Mapping Urban Greenness and Poverty Using Normalized Difference Vegetation Index (NDVI) and Night-Time Light Data from Satellite Images

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***Abstract*— Millions of people globally are still impacted by poverty, which also makes it more difficult to achieve the Sustainable Development Goals. The United Nations' primary goal for the world's sustainable development by 2030 is to eradicate poverty. However, to provide a workable, focused response to this issue, a precise poverty map is needed. Since the national statistics division of India only provides data once every five years, there is a lack of consistent and trustworthy data regarding indicators of the poverty line, particularly in rural areas. In this study, we examine mapping poverty from space utilizing medium and high-resolution satellite imagery as an alternative to the cumbersome and inefficient ground-based data collection process. Using satellite imagery of India, we review how machine learning tools like convolutional neural networks have been harnessed to efficiently identify image features that help us effectively predict socio-economic indicators of poverty. Appropriate management of agricultural risks could prevent smallholder farmers in India from falling into poverty traps. We also explore how these methods offer promising means for policymakers to tackle poverty at the grassroots level and a potential for application across several domains of science.**

Keywords— Poverty Mapping, Remote Sensing, Satellite Imagery, Machine Learning, Convolutional Neural Networks (CNN), Socio-economic Indicators, Sustainable Development Goals (SDGs), Data Scarcity, Policy Planning, Agricultural Risk Management.

I. Introduction

Poverty is a serious issue in most parts of the globe, especially in developing countries such as India. To make improved plans and decisions, it is important to know the areas where poor communities are located and how their living conditions are evolving. Information regarding poverty is normally collected using surveys, which is costly, time-consuming, and labor-intensive. Additionally, surveys may not be up to date and do not necessarily address all issues. Therefore, we should track poverty sooner and wiser.

Through this study, I tried to work on a method that can draw poverty concentrations from different areas on the map via deep learning and satellite imaging. Bangalore was the city I decided to study in. Bangalore has a combination of highly established and emerging regions, which is why I chose it. Because of this, it's an ideal area to evaluate the effectiveness of a poverty detection system.

I used two kinds of satellite data—Night-Time Light (NTL) and Normalized Difference Vegetation Index (NDVI)—to gain an understanding of poverty from space. An area's level of greenness or vegetation, which is frequently correlated with its environment and land use, can be measured with the use of the NDVI. However, NTL provides a sense of how developed or dynamic a place is at night, which can be connected to economic activity and infrastructure.

Small patch images were created out of the merged data, and I then trained a Convolutional Neural Network (CNN) to classify the patches into Low Poverty, Moderate Poverty, and High Poverty classes. Then, I created a colourful heatmap of Bangalore's poverty level. Finally, I overlayed the predicted heatmap onto a real map of Bangalore using the help of tools like OpenStreetMap in order to make the representation and interpretation easier.

The purpose of my project is to show that with satellite data and machine learning, we can find cheaper and quicker ways of monitoring poverty, especially in large cities where things are likely to shift very rapidly. Such a system can be of benefit to local authorities, NGOs, and researchers who have to focus their support and action where it will do the most good.

II. Literature Survey

This section highlights related works which use satellite images and geospatial data for extracting various features for poverty prediction with the help of machine learning and deep learning techniques. It gives an overview about the challenges involved in developing this overall study. Ayush and colleagues' 2020 study created poverty maps for Uganda using high-quality daytime satellite pictures to determine the amount of money spent in various regions. They have used object detection technique to find objects in those photos, such as buildings, trucks, automobiles, and construction sites. To do this, they trained a YOLOv3 model using the x-View dataset, which has many satellite image samples with different types of objects. After finding these objects in the images, they counted how many of each object was present in each area.

