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Slum Analysis Based On Satellite Mapping

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Abstract: The government is unable to estimate the socio-economic status of a remote area and also they are unable to help them. Because the government only has their satellite image as a record and they can only see that area through a map but through this image they cannot get status about that area. So, considering this satellite image of an area, there is a profound need to detect the status of the remote area. In this project, we propose an advanced framework to identify socio-economic status of an area through satellite image. We are considering some major factors or attributes like water supply, rooftops and agriculture landfill and we are going to train some datasets through CNN technique then input satellite image is compare with train datasets and if there is presence of this factors in input image then we classify status of the area as poor, rich or medium.

Keywords: Machine Learning, Malnutrition, CNN, Poverty Prediction

INTRODUCTION

There are such a big amount of regions within the world wherever humans exist, however they need no facilities for his or her support. They don't even have basic wants of life like water, food and so on. Some regions lack only 1 issue and a few regions lack all the factors. Some regions have water however not electricity whereas another region has home however not the other wants. For such styles of regions, some organizations are able to facilitate them with the support of the government of that country; however, thanks to lack of communication from that region, the organization is aware solely of the situation of that region. They don't even understand what the fundamental wants of that region are?

In that case, the organization will solely have the satellite image of the region and that they attempt to confirm wants by perceptive satellite pictures. However, by solely perceiving that region through satellite image we have a tendency to cannot estimate the presence of the factors on it region. Therefore, to resolve this sort of downside we have a tendency to introduce associate degree applications to predict socioeconomic standing of a neighborhood.

The system that we have a tendency to area unit coming up with has the flexibility to spot some major factors that area unit terribly basic wants of {a region|a neighborhood|an area unita|a district|a locality|a vicinity|a part|a section} and that they are electricity, installation, agricultural field. An additional factor we have a tendency to area unit victimization for estimate standing of region is roof high of the house. Roof high could be a terribly essential issue for our system. For prediction of socio-economic standing, our system takes satellite image then this satellite image is compared with our trained model that contains of these major factors gift among it and when comparison these factors we have a tendency to get prediction of the standing of that satellite image within the variety of proportion of presence of things within the image and by considering this percentages of things we have a tendency to area unit predicting socio-economic standing.

The summary of survey paper is that it contain literature survey so it contain System design so conclusion and references at the side of URL of datasets of satellite pictures.

Currently, concerning one-quarter of the world's urban population lives in slums, that ar outlined by UN-Habitat as informal settlements or areas empty access to safe water, acceptable sanitation, and sturdy housing; additionally to being aras that are overcrowded and lack legal right security . Over the last fifteen years, there has been revived interest in slum improvement and wipeout by native and international organizations handling development problems. throughout this era, slums became a additional distinguished subject of remote sensing (RS) image analysis. Supported by accumulated availableness of very-high-resolution (VHR) information and method advances, several RS studies aimed to supply info on the geographics and dynamics of slums.

PROPOSED SYSTEM

We propose an advanced framework to identify socio-economic status of an area through satellite image. We are considering some major factors or attributes like water supply, roof tops, electricity and agriculture field and we are going to train some datasets through CNN technique then input satellite image is compared with train datasets and if there is presence of these factors in input image then we predict the poverty status.

