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Prediction of Population Density & Poverty Rate Using Uncertain Mosaics with Satellite Imagery

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Abstract: This research work involves combination of Random Forest optimization along with Satellite Imagery (SIML) which is having potential for addressing major global problems by remotely accessing socio-economic and meteorological conditions in data poor areas, although SIML's resource requirements will limits its access and utilization. The Random Forest along with Satellite Imagery (SIML) is enabling better characterizations for population densities and poverty Rates. Further, this Random Forest Applications proves to be a path which is effective to convert such huge amount of uncertain image data into formed assess of conditions of ground.The satellite imagesare collected from GIS (Geographic information system) and then process collected images to RFO for removing mosaic with regression concept. This proposed model generates accuracy 98.78%, recall 97.34%, throughput 97.75% sensitivity 98.45% and efficiency 96.25%. The following outcomes has been competed with present technology and out performers the methodology.

Keywords— *Random Forest, Satellite Imagery, Image encoding, CNN, Mosaic, Regression, SIML*

1. Introduction

The capital requirements to group SIML technologies, although, restrict their obtainability and practice. Satellite based dimensions are especially underutilized in less income circumstances, Where the high-tech capability to enactment SIML maybe less, but those dimensions would probably disclose the utmost advantage [1]. For instance, government authorities in less income context might want to grasp local water pollution, unlawful field's usage and also mass relocations [2]. However, SIML, residue mainly not able to reach the possible end user, as present-day paths need the crucial resource comprehensive endeavour, compelling an integration of particular task proficiency, Remote-Sensing and skill of Engineering, accessing the images, customization including attuning knowledgeable Random Forest architectures, and huge computational assets [3].

To detach obstacles, a new path to SIML is required which empower the non-experts by gaining the level of development performance by not using the particularised computational assets or even by advancing the complicated procedure for prediction [4]. This single performed task sceptic encoding which converts the satellite images into features (vector of variables) empower this path by decoupling users from expensive handling of images. While anterior work has pursued an unsupervised method to convert these satellite images into a data of single set of features to accomplish competitive-performance with methods of deep learning including a mixture of tasks to scale them globally [5]. Our path permits familiar sources of images to change into compacted sets (features) which analysers can acquire, where individuals solve the tasks which are heterogeneous, this will separate the further people (users) to avoid the expensive steps like procuring, handling, image storage, and to process the images . Immensity of these results will increase in size by enlarging SIML user community & also the global imagery data measure [6]. This system of SIML naming (MOSAIKS)"Multi-task Observation using Satellite Imagery and Kitchen Sinks" will make (SIML) more approachable & broad-based by dividing the process into 2 different stages: a single performed "Featurization step" by transforming the satellite images into a short-vector representation (satellite image → a), and the "Regression step" which will grasp the particular task quantity by mapping the sets (features) to the outputs of taken (given) task (a→b). For every satellite-image this featurization process will be done only once to get one set (outputs), where these sets will be used further to solve various dissimilar functions by repetition of this regression process through numerous individualistic users [7].

A. Objectives

1. Enabling the users with basic resources to easily predict the Population Density and Poverty Rate by using only Satellite images.

B. Problem Statements

Many biggest global challenges like managing poverty rate & population density etc., are necessary for nation's ecosystem development. Planet scaled which are based on ground, these systems are generally monitored at restrain cost, satellite image represents an alternative for gathering comprehensive data globally. For data poor regions it is the difficulty is more to analyze and predict population density. This project mainly looks into the problem to predict the assets of some small regions like

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population density in a single time period, by considering the inputs which are only the day-time satellite images with high resolution.

2. Related Work

In the year 2018, Abhishek P and others used various random forest techniques for the prediction of land coverage from the images obtained from a satellite. For obtaining features of the input from satellite image they have used a time series technique called NDVI. They have executed their work mostly using Python and they have observed that K Nearest Neighbor algorithm is the most accurate technique for their work. [8].

In the year 2018, Shailesh P and others proposed an approach for predicting and calculating the poverty rate in the rural areas in India. The Google Static Maps API to extract images for the villages from the determined geocodes. To begin with, they sought to train a multi-task fully convolutional model. Then they attempted to forecast poverty rates[9].