Various factors like the intensity of night-time light(NTL), land cover, vegetation index, land surface temperature, built-up areas, and points of interest are considered to predict poverty in Thailand (Puttanapong et al., 2022). The study states that NTL acts as a proxy measure of level of economic activity in a given area. Data was obtained from Google Earth Engine, open cloud-based data storage and computing platform which provides access to satellite imagery for free. Point Of Interest (POI) data was obtained from OpenStreetMap. Among the 4 techniques used for prediction, Random Forest Regressor produced the best results.

The work (Putri et al., 2023) proposes a novel approach to generate poverty maps for East Java, Indonesia using machine learning and deep learning approaches. The first approach involves the use of multisource satellite images and point of data utilising zonal statistics feature extraction. Indicators of poverty derived from images include Normalised Difference Water Index (NDWI), Normalised Difference Vegetation Index(NDVI), Built-Up Index (BUI), Carbon monoxide (CO), Nitrogen dioxide(NO2), and Sulphur dioxide (SO2) for detecting economic activity, Land-Surface Temperature (LST), and Night-time Light (NTL) intensity. Google Earth Engine and OpenStreetMap were used to collect and process the data. In the second approach, the deep learning architecture of Resnet-34 transfer learning feature extraction is used to build the model from daytime multiband and night-time light intensity satellite images. The CNN-1D model was determined to be the best model in the first scenario and the Resnet-34 + MLP model to be the best model in the second scenario.

The work (Babenko et al., 2017) estimates poverty directly from high and medium resolution satellite images for Mexico. The study uses satellite imagery provided by both Planet and Digital Globe. Out of two CNN based architectures that were used, GoogleNet architecture outperformed the VGG architecture.

A method that combines deep learning along with satellite imagery for poverty prediction was also proposed (Jean et al., 2016). The study maps daytime satellite photos to equivalent night-time light intensity levels using convolutional neural networks. Poverty mapping estimation was done by applying transfer learning Resnet-34 feature extraction on daytime satellite data for five African countries - Nigeria, Tanzania, Uganda, Malawi and Rwanda.

III. METHODOLOGY

The purpose of this project is to map poverty rates over Bangalore city through remote sensing data and deep learning methods. The methodology is systematic and structured, consisting of phases of data acquisition, pre-processing, model construction, and visualization of predictions. The approach involves the integration of satellite data analysis and sophisticated machine learning techniques to offer insights into poverty in Bangalore that can prove to be extremely useful in urban planning and development policies.

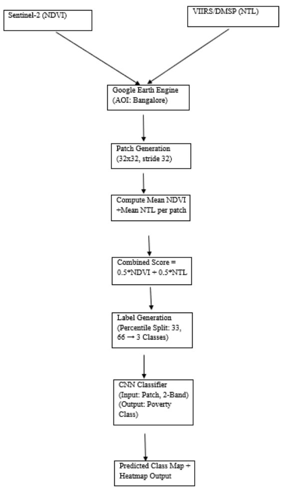

Fig. 1. System Architecture.

A. *Area of interest and data sources*

geospatial platform, with the ability to perform high-speed processing of large-scale satellite imagery. GEE possesses a vast database of available satellite data, thus being appropriate for this project, two broad types of satellite data were utilized:

Normalized Difference Vegetation Index (NDVI): It is an indicator based on satellite imagery from the Sentinel-2, and it is a fundamental measure of plant health. The values of NDVI are in the range of -1 and 1 and increase with improved vegetation health. It is used to map green spaces and plant cover, usually indicating socio-economic conditions in a city.

Night-Time Light (NTL) data: This data, collected by the Visible Infrared Imaging Radiometer Suite (VIIRS), reflects the brightness of artificial light produced by urbanized areas at night. NTL observations are employed as an indicator of human development, infrastructure, and urbanization level. Rich areas are likely to be characterized by strong night-light levels, whereas dark spots are likely to represent underdeveloped or poor regions.

These two data sets form a fascinating pair for poverty level determination since vegetation condition (NDVI) is associated with socio-economic development, whereas human development and infrastructure are monitored through NTL observations.

