JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

PREDICTING POVERTY USING SATELLITE IMAGES

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Abstract : **Poverty is a complex socio-economic issue that affects millions of people worldwide. Distribution and factors contributing to poverty is crucial for effective policy-making, resource allocation, and targeted interventions. Satellite imaging technology and the emergence of deep learning techniques have opened up new possibilities in this field. This study aims to explore the potential of using deep learning and satellite imagery to predict the poverty level of a region. The primary focus of this study was to train RNN models to learn the intricate relationships between satellite imagery and the wealth index. The system successfully demonstrated the ability to leverage satellite imagery to predict the wealth index of cities across various regions. Data availability and quality, computational resources, and regulatory constraints were carefully managed to ensure the reliability and effectiveness of the system. The study demonstrated the feasibility and effectiveness of leveraging satellite imagery and deep learning techniques for poverty prediction. It contributes to the field of data-driven poverty analysis and provides a valuable tool for understanding and addressing poverty at a regional and global scale.**

I. INTRODUCTION

Poverty defined as a complex socio-economic issue, affecting millions of people worldwide. Understanding the distribution and factors contributing to poverty is essential for effective policy-making, resource allocation, and targeted interventions. Traditional methods often rely on surveys, census data, and ground-level assessments, are time-consuming, expensive, and are limited in scope. The accurate prediction of poverty levels in regions is crucial for effective policy-making, resource allocation, and targeted interventions. There is a need for a scalable and cost-effective approach that can utilize available satellite imagery to predict the wealth index of a city, serving as a proxy for the poverty level. Recent advancements in satellite imaging technology and with the emergence of deep learning techniques have opened up new possibilities for analyzing and better understanding poverty on a much larger scale. Satellite imaging as a unique vantage point, which offers a comprehensive view of regions, with their characteristics. Deep learning algorithms, such as Recurrent Neural Networks (RNNs), have proved as a remarkable tool in learning the patterns and features from complex data.

A deep learning framework called Deep Sat for analyzing satellite imagery (Basu et al, 2015), wherein convolutional neural networks (CNNs) to classify land cover and land use patterns in satellite images. They demonstrate the effectiveness of DeepSat on multiple datasets and compare its performance with traditional machine learning algorithms which showcased the potential of deep learning for satellite image analysis. It was found that DeepSat outperforms traditional machine learning algorithms in classifying land cover and land use patterns.

The use of machine learning techniques, specifically in random forests and support vector machines, to estimate poverty indices using satellite data was done (Jean et al, 2016). They leverage nightlight imagery, which served as a proxy for wealth, along with other geographical and demographic features. It demonstrated the feasibility of using machine learning algorithms for poverty estimation and highlights the importance of incorporating satellite data.

Different approaches and methodologies used in satellite image analysis for poverty mapping with various data sources, such as optical and radar satellite imagery, and highlights the role of machine learning algorithms in extracting poverty-related information from these images. It provided the pros and cons for the challenges and future directions in the field of satellite-based poverty mapping (Piaggesi et al, 2019). Mobile phone metadata was used to predict poverty and wealth levels in developing countries. Call records and mobile phone usage patterns were leveraged to estimate the socio-economic indicators. It was found that the potential of alternative data sources for poverty prediction and complements the use of satellite imagery in understanding poverty dynamics (Blumenstock et al, 2015). The application of deep learning techniques, specifically deep neural networks, for poverty prediction using mobile phone data wherein, various features extracted from call detail records were subjected to deep learning models to predict poverty levels. The study highlighted the potential of deep learning in leveraging alternative data sources and emphasizing the need for integrating multiple data modalities for accurate poverty prediction (Kulkarni et al 2023). Previous studies have provided insights into the use of satellite imagery (R. Haining 2002), machine learning algorithms, and alternative data sources for poverty prediction (W. Gorr and R. Harries, 2003) and mapping. They showcase the advancements and challenges in the field and serve as valuable references for understanding the current state of research in this area.