To anticipate and quantify population density using remote sensing data, Stefanos G and coworkers in 2019 created an implementation of RandomForest dubbed Geographical Random Forest (GRF) (High Resolution). To model heterogeneous remote sensing data, they found that the strategy they provided worked better than the previous one [10].

In the year 2020, Fariha S and others proposed a method which involves mapping(agricultural) and monitoring in the area of Habiganj for the prediction of growth of crop and also yield. They obtained high resolution images from Landsat-8 to monitor the area of Habiganj and those images are processed and obtained indices which were correlated to growth and crop yield. Time-series methods like Long Short-Term Memory and Autoregressive Integrated Moving Average have been used to forecast the yield [11].

In 2020, M. Das's proposed paper consists of two parts one is preprocessing of data and another is autonomous learning or prediction. They have used an online prediction model which is an autonomous prediction model 'OPAL' .Recurrent Neural Network was used in OPAL technique for enabling the online prediction [12].

In 2020, Tianjun W and others tried to perform population mapping, here they have used residential geo objects and treated their model as spatial prediction model for performing mapping predictions and they have used random forest methods with satellite images that have high resolution. They have observed that their model provided better results for finding distributions of population [13].

In the year 2021, B. A. Gebreegziabher's tried to solve the supply chain crisis by obtaining road pavement quality information, they have obtained imagery from Sentinel2A Satellite. Several deep learning techniques were used to obtain road pavement information. He had observed that deep learning techniques such as U-Net and IoU provide better accuracy than other random forest techniques such as Random Forest [14].

In the year 2021, M.S. Andreano and others tried to address and solve the digital divide between people .The main cell phone parameters they have taken into account are cost of service and cell phone adoption. They have observed that image recognition approach (predicting 40% data variance) is better than baseline approach (predicting 20% data variance).Among different approaches they have observed that CNN method provides 41% data variance [15].

In the year 2021 R. Jarry and others observed that to make proper prediction of poverty rate they need reliable poverty indicators. They also concluded that by only taking nighttime satellite imagery is not a good approach for poverty prediction so they decided to use CNN approach where they obtain different features from satellite images and they perform regression techniques to obtain better results for poverty prediction [16].

3. Proposed Work

In this research work an advanced random forest optimization (RFO) based GIS application is implemented for future population density and poverty estimation. In this contest N number of images are taking ino K-dimension features, the extraction can be processed to computing block. The algebraic expressions via matrix format have been given exact population density of selected GIS image. The computing process as well as classification process has been concentrated on poverty estimation . The experimental output of this proposed model can generate population estimation via GIS-RFO. The X1, 1...x1, k are features in tabular matrix, X1, 1...x1, k ……Xn, 1...xn is resulting matrix of poverty estimation.