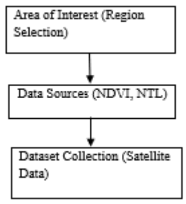

Fig. 2. Area of Interest and Data Sources.

B. *Preprocessing and Patch Creation*

After the raw NDVI and NTL data were collected, the following task was to pre-process and merge the datasets for analysis. The individual NDVI and NTL images were merged into each other, forming a multi-band image in which each pixel will hold NDVI and NTL values for a particular place in Bangalore. To prepare the data for the deep learning models, the images were divided into non-overlapping 32x32 pixel patches. The patches were taken as individual samples for the subsequent model training and examination. Processing of small image patches enabled the model to handle local city features efficiently, identifying fine-grained vegetation and night-time light intensity variation. Mean NTL and mean NDVI were calculated for each of these patches of imagery. This made it possible to construct a blended poverty score for every patch, based on the following weighted formula:

Poverty_score = 0.5 × NDVI_mean + 0.5 × NTL_mean

The computed poverty scores were subsequently employed in ranking each patch into one of three levels of poverty:

High Poverty: The class was linked with patches having poor NDVI (deteriorated vegetation) and low NTL (meaning poor human activities and infrastructural developments).

Moderate Poverty: These patches exhibited medium levels of both NDVI and NTL, indicative of a fairly balanced level of development.

Low Poverty: This class was described by high NDVI (green vegetation) and high NTL (pointing towards affluent urban areas with excellent infrastructure).

By applying a weighted mix of NDVI and NTL, this method supports the mapping of poverty using environmental and urban infrastructure factors, making it more reflective of socio-economic conditions.

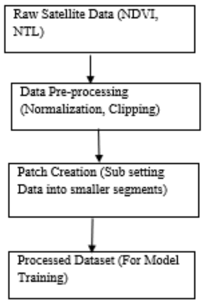

Fig. 3. Pre-processing and Patch Creation.

C. *Dataset Balancing and Label Encoding*

Since the dataset could have a non-equal distribution of poverty classes, addressing class imbalance during model training was a must. If some classes (e.g., high poverty zones) have fewer samples, the model may learn to have biases towards predicting the majority class.

To address this, we used up-sampling methods. For every poverty class (High, Moderate, Low), the same number of patches were randomly sampled from images with replacement so that the classes were still proportionally balanced in the training set. Balancing strategy made sure that the model would never stay excessively biased towards either the higher poverty or lower poverty class.

The poverty labels were also one-hot encoded to transform the categorical labels into multi-class classification structure. One-hot encoding transformed the labels into binary vectors with each vector having a 1 at the class position and 0s for the other places. This enabled the deep learning model to classify the patches properly into the relevant poverty levels.

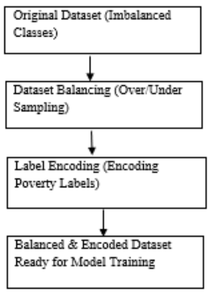

Fig. 4. Dataset Balancing and Label Encoding.

D. *CNN Model for Classification*

The foundation of the methodology of this project is structuring and training a Convolutional Neural Network (CNN) since it is one of the successful deep learning models that have been extensively used in the task of image classification. The CNN was structured to classify the patches of the images into one of the three poverty levels as measured from the NDVI and NTL values.

There were several layers that constituted the CNN architecture:

Convolutional Layers: These layers carried out feature extraction by convolving the filters over input patches of the image to identify patterns like edges, textures, and other prominent features.

ReLU Activation: Following convolution, ReLU (Rectified Linear Unit) activation was used to provide non-linearity so that the network could learn complex patterns.

Max Pooling: Pooling layers were utilized to downsample the feature maps to decrease the computational complexity and enable the model to generalize more effectively.

Batch Normalization: This method was utilized to normalize the input to each layer for enhanced training speed and stability.

Dropout: Dropout layers have also been included at training time to avoid overfitting, which stochastically reset a percentage of input units to 0 at every update to compel the network to find more general features.

