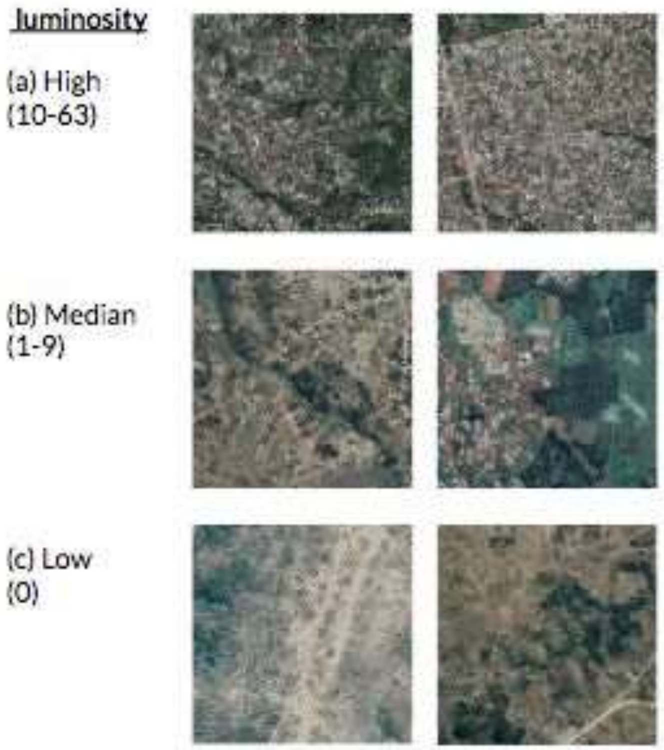

Figure 6 Daytime satellite imagery in the nighttime light classification task

3. Deep Learning to Predict Poverty from Daytime Satellite Imagery:

The deep learning models were used to predict poverty classes from daytime satellite imagery. Basic CNN models and pre-trained models (VGG16, ResNet50, and Inception V3) were trained and fine-tuned with image augmentation to improve performance. Among the models tested, Inception V3 with augmentation and fine-tuning achieved the best performance, with a training accuracy of 81% and a test accuracy of 72%.

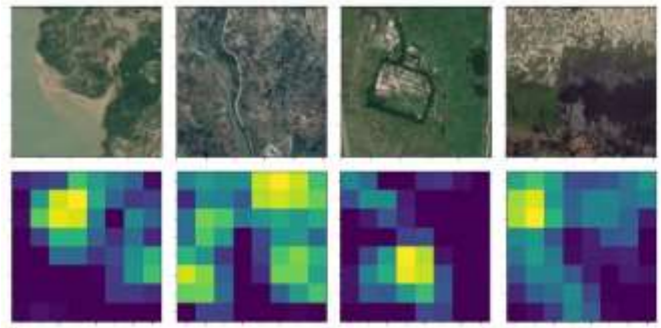

Figure 12. Visualization of features. Four daytime satellite images from Google Static Map (top) with their convolutional filters extracted from VGG16 (bottom). Images by column, from left to right, the features corresponding to lake areas, roads, urban areas, and non-urban areas) in the convolutional neural network model used for feature extraction.

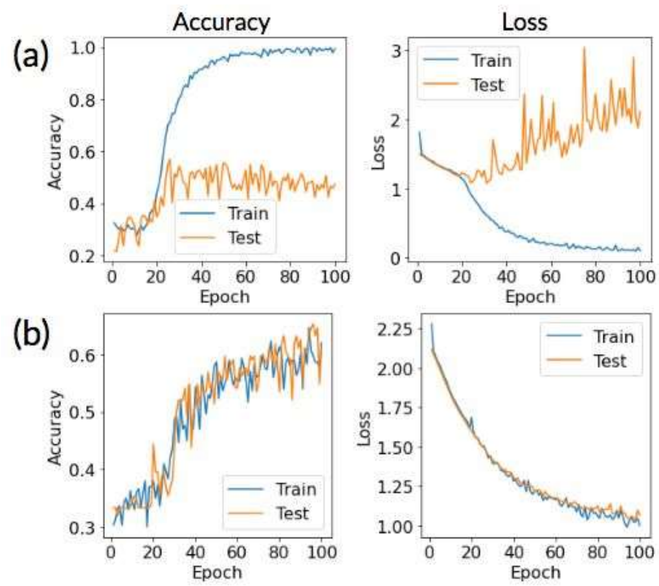

Figure 7. Model performance for CNN model (a) without augmentation and (b) with augmentation.