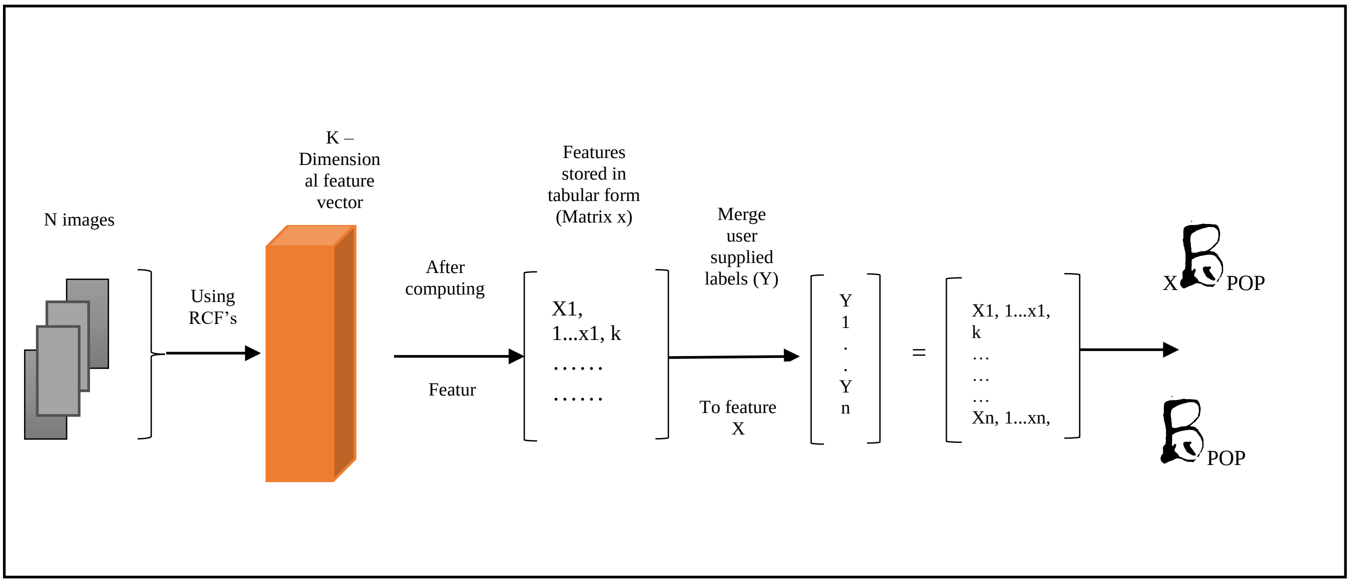

Figure. 1. Proposed Model Block Diagram

The above figure 1 clearly explains about proposed block diagram for GIS based population and poverty estimation . The step-by-step process of this model with matrix analysis is providing mathematical computations related to population estimation.