The output layer had softmax activation, which had an impact on the model to give the probability of each one of the three classes (High, Moderate, Low poverty). It gave not only a hard prediction but also the confidence of the model in every class. The model was trained on the balanced dataset and tested on a hidden test set so that the model is able to generalize unseen data.

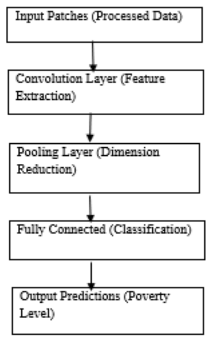

Fig. 5. CNN Model for Classification.

E. *Heatmap and Visualization*

After the CNN model had predicted, the last step was to visualize the output in a form that was easily interpretable and analyzable. The predictions were remapped in their original spatial arrangement, transforming the predicted class labels for each patch back into a full map of Bangalore.

For better visualization, the heatmap was superimposed on an interactive map of Bangalore with Folium and OpenStreetMap tiles. This allowed for easy navigation within the poverty projections, with users being able to zoom in or out to view individual parts of the city.

The heatmap provided a visually perceptible method of looking at the spatial configuration of poverty, which determined Bangalore areas that should be intervened and those Bangalore areas which are relatively better developed. It is an informative tool for policymakers and city planners since it provides meaningful information in relation to the socio-economic composition of the city in making sensible decisions for resource allocation and social development interventions.

IV. RESULTS AND DISCUSSION

Initially, satellite image taken from an area within Bangalore city. It is a raw original image prior to any processing such as NDVI or NTL. This patch was used because Bangalore consists of both urban expansion, semi-urban patterns, and even green areas, making it perfect to test in terms of poverty and vegetation cover.

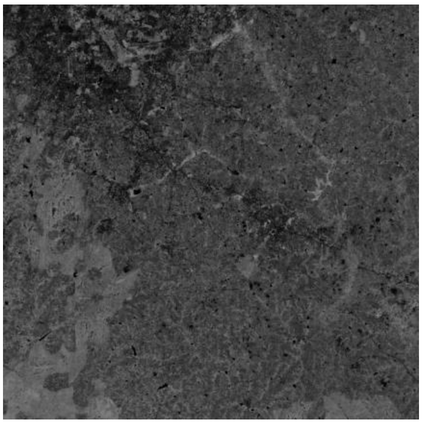

Fig. 6. Satellite Image of Bangalore City.

Fig.7. is the NDVI (Normalized Difference Vegetation Index) output for the same Bangalore city area from Figure 1. After running the NDVI formula on the satellite image, we obtain this colored visualization that marks the vegetation spread over the area. NDVI essentially employs the red and near-infrared bands of the image to identify green cover — so the greater the value, the greener and more vegetated the area is.

Areas that appear in greenish tones are where NDVI is high, indicating dense vegetation — like parks, tree cover, or even agricultural patches within or near the city. Darker or lighter-colored areas, on the other hand, indicate lower NDVI values, which mark built-up areas like roads, buildings, and commercial areas where vegetation is minimal or none.

Why this number is significant is that it graphically distinguishes regions on the basis of levels of greenery. Because most poor and rural tracts of land in urban areas continue to rely on natural cover for farming purposes or to survive, NDVI can indirectly inform about economic status.

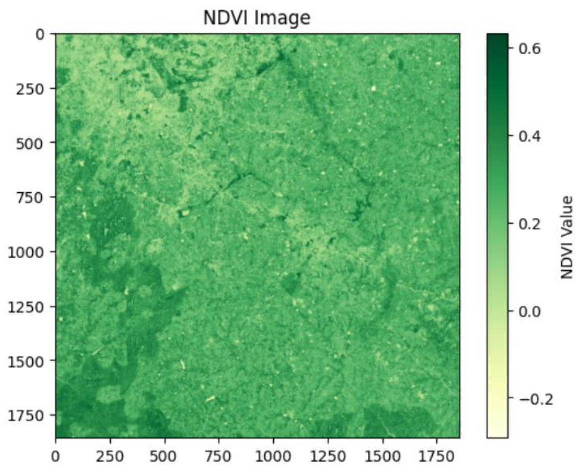

Fig. 7. NDVI Image of Bangalore City.