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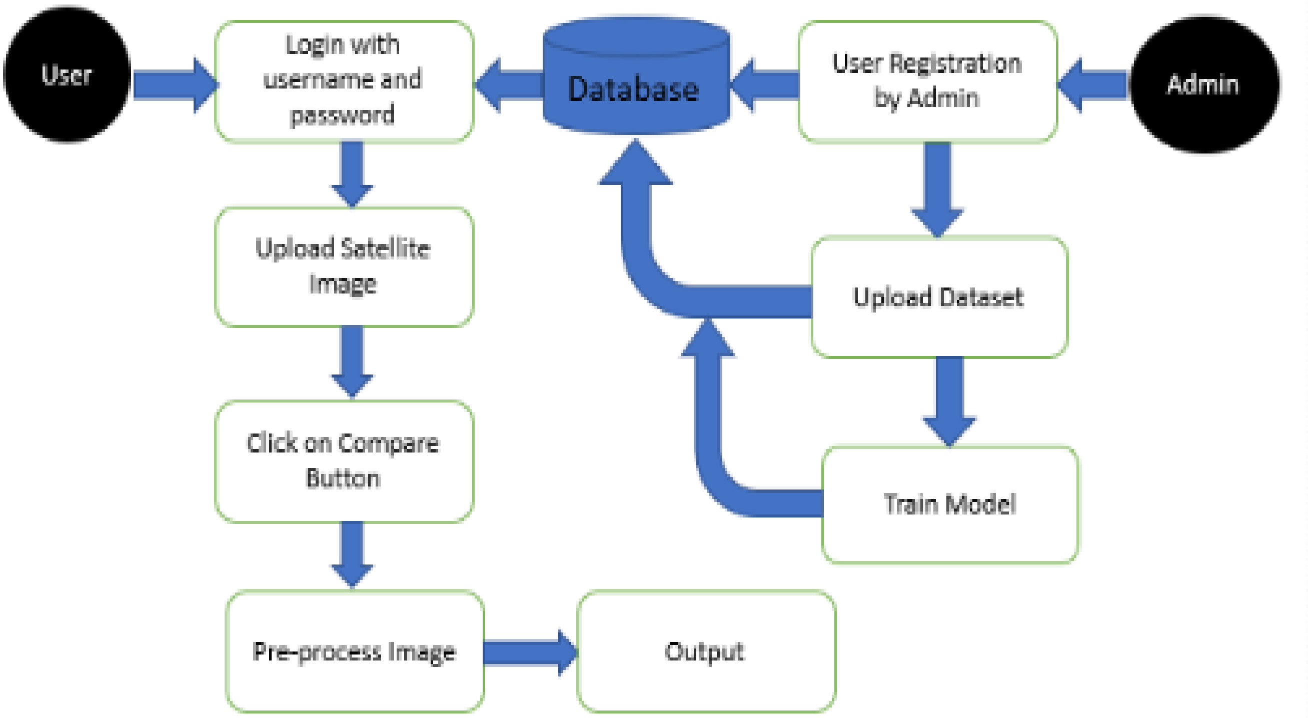

Fig. 2 System Architecture

Flow:

1. The whole architecture is made by PyQT library used in python language. PyQT library gives all the necessary stuff related to GUI design. PyQT provides us display screen, buttons and so on. So, In this way PyQT helps us in design GUI.

2. After designing of GUI, another task is to authenticate valid user for operating application. To deal with this task, we are using MySQL database to store data of username and password and through this, user can authenticate easily.

3. Another task is to preprocess the input image which can be done by the OpenCV library of python. By using this library, the image is converted into grayscale image, contour image and smoothen image.

4. The major task of this survey paper is to collect datasets of satellite image and to achieve this result, we are working on google Earth images, LandSat 7 images and also take help of magic puzzle application on which, we are providing latitude and longitude of a particular area and as a result, we are getting satellite image of that area. In this way, we achieve all the tasks to achieve our project goal.

Goals And Objectives

A. To predict poverty from satellite image.
B. To analyze agriculture land, water resources, etc. from satellite images using machine learning.
C. To Minimize the fraud
D. To minimize manpower, money and time to predict poverty.
E. To predict the status of a satellite image, we have to use preprocessing of an input image and in the training and testing, the dataset of satellite images were used to train the model.
F. For training and testing of models CNN method is used where only 3 rounds are sufficient to predict accurate results of socio-economic status.

Mathematical Equations

Let S be the Closed system defined as,

S = {Ip, Op, A, Ss, Su Fi}

Where, Ip=Set of Input, Op=Set of Output, Su= Success State, Fi= Failure State and A= Set of actions, Ss= Set of user's states.

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Set of input=Ip={username, password}

Set of actions =A={F1,F2,F3,F4,F5,F6} Where,
F1= Authentication of user
F2 = input the satellite image
F3 = system detect the object's image
F4 = Perform operation Image Processing and Machine Learning
F5= Detecting of various sources
F6= This result show and stored the database

Set of user's states=Ss={registration state, login state, selection satellite image, classified image, logout}
Set of output=Op={Show results}

Su=Success state={Registration Success, Login Success}

Fi=Failure State={Registration failed, Login failed}

Set of Exceptions= Ex ={Null Pointer Exception while registration state, RecordNotFound (InvalidPassword) while login state , Null Values Exception while showing state}

FIGURE AND TABLE

Sr. No.	Description	Class	Result
1	Upload Satellite Image	Image	Image Upload to the System
2	Preprocess	Image Process	Images Processing can Apply
3	Perform CNN	Algorithm Process	Apply Machine Learning Technique
4	Poverty Prediction	Prediction	Here we get final result

Table 1. User classes and characteristics.