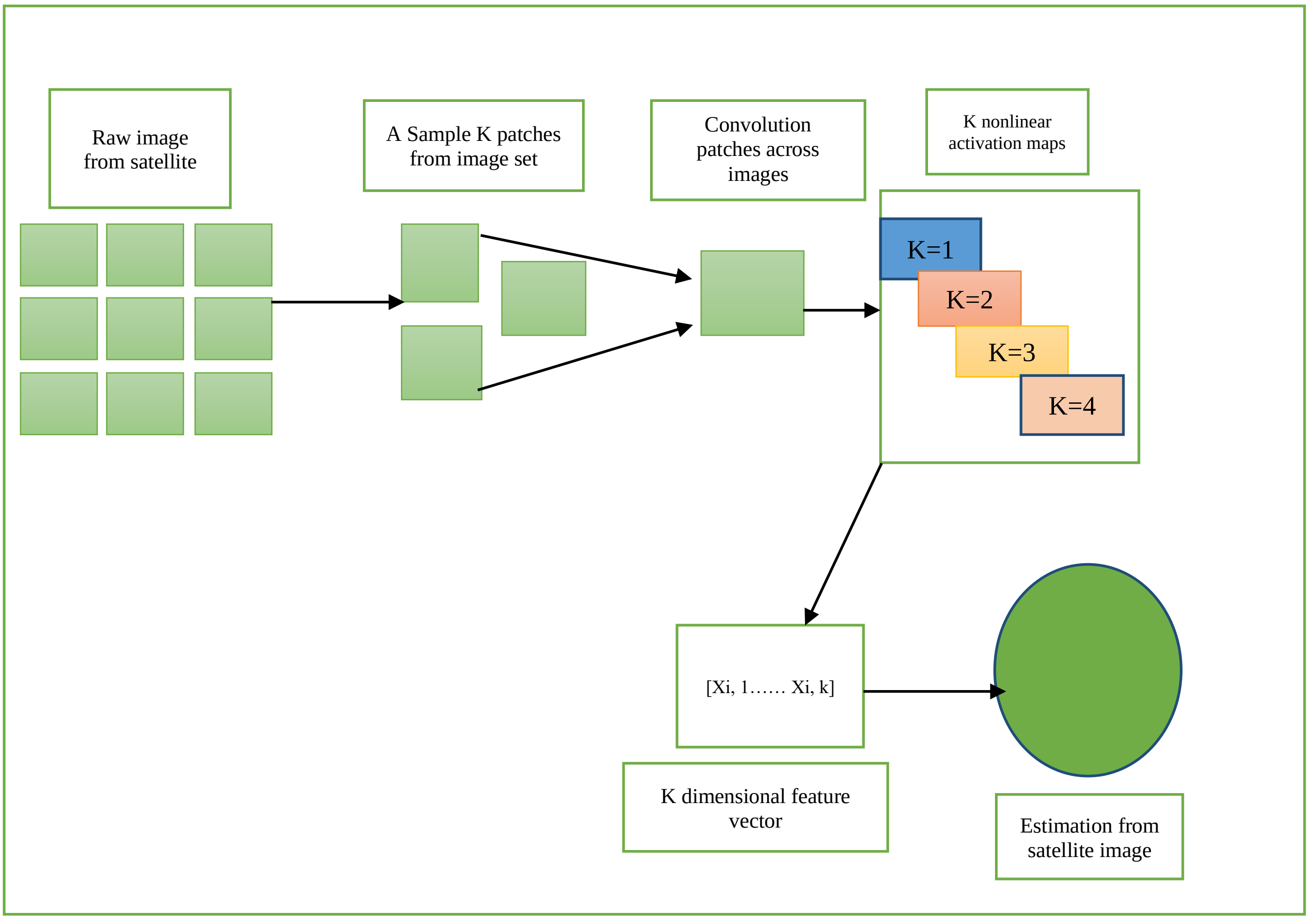

Figure. 2. Process of Futurization steps

The figure 2 is clearly explains about futurization steps of RFO based GIS application, in this 1st step raw satellite images has been collected from database. The k patch samples has been processed through convolutional layers. The non-linear layers and activation maps are concentrated on [Xi, 1…… Xi, k] k-dimensional features. The final estimation was performed from feature vector of GIS images [17].

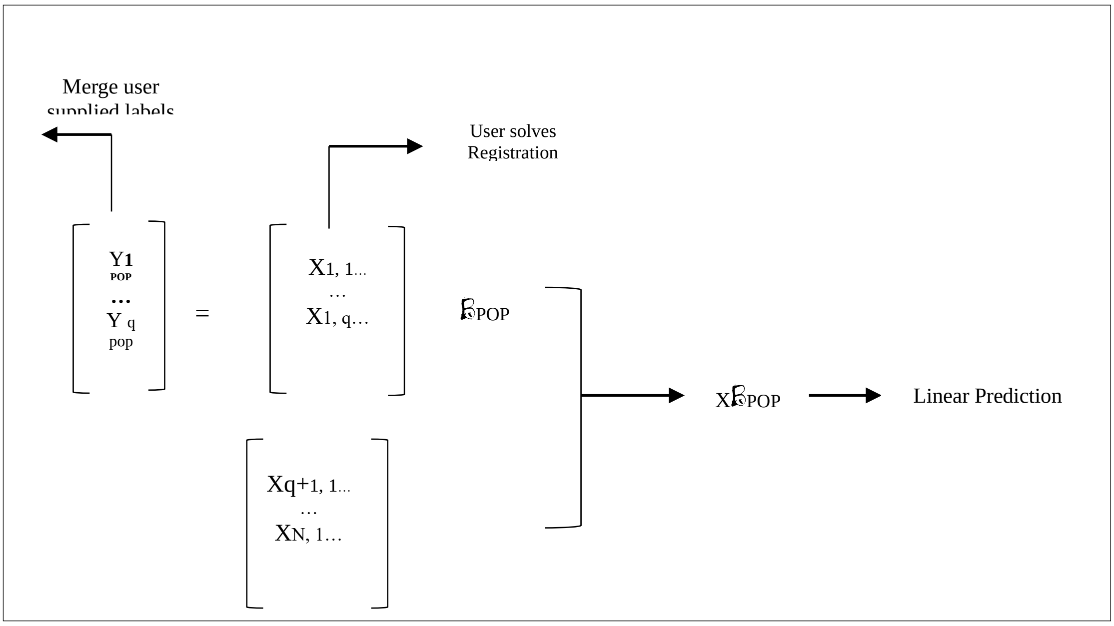

Figure. 3. Process of Regression Step

Satellite images are included with various potential functions. For instance, 9 satellite-images consisting of population density and poverty rate from the India are taken, both having distinct identified features which are observable in each and every image. As per figure.1 proposed model block diagram N is satellite-images will be converted using RCF's into k-dimensional feature vector which is highly descriptive before labels are well-known. After computing these features, they are kept in a table form known as matrix X is shown in figure 3. Process of Futurization steps. It will be useful for various functions excluding re-computation. The people (users) having a new function (z), can mix their self-taken labels to given features and can train them on their own. Linear prediction and total MOSAIKS sample consisting of features will give SIML assess (labels) at any locations [18].