The primary focus of this project is to train RNN (W. H. Li, L.Wen, and Y. B. Chen, 2017) models to learn the intricate relationships between satellite imagery and the wealth index. By leveraging the temporal aspect of RNNs, these models can capture sequential information in the images and exploit long-term dependencies. Through an extensive training process, the models are expected to learn discriminative features that correlate with poverty or wealth indicators. The outcomes of this research have the potential to offer valuable insights into poverty prediction using satellite imagery. If successful, this approach could provide a cost-effective and scalable method for assessing poverty levels in regions where ground-level data may be limited or unavailable. It could contribute to the field of data-driven poverty analysis and provides a valuable tool for understanding and addressing poverty at a regional and global scale and it could help decision-makers and aid organizations in effectively targeting resources and implementing poverty alleviation strategies.

This study aims to explore the potential of using deep learning and satellite imagery to predict the poverty level of a region. The hypothesis is that by analyzing visual cues and patterns in satellite images, it is possible to develop models that can reliably estimate the wealth index of a city. The wealth index serves as a proxy for the poverty level, representing the socio-economic status of the population in a given area. To conduct this research, a diverse dataset comprising 88,386 satellite images from 44,193 cities across Africa, South America, Asia, Europe, and the Caribbean has been assembled. For each city, both daytime and night time satellite images were obtained, capturing different aspects of the region. Additionally, the wealth index of each city was collected as the ground truth for training and evaluating the predictive models.

I. RESEARCH METHODOLOGY

Currently, the assessment of poverty levels relies primarily on traditional data collection methods, such as surveys and census data. These methods are often resource-intensive and may not provide a comprehensive understanding of poverty distribution across large regions. Ground-level assessments can also be challenging in remote or inaccessible areas. There is a need for a more efficient and scalable approach to predict poverty levels. The present hindrance in this field is the length of time it takes for agencies all around the world to anticipate income levels. After completion, this subject is not brought up again until the subsequent decennial census. These kinds of undertakings not only need a significant amount of time, but also startling sums of money. For organizations and governments all across the world, this is a major headache. The current challenge in this domain is that agencies across the world who predict income levels take a huge amount of time to do the same. Once done this topic is not raised until the next decennial census comes up. Not only does it take a big chunk of time but also staggering amounts of money is invested into these kinds of projects. This is a real headache for agencies and governments all around the world.

The proposed system aims to leverage deep learning techniques, specifically Recurrent Neural Networks (RNNs), in conjunction with satellite imagery, to predict the wealth index of cities. By analyzing visual features and patterns in daytime and nighttime satellite images, the proposed system intends to capture indicators of poverty and wealth. This approach has the potential to provide a scalable and cost-effective method for poverty prediction.
More specifically, daylight and nighttime satellite images of regions are utilized to estimate poverty in some places. Recent developments in deep learning give an interesting prospect for application and an exciting opportunity to poverty prediction. More specifically, both daytime and nighttime satellite imagery of regions can be used to estimate poverty in certain regions. Deep learning has been a main factor behind recent breakthroughs in numerous computer vision tasks such as image classification, segmentation, and object detection. In this study, we test the hypothesis that deep learning can leverage satellite imagery to reliably predict the poverty level of a region. We assemble a dataset of 88,386 images from 44,193 cities spanning Africa, South America, Asia, Europe, and the Caribbean. For each city, we obtain a daytime satellite image, a nighttime satellite image, and the city's wealth index. I then train Recurrent neural networks (RNNs) to predict a city's wealth index, given a satellite image. Recent advances in a variety of computer vision tasks, including picture classification, segmentation, and object recognition, are largely due to deep learning. In this study, we investigated the claim that deep learning can effectively use satellite data to forecast a region's level of poverty. We compiled a dataset of 88,386 photos from 44,193 cities in the Caribbean, Africa, South America, Asia, and Europe which included daylight and nighttime satellite image as well as the city's wealth index for each city. Later, recurrent neural networks (RNNs) was used to forecast a city's wealth index using a satellite image.