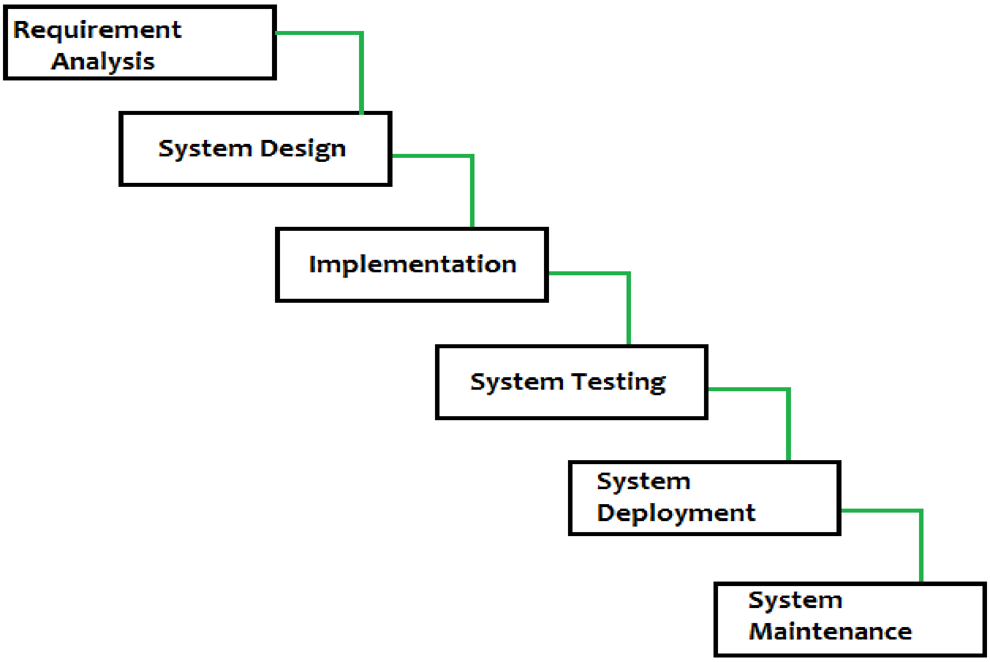

Fig. 2 SDLC Mode

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APPLICATIONS

A. Government uses for poverty detection.
B. For builders to understand land quality.
C. For industrialists to understand resources.
D. Military can use it to understand rivalry movements over time.

BACKGROUND AND RELATED WORK

Deprived financial condition settlements feature a characteristic structural sort in several cities of the worldwide South. numerous approaches to detection slums, starting from machine learning techniques to object-based solutions, are bestowed in Section II-A. Within the past five years, deep learning procedures for linguistics segmentation of slums are ready to surpass ancient mapping ways in their ability to attain mapping accuracies. These techniques for pixelwise classification are bestowed in Section II-B.

A. *Mapping Urban financial condition With Satellite knowledge*

To describe physical slum characteristics victimization remote sensing knowledge, the morphological options of urban financial condition ought to be well understood. Thus, the information should be ready to represent the physical properties of slum settlements. For instance, since many slum buildings area units significantly below one hundred money supply and slum areas typically solely angular distance a size of one ha [10], [15], [16], the connected images for his or her identification need a high abstraction resolution. Moreover, roof surfaces are oftentimes not undiversified in shape and color; once victimization high-resolution knowledge, a number of the roof pixels can encompass mixed roofing materials. Thus, a selected geometric resolution is required to capture the morphological poverty options. At identical time, once talking concerning mapping poverty in multiple globally distributed cities, knowledge availability also must be taken into thought. This favors each the Copernicus mission Sentinel-2 and Planet Labs knowledge from the PlanetScope satellite as optical detector solutions, since both products area unit globally accessible. In [17], Sentinel-2 knowledge were used to map slums and [18] compared Sentinel-2 knowledge and really high resolution knowledge. each studies conclude that whereas mapping urban poor area unitas are doable in high-resolution 10-m ground sampling distance, it's a really limiting issue, particularly considering mapping smaller slum patches. Given this circumstance, PlanetScopes 3-m geometric resolution strikes an ideal balance between knowledge availability and high abstraction resolution. In the connected scientific literature on slum mapping, various methods are bestowed. In [17] and [19], the studies aimed at characteristic complete slum patches employing a combination of machine learning and textural feature engineering. Other work has been done victimizing socioeconomic knowledge and abstraction features to see financial gain levels of slum settlements on a neighborhood level [9], [20], [21]. In [22], solely the road network was accustomed to predict slum areas in an exceedingly combination of traditional machine learning and artificial neural networks. In [7], [8], and [16], poor urban areas were analyzed on the extent of individual buildings victimization associate degree object-based approach to spot the forms of slums and their temporal changes.