Fig.8. shows the classified vegetation levels over Bangalore city after using NDVI thresholds. In contrast to the raw NDVI map indicated in the earlier figure, in this case pixel values have been classified into different vegetation classes — e.g., high, medium, and low vegetation. This facilitates easier interpretation of the green cover in terms of spatial patterns and intensity.

From the map, we can see that some parts of Bangalore exhibit high vegetation, which are bound to be big parks, forest clusters, or unconstructed green lands. These are crucial in determining how much greenery is dispersed across the city. We find medium-level vegetation scattered across residential colonies with average tree cover or plots with a combination of houses and gardens. The low vegetation areas, typically represented in darker colors, indicate densely populated residential or industrial areas.

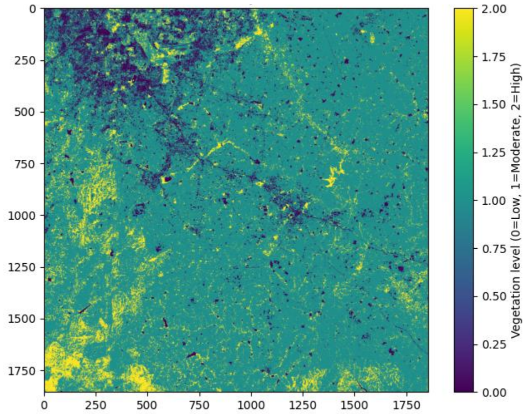

Fig. 8. Vegetation Levels of Bangalore City.

Fig.9. represents the histogram of the NDVI values derived from the Bangalore city satellite image. Along the x-axis, we have the NDVI values — normally ranging from -1 to +1, but in actual land cover data, most will range between 0 and 1. The y-axis is the number or frequency of pixels that belong to each NDVI value range. From the shape of the histogram, we can clearly observe that most of the pixels are severely aggregated in the mid to low NDVI values, i.e., most of them lack dense vegetation. Very few places have high NDVI values, which indicates there are extremely limited areas with greenery.

This distribution provides a concise statistical snapshot of vegetation cover within the city. It serves to verify what visually was observed in the NDVI image.

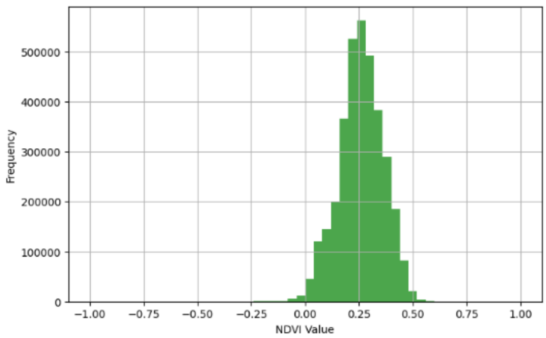

Fig. 9. NDVI Distribution Histogram.

Fig.10. depicts the outcome of greenness prediction for the individual Bangalore satellite image patches. We had

calculated the NDVI values and established threshold ranges, and then we classified every patch into levels of greenery — low, medium, or high greenness. Every patch in the image is colored differently based on the level of greenness. The model labels each patch according to the amount of vegetation it contains, using the NDVI values as input.