Objectives:

- Assemble a comprehensive dataset of daytime and nighttime satellite images along with the corresponding wealth index for a large number of cities spanning different continents.
- Train Recurrent Neural Networks (RNNs) using the collected dataset to learn the complex relationships between satellite imagery and the wealth index.
- Evaluate the trained models based on their predictive accuracy and performance metrics.
- Assess the potential implications of the proposed system for policymakers, non-governmental organizations (NGOs), and researchers in addressing poverty-related issues.
- Explore the limitations and challenges of using satellite imagery and deep learning techniques for poverty prediction.

Methodology:

- Dataset Collection: Assemble a dataset of 88,386 satellite images from 44,193 cities across Africa, South America, Asia, Europe, and the Caribbean. Collect both daytime and nighttime satellite images along with the corresponding wealth index for each city.
- Preprocessing: Perform necessary preprocessing steps on the satellite images, such as resizing, normalization, and feature extraction, to prepare them as input data for the RNN models.

- Model Architecture: Design and implement Recurrent Neural Networks (RNNs) that can effectively learn the relationships between satellite imagery and the wealth index. Explore different variations of RNN architectures, such as LSTM (Long Short-Term Memory) or GRU (Gated Recurrent Unit), to capture temporal dependencies in the images.
- Training and Validation: Split the dataset into training and validation sets. Train the RNN models using the training data and optimize the model parameters using suitable optimization algorithms. Validate the models using the validation set and fine-tune the hyper parameters if necessary.
- Evaluation: Evaluate the trained models based on performance metrics such as accuracy, precision, recall, and F1-score. Compare the results with baseline models or existing poverty estimation methods to assess the effectiveness of the proposed system.