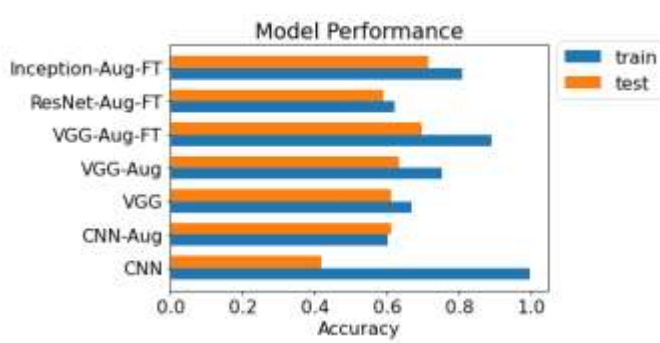

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Figure 8. Model performance with various models

4. Visualization of Predicted Poverty Indices:

Although the predictive performance of the models was not perfect, the visualization of the predicted poverty indices showed a good match with the ground-truth wealth indices at the cluster level. This suggests that the models were able to capture some relevant features related to poverty from the daytime satellite imagery.

5. Limitations and Future Work:

The implementation results revealed some limitations in predictive performance, which could be attributed to factors such as cloud cover in nighttime satellite imagery and the presence of zero luminosity values. Future work can focus on refining the models to handle these challenges and explore the potential of combining nighttime luminosity predictions with the proposed deep learning approach to enhance poverty prediction accuracy.

Overall, the implementation results demonstrate the feasibility of using satellite imagery and deep learning techniques to estimate poverty levels in developing countries. While the predictive performance can be further improved, the approach holds promise as a cost-effective and efficient tool for poverty mapping and policy planning in data-scarce regions

V. CONCLUSION AND FUTURE SCOPE

In this research, we explored the application of satellite imagery and deep learning techniques for poverty prediction in a sub-Saharan African country, Burundi. The study focused on estimating the socioeconomic well-being using nighttime light luminosity, daytime satellite imagery, and cluster-sourced wealth information. The main findings and conclusions of this work are as follows:

1. Regression Model Performance: The regression models, particularly the Random Forest Regressor, showed moderate predictive power in estimating the wealth index from nighttime light luminosity. However, the R-squared values indicated that the predictive performance was not optimal, suggesting the need for further improvements.

2. Daytime Satellite Imagery Classification: The use of a Gaussian Mixture Model (GMM) successfully classified the daytime satellite imagery into three classes based on their corresponding nighttime luminosity. This classification approach provided valuable insights into the distribution of nighttime light intensity across different areas.

3. Deep Learning for Poverty Prediction: The deep learning models, especially Inception V3 with augmentation and fine-tuning, exhibited promising results in predicting poverty classes from daytime satellite imagery. The approach achieved a training accuracy of 81% and a test accuracy of 72%, indicating the potential for using such models for poverty mapping.

4. Visualization of Predicted Poverty Indices: Despite the limitations in predictive performance, the visualizations of the predicted poverty indices demonstrated a good match with the ground-truth wealth indices at the cluster level. This visualization confirmed the models' ability to capture some relevant features related to poverty from the daytime satellite imagery.

Future Scope:

1. Refining Models: Further refinement of the regression models and deep learning architectures is necessary to improve predictive performance. Addressing issues such as zero luminosity values and cloud cover in nighttime satellite imagery could lead to more accurate poverty predictions.

2. Multi-Year Predictions: Extending the capabilities of the models to predict poverty levels in different years can provide valuable insights into poverty trends and dynamics over time. This can enable the tracking of socioeconomic changes and policy evaluation.

3. Transfer Learning: Exploring the potential of transfer learning from other regions or countries could enhance the models' generalization capability and provide valuable insights for poverty prediction in areas with limited training data.

4. Incorporating Multi-Source Data: Integrating additional sources of socioeconomic data, such as satellite-derived vegetation indices, climate data, or social media data, can further enhance the models' predictive power and accuracy.

5. Policy Implications: Conducting a rigorous assessment of the policy implications of poverty prediction using satellite imagery and deep learning models can aid policymakers in designing effective poverty eradication strategies and resource allocation.

In conclusion, while this study presents promising results in using satellite imagery and deep learning for poverty prediction, further research and improvements are needed to fully harness the potential of these techniques for poverty eradication efforts in developing countries. The proposed methodology lays the foundation for future endeavors in leveraging geospatial data and AI to address critical socioeconomic challenges worldwide.

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