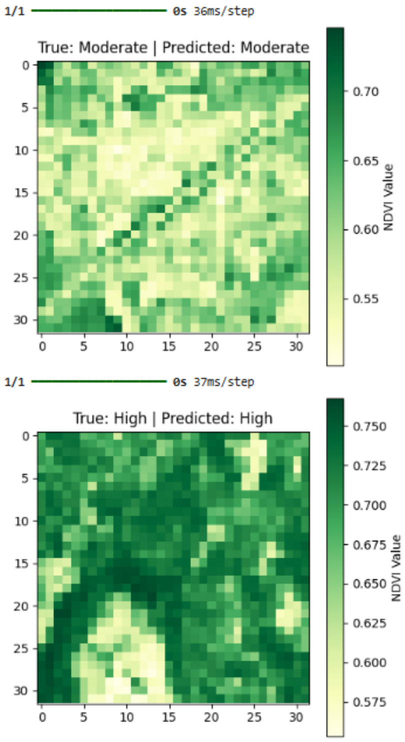

Fig. 10. Greenness Prediction on Image Patches.

Fig.11. provides the heatmap visualization of the predicted levels of vegetation for various areas of Bangalore city. As opposed to the previous figure showing greenness at the patch level, this heatmap presents a more continuous and intuitive visualization of vegetation distribution over the whole area.

Here in this heat map, colors are used to show the level of greenery. Red color is used to represent poor vegetation, while cool colors like green represent a lot of vegetation. This helps one easily know which parts of the city are greener and which parts are more urban or barren. We can observe from the heatmap that the city center areas appear to have fewer greens, which is understandable as they would be more built-up and developed. Alternatively, the fringes or certain enclaves in the city are emitting more greenness, which would indicate the existence of parks, trees, or semi-rural areas.

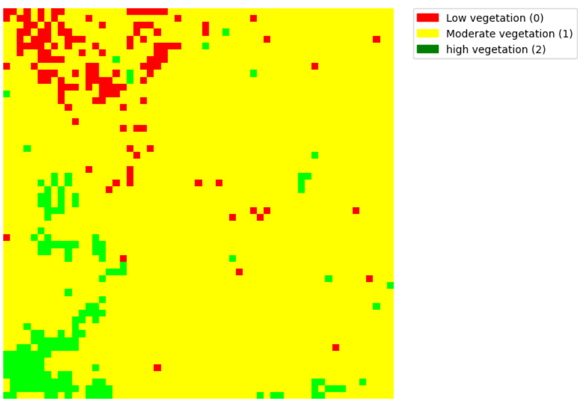

Fig. 11. Heatmap of Vegetation Level Prediction in Bangalore.

Fig.12. depicts the Night-Time Light (NTL) image of Bangalore city, which was derived from satellite data recording artificial light emissions during night-time. Every pixel in this image is a measure of the intensity of light recorded from the ground, with brighter pixels representing greater light intensity and darker pixels reflecting little or no light.

We can easily observe that the inner regions of Bangalore are much brighter, indicating highly urbanized and economically active areas. These would most probably be areas with well-developed infrastructure, commercial centers, residential high-rises, and street lighting. As we proceed towards the city limits, the brightness reduces, which could mean either lower population density or less developed areas, and possibly lower economic activity.

NTL data is a strong indirect measure of poverty. Brighter areas generally tend to be in regions with improved access to electricity, services, and economic opportunities — i.e., lower poverty. Dim or dark areas can, on the other hand, represent underdeveloped or poorer areas, particularly where lighting and infrastructure are not developed. But what is to be stressed here is that not all dark patches are poor ones — some may be forest patches, lakes, or industrial areas that do not give off light.

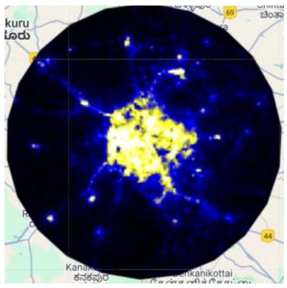

Fig. 12. NTL Image of Bangalore City.

Fig.13. illustrates the distribution of the aggregate scores produced by combining NDVI (green level) and NTL (night light intensity) values for each patch of an image. The rationale behind this step is to combine two disparate indicators — vegetation and light — to measure both environmental and infrastructural dimensions of urban poverty.