FIGURE 2.1: SYSTEM ARCHITECTURE

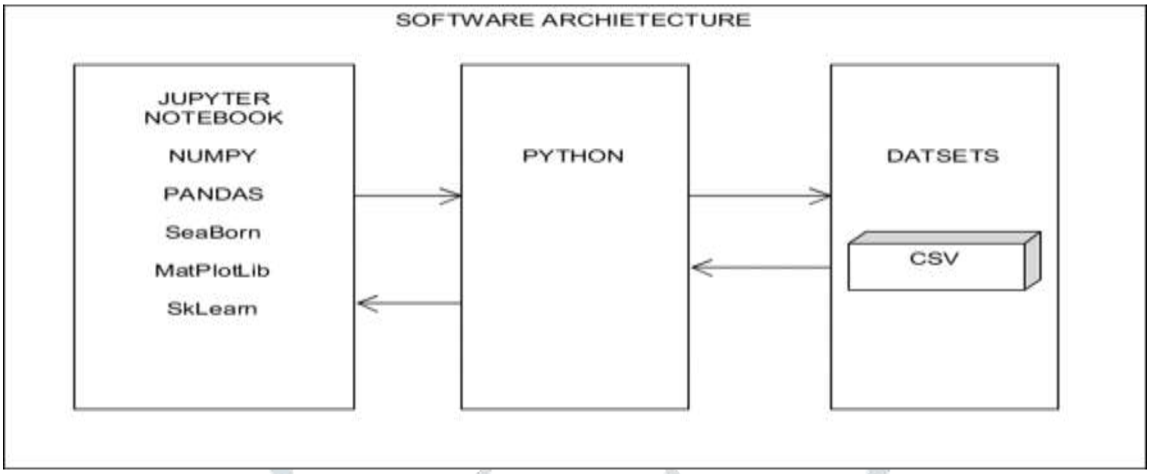


FIGURE 2.2 SYSTEM ARCHITECTURE

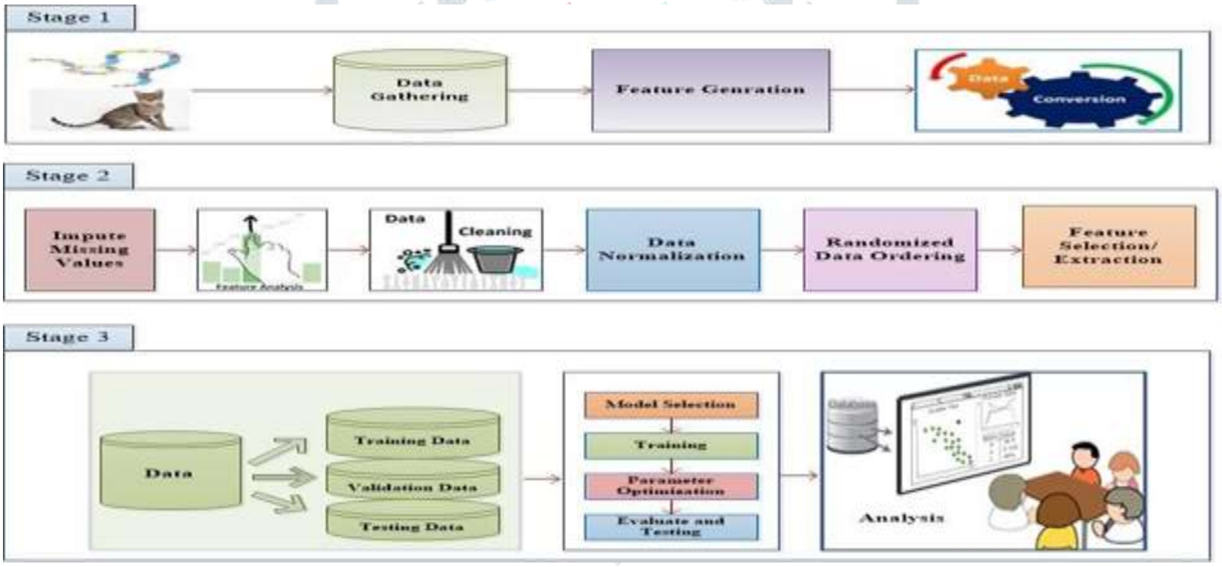