$$W_{h,v} = \frac{1}{prob(h \mid PSU)} \frac{1}{prob(PSU)} \quad (1)$$

PSU selection odds are inversely proportional to this second element in Equation 1.

$$prob(h \mid PSU) = \frac{HU_{Sample}}{HU_{PSU}} \quad (2)$$

HU sample represents the number of household units in the sample, and HUpsu indicates the number of household units in the corresponding PSU Each housing unit in a PSU has an equal chance of being selected, according to Equation 2. Using the HIES sample as a numerator, the denominator may be quickly derived from the sample weights [19].

$$Prob(PSU) = Prob\left(\frac{PSU}{v}\right) * Prob(v) \quad (3)$$

Rather than a description of the proposed study, this decomposition is a mathematical identity. As a result, Equation 3 may be reworked to look like the following:

$$Prob\left(\frac{PSU}{v}\right) = \frac{HU_{psu}}{HU_v} \quad (4)$$

Only villages with precisely one PSU have this identification, and that accounts for 97% of the villages in the HIES sample. 26 Formula 1 is rewritten as follows by using Equations 2, 3, and 4: [20]

$$W_{h,v} = \frac{HU_v}{HU_{Sample}} * \frac{1}{prob(v)} \quad (5)$$

$$HU_v = W_{h,v} * HU_{Sample} * Prob(v) \quad (6)$$

Household h's sample weight is the first term on the right-hand side of Equation 6. Another factor to consider is the total number of households in the town that were included in the survey.

$$Prob(v) = 1 - \prod_{i \neq 0} \frac{HU_v}{HU_{contry} - \sum_{j=1}^{i} HU_j} \quad (7)$$

A. Featurization Step

This step is to convert satellite images into vector-representations (images→x). The victory of generalizability depends on how these images are converted into features. The layout of featurization function improves on the conceptually grounded-random forest idea random Kitchen-sinks, where it will be put into images by forming Random-Convolutional-Features (RCF's). RCF's will capture a pliable measuring of similarity among sub-images of mixed set of images by not considering the circumstantial and any other details. Regression process here tends features 'q' on a point to predict 'r'. This can be non-linear functioning of images [21].

$$W_{h,v} = \frac{1}{prob(h \mid PSU)} \frac{1}{prob(PSU)} \quad (8)$$

A weight W (h,v) is given to each family h in each village v.

B. Regression Step

Satellite image is in figure.3 Process of Futurization steps every image this process will be done once to get a single set (outputs), where these sets will be used further to solve various dissimilar functions by repetition of this regression process through numerous individualistic users. Here we used Ridge Regression. In this Ridge Regression, it is of the form Y=XC+e. Here Y is the user contributed labels i.e., labels (population density) for 1 to q locations. X is the K- dimensional feature vector. Every user solving a linear regression (single) for C. The linear forecasting by βs and total MOSAIKS sample of features 'q', will give SIML assess (labels) at any locations [22].

C. Multi Task Performance of Mosaiks

100,000 daytime images were taken and by featurizing the images by running them via MOSAIKS feature extraction method which produces 8,192 features and stored. Here got K= 8,912 features per image which then repeating regression process by using ridge regression which is cross validated, for every function to easily forecast the population density and poverty rate. This can also be extended for elevation predictions by considering only the matrix of features (X) which is generated. The tasks are selected on a basis of exploration and diverseness. By using the same procedure, the predictions for each task are generated [23].

$$P_v = \exp(\beta_0 + \beta_0 X_v + \beta_2 \mathrm{Ln\ area}_v + \beta_s + \beta_d) \quad (9)$$