Every patch from the satellite data has both an NDVI rating (how green it appears) and an NTL reading (how light it appears at night). Blending them together, we developed a more balanced rating that will approximate the general condition of each area. A zone that has low NDVI and low NTL, for instance, may mean that it's poor or under-maintained, while high ratings in both could mean that it's more developed and better off economically.

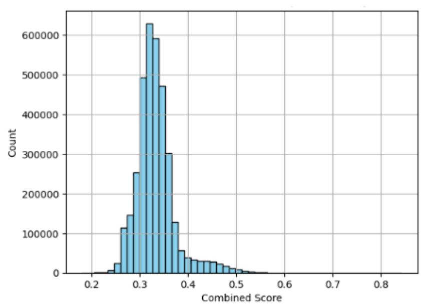

Fig. 13. Combined Score Distribution (NDVI + NTL).

Fig.14. displays the accuracy curve of the Convolutional Neural Network (CNN) model employed in poverty mapping. The curve depicts how the accuracy of the model changes over time as measured over a sequence of multiple epochs of training.

The horizontal axis of the chart is the number of epochs in training — i.e., the number of times the model cycled through the whole dataset. The vertical axis represents the percentage of accuracy. We can observe at the start of training that the accuracy is low because the model is learning and adapting its weights. But with an increase in epochs, we can see the accuracy increasing gradually, which indicates that the model is learning effectively from the data and optimizing its predictions. Towards the later epochs, the accuracy graph starts to plateau, indicating that the model has reached its best performance.

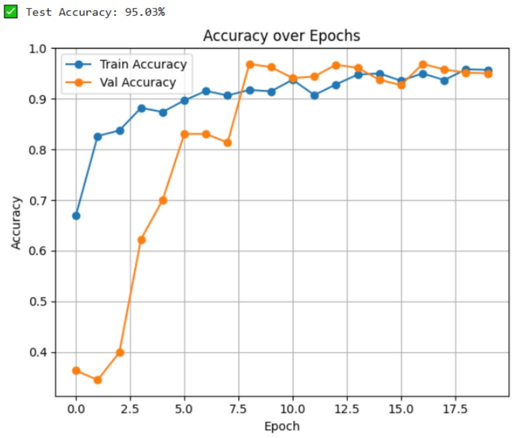

Fig.14. Accuracy Graph for the CNN Model.

Fig.15. depicts the confusion matrix for the CNN model, which is a measure used to assess the performance of the model based on its classification accuracy. The confusion matrix gives insight into how well the model is predicting each class — in this instance, the various levels of poverty based on combined NDVI and NTL data.

Classification Report:

	precision	recall	f1-score	support
High Poverty	1.00	0.89	0.94	243
Moderate Poverty	0.87	0.94	0.91	188
Low Poverty	0.96	1.00	0.98	213
accuracy			0.94	644
macro avg	0.94	0.94	0.94	644
weighted avg	0.95	0.94	0.94	644

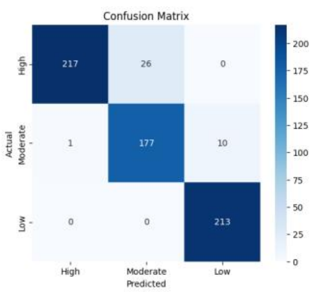

Fig.15. Confusion Matrix for the CNN Model.

Fig.16. illustrates NDVI (vegetation quantity) and NTL (night-light brightness) are combined to predict the poverty quantities for different image patches of the city of Bangalore. Every patch, based on its NDVI and NTL, is labeled with one of a set of poverty levels — typically low, medium, or high poverty. In the image, we can observe how the regions of greater vegetation and brighter night-time light are projected as lower poverty areas, while regions of lesser vegetation and duller lights are marked as higher poverty areas.