FIGURE 2.3 FLOW DIAGRAM

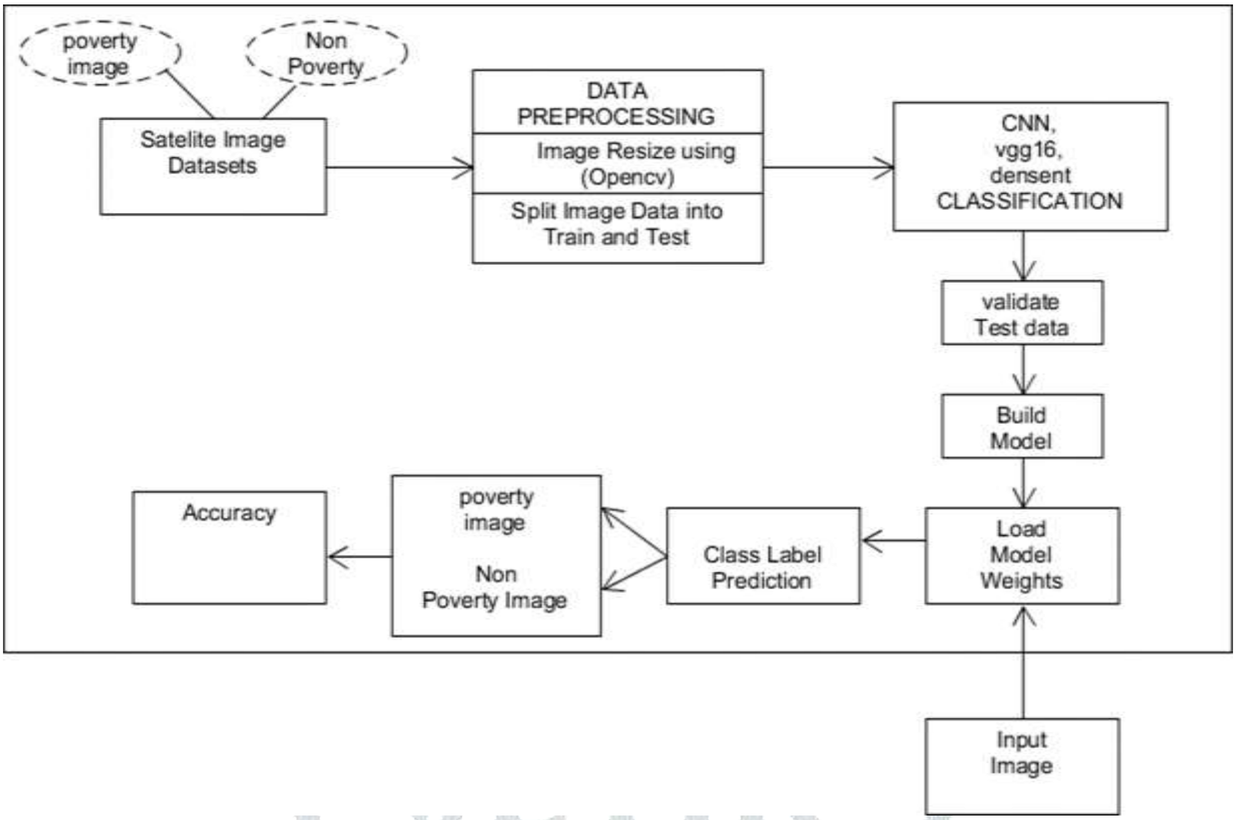
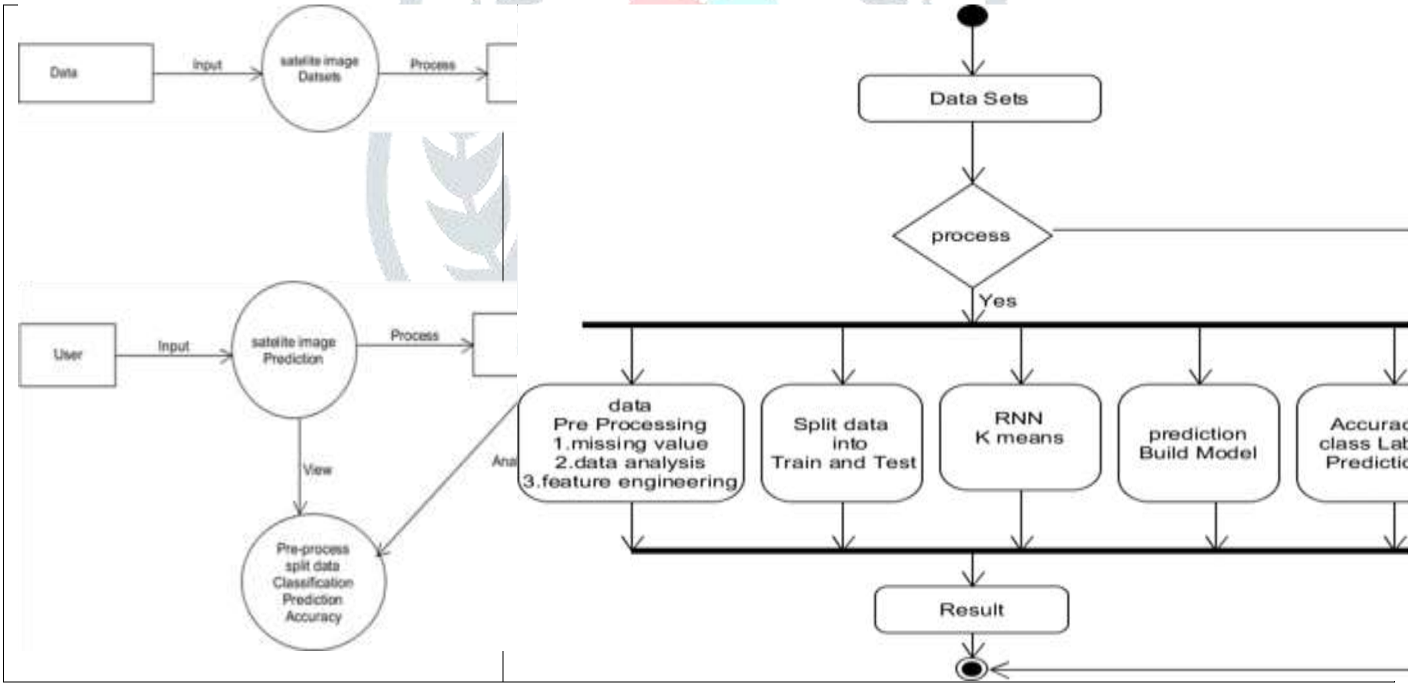