In the past 5 years, victimization deep learning techniques has become a well-liked trend, because it has been shown that mapping accuracies improved rule-based approaches considerably for mapping slum patches [18]. In [23] and [24], nighttime lightweight intensities were used as a proxy for poor urban areas to transfer learning from a CNN to high-resolution remote sensing knowledge. In [25]–[27], fully convolutional neural networks (FCNs) were accustomed map slums on either high-resolution or terribly high-resolution knowledge, whereas Wurm et al. [18] and Stark et al. [28] used completely different transfer learning techniques to map slums between completely different satellite sensors within the same town and between geographically separated cities, severally. The authors all over that not solely a lot of data, however additionally a unique deep learning design and a lot of rigorous regularization is important for strong segmentation of slums on an oversized scale.

B. linguistics Segmentation victimization Deep Learning

Semantic segmentation suggests that understanding a picture at a pixel level. whereas ancient CNN aim to classify an entire image patch, FCNs classify every component of a picture, giving a lot of information concerning the world and form of the target category. First introduced in [29], FCNs replace the totally connected layers of a standard CNN with convolutional layers and expanded convolutions for upsampling to the initial input dimensions. within the past five years, a lot of advanced ways for linguistics segmentation using deep learning techniques are explored. enhancements within the backbone design additionally because the upsampling phase will are according. each U-Net [30] and SegNet [31] improved upsampling techniques, introducing long distance skip connections and convolutions throughout the upsampling part, for linguistics segmentation. whereas the initial FCN in [29] used vgg16 design [32], these days deeper and a lot of economical backbone models area unit accessible. GoogLeNet [33] and its origin versions [34], [35] introduced deeper and a lot of advanced implementations of victimization network in network approaches, whereas

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ResNet variants [36] introduced skip connections and significant batch standardization. Currently, not solely the depth of the network but additionally its potency is major issue to be taken into thought. whereas recently, the trend has been to travel deeper with convolutions, networks like Xception [12], and EfficientNets [37] will crush deeper variants whereas having fewer parameters to train. Specific enhancements for linguistics segmentation in remote sensing knowledge can be achieved in [38], wherever relationaugmented FCNs area unit used, in [39], with a gated graph CNN and structured feature embeddings, and in [40], by fusing terribly high-resolution knowledge with auxiliary knowledge. coaching a CNN from scratch needs a major quantity of knowledge and process power. it's additionally terribly time overwhelming [41], that is why fine tuning or transfer learning approaches area unit typically employed in order to handle less coaching knowledge or transfer data from a supply domain to a target domain. Fine-tuning a CNN from an oversized dataset, like ImageNet [42], Coco [43], or PascalVOC [44], was extremely popular within the initial stages of adapting deep learning techniques into to the remote sensing domain [41], [45], but feature transformation from typically low-quality natural pictures to multichannel remote sensing knowledge suggests that sacrificing valuable data info within the spectral and radiometric resolution of the satellite pictures [41]. Therefore, coaching a CNN from scratch specifically on remote sensing knowledge typically yields higher results [46]–[49]. to require full advantage of the information richness gift in remote sensing knowledge, coaching from scratch offers nice potential in learning high-quality feature illustration once enough knowledge and procedure power area unit accessible.

CONCLUSION

Detecting urban poverty from remote sensing data is still a major challenge. It must deal with fuzzy feature spaces between formal and informal settlements, often with a significantimbalance of slum occurrences within the urban landscape and an inter-and-intra urban variability of morphological slum features between different geographical regions. In this paper we propose a transfer-learned convolutional Neural network (CCN), which is trained on three experiments,testing whether it is possible to learn slum features in geographically separated regions. We have found that the success of transfer learning is not only dependent on the training dataset components, e.g., high slum sample percentage anda higher number of training patches, but also on the different slum morphologies. The combination of both the dataset and distinct slum morphology features are of importance to reach high mapping accuracies. In cases where the training dataset components are not ideal, the CNN trained on various slum morphologies is able to match or surpass accuracies compared to training the CNN within the same city. The best overall results were achieved when the CNN was transferred from a large-scale poverty dataset to a smaller local dataset. Comparing the results from the five-dimensional input data, which consisted of only remote sens-ing data, and the six-dimensional data, where the proximity to the road network was added as an additional input dimension,accuracies improved segmentation outcomes in most cases.This shows that additional data can be of major importance to detecting urban poverty. Using more auxiliary data to accompany remote sensing data for mapping slums and novel deep learning architectures could potentially further increase accuracies; thus data sources outside of remote sensing data could be used to make the decision process more robust during training to map slum settlements on a global scale.

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