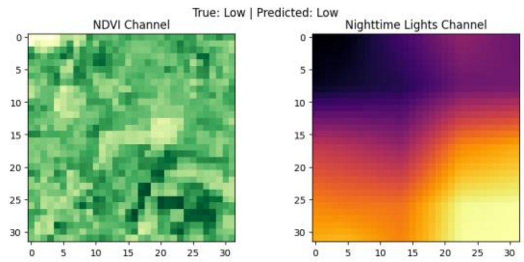

Fig. 16. Poverty Prediction Using NDVI and NTL on Image Patches.

Fig.17. illustrates the poverty estimation heatmap of Bangalore city based on the integration of NDVI (vegetation cover) and NTL (nightlights intensity) data for poverty mapping. In this heatmap, higher poverty levels are indicated by warmer colors like red and lower poverty levels are indicated by cooler colors like green. The regions of bright red usually match zones of lower vegetation and low nighttime light intensity — and are bound to be economically underdeveloped zones or sparse infrastructure and services zones. In contrast, green regions, indicating more vegetation and more light, are likely to be richer, having greater access to resources and infrastructure.

This heatmap allows us to simply visualize the poverty spread across the city. The heatmap is a powerful visualization technique that makes it simple to understand the spatiality of poverty, allowing policymakers and development agencies to target interventions successfully.

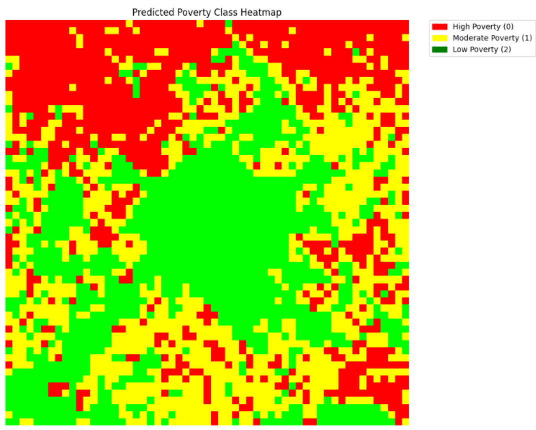

Fig. 17. Poverty Prediction Using NDVI and NTL in Banglore City.

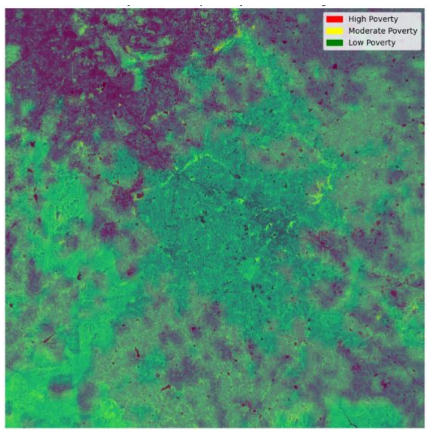

Fig. 18. Poverty Class Heatmap Overlay on Satellite Image.

V. CONCLUSION

This project Mapping Urban Greenness and Poverty Using Normalized Difference Vegetation Index (NDVI) and Night-Time Light Data from Satellite Images has a potent aim — to learn and chart poverty rates in Bangalore through satellite imagery and the capabilities of deep learning. By taking NDVI (which provides us with a notion of vegetation and environmental health) and Night-Time Light (NTL) data (which indicates human activity and infrastructure), we could observe both the natural and economic aspects of urban poverty.

With preprocessing, patching, and judicious balancing of the dataset, we trained a CNN model that could identify varying levels of poverty across the city. The heatmaps and visualizations that ensued did not merely produce data — they narrated a story. A tale of disparity, developmental gaps, and where help was needed the most. From the green patches of wealth to the blackened spots symbolizing conflict, each photograph spoke volumes about Bangalore's socio-economic terrain.

What makes this method so special is that it is scalable. This technique does not depend on costly surveys or labor-intensive fieldwork. With only satellite imagery and machine learning, we can quickly measure poverty at scale and near-real time. This unlocks opportunities for urban planners, NGOs, and policymakers to locate underdeveloped regions and plan interventions with data-driven confidence.

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