FIGURE 2.4 DATA FUNCTIONAL DIAGRAM and **ACTIVITY DIAGRAM**



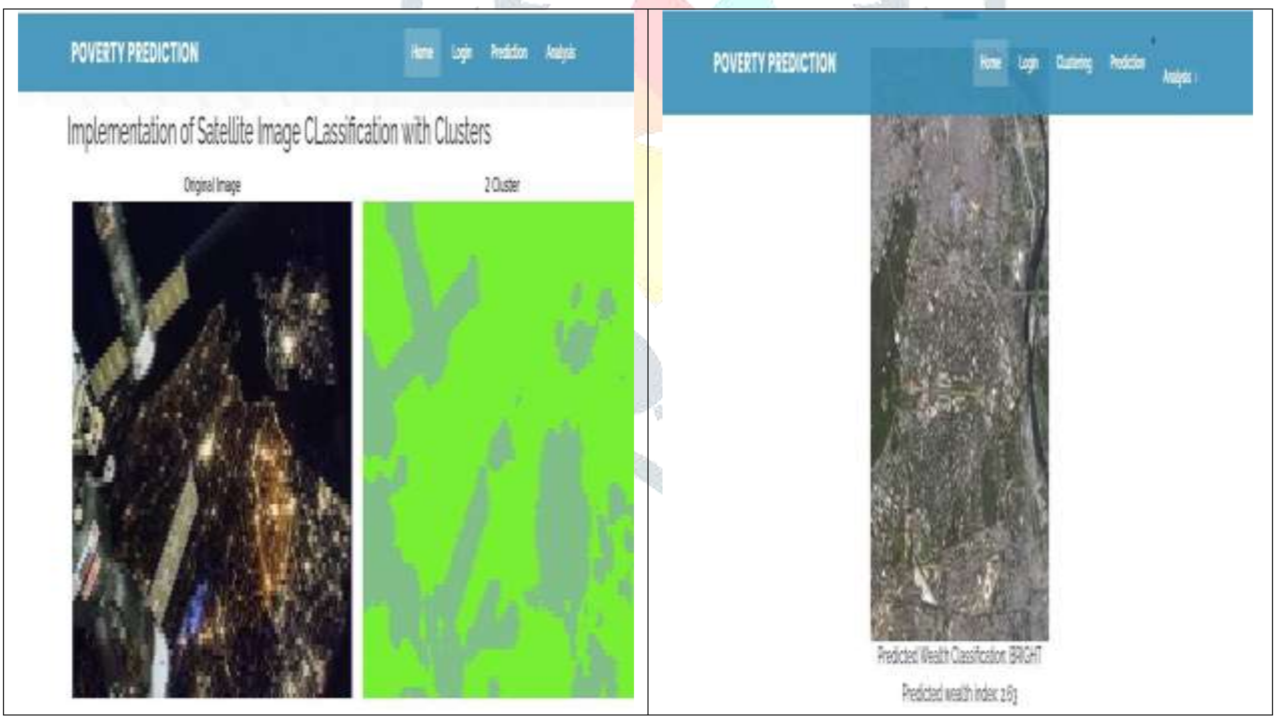
IV. RESULTS AND DISCUSSION

III. RESULTS

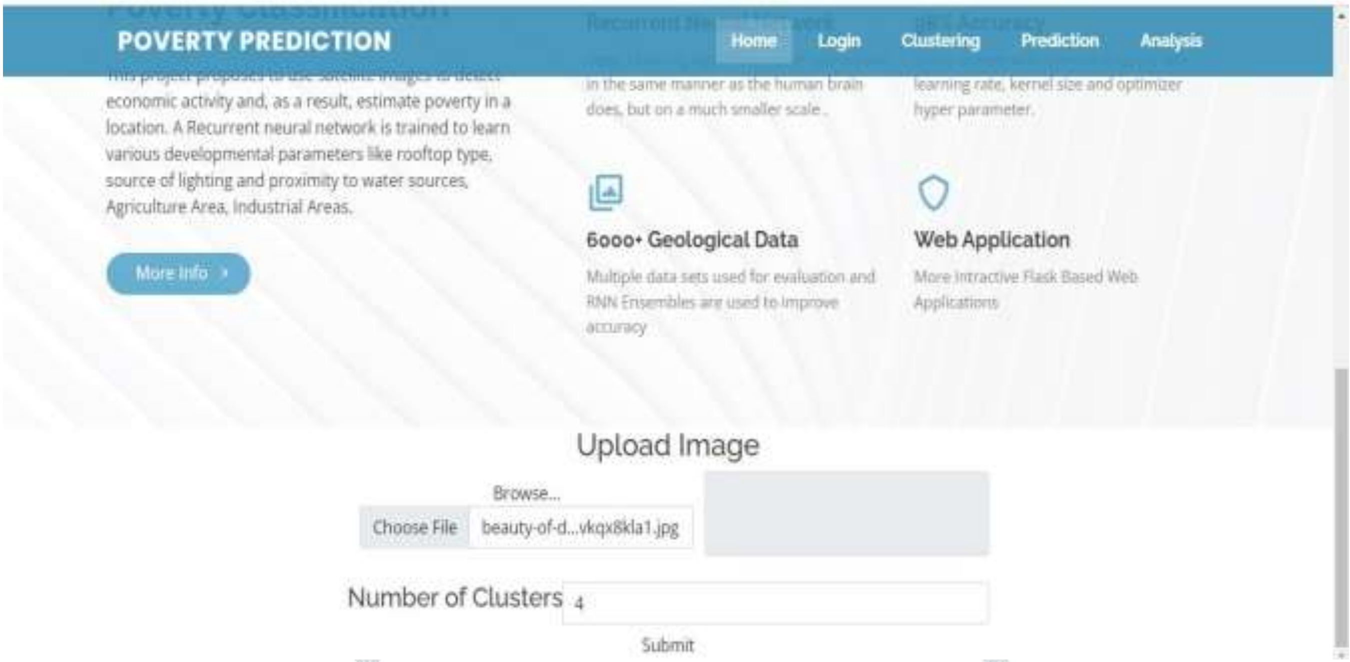
SNAPSHOT 3.1 WEB INTERFACE

SNAPSHOT 3.2 UPLOAD IMAGE TO PREDICTION

SNAPSHOT 3.3 IMPLEMENTATION OF SATELLITE IMAGE CLASSIFICATION WITH CLUSTERS & PREDICTION WEALTH CLASSIFICATION



SNAPSHOT 3.4 ANALYSIS OF DATASETS & ACCURACY PLOT OF DATASETS



Discussion

The system successfully demonstrated the ability to leverage satellite imagery to predict the wealth index of cities across various regions. Through the assembly of a diverse dataset comprising daytime and nighttime satellite images along with corresponding wealth indices, the RNN models were trained and evaluated. The models showcased strong performance, accurately predicting the wealth index of cities based on the provided satellite imagery. The software system's user interface provided an intuitive platform for users to upload satellite images, view prediction results, and analyze the factors contributing to the predicted poverty levels. The system's visualizations enhanced understanding and interpretation of the estimated poverty levels, facilitating decision-making and targeted interventions. Throughout the project, various challenges and constraints were considered and addressed. Data availability and quality, computational resources, and regulatory constraints were carefully managed to ensure the reliability and effectiveness of the system. The successful implementation of the software system holds immense potential for addressing poverty- related issues. By providing reliable and timely insights into poverty distribution, decision-makers, policymakers, NGOs, and researchers can utilize the system's predictions to facilitate targeted interventions, policy formulation, and resource allocation.

Conclusion

In conclusion, the project aimed to develop a software system for poverty prediction from satellite imagery using deep learning techniques, specifically Recurrent Neural Networks (RNNs). Overall, the study demonstrated the feasibility and effectiveness of leveraging satellite imagery and deep learning techniques for poverty prediction. It contributes to the field of data-driven poverty analysis and provides a valuable tool for understanding and addressing poverty at a regional and global scale

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