Village v's density of population (persons/km2) is Pv. Xv is the collection of satellites imagery-based indicators for the village v described in Xv. Normal logarithmic of village area (Ln areav) and an indicator for urban villages (S) are included in the dataset. The binary indication 15 d denotes [24].

$$\min_{\beta_0,\tau} -\frac{1}{N} l(\beta_0, \tau \mid X, Y) + \lambda \sum_{j=1}^{p} |\tau_j| \quad (10)$$

In 2021, Kuldeep C and others tried to predict the types of land coverage. For this purpose they have used raw images from Sentinel2A Satellite and also they have used classification techniques such as Support Vector Machine, Random Forest and other classification techniques, they also tried to obtain the accuracy of these classification techniques and they have observed that Random Forest classification technique (95.67% accuracy) provides better results than others [25].

$$\min_{\beta_0,\tau} -\frac{1}{N} l(\beta_0, \tau \mid X, Y) + \lambda((1-\alpha) \sum_{j=1}^{p} \frac{\tau_j^2}{2} + \alpha \sum_{j=1}^{p} |\tau_j|) \quad (11)$$

The log conditional probability of the Poisson model with parameters 0 and has a value of l, and the regularisation value is a non-negative number. Unconstrained estimates of Poisson regression are obtained by setting = 0, whereas big penalises the real numbers of variables.

$$INHIES_v = \alpha + \beta_{lassov} + \lambda_v \quad (12)$$

4. Algorithm

Algorithm: RFO ridge regression

Step :1 The Prediction procedure is a twostep process i.e. futurization and Ridge Regression. The overall Approach can be defined with a simple algorithm as follows:

Merge X, Y
Ridge Regression (X, Y)
Predict Y

Were,

Step :2 X is the Feature matrix obtained in Featurization Step, Y is the User supplied labels, Here the User supplied labels are Population Density and Poverty Rate.

The Featurization step includes Grid Creation, Feature Extraction and Label Creation.

The Regression Step mainly focuses on two steps i.e. loading Feature matrix X and Running Regression.

Step :3 Loading Feature Matrix

```
X = {}
latlons = {}
X[“POP”], latlons[“POP”] = io.get_X_latlon(c, “POP”)
X[“POV”], latlons[“POV”] = io.get_X_latlon(c, “POV”)
```

Where,
POP is the labels of Population density
POV is the labels of Poverty Rate

Step :4 Regression

```
Regression ()
{
subset_n = slice (None)
subset_feat = slice(None)
solver = solve.ridge_regression    }
with open(save_path_validation, "wb") as f:
    pickle.dump(data, f)
  results_dict = r2_score(truth, preds)
}
```

$$\min_{\beta_0,\tau} -\frac{1}{N} l(\beta_0,\tau\ |X,Y) + \lambda\Big((1-\alpha)\sum_{j=1}^{p}\frac{\tau_j^2}{2} + \alpha\sum_{j=1}^{p}|\tau_j|\Big) \quad (13)$$

Step :4 stop the process

The above RFO ridge regression algorithm can be explained clearly with following mathematical computations. The usages of above technique have been useful for GIS based poverty as well as population density estimation on uncertain data-set.

5. Results

In this section a brief explanation of RFO based GIS population estimation and poverty line analysis has been performed. The Indian population density and density score had been estimated on India map through GIS application.

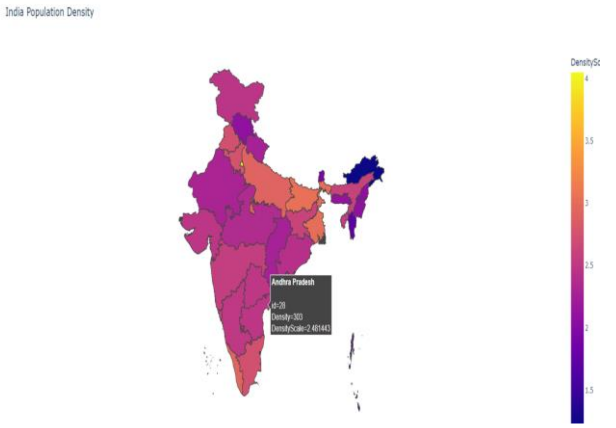

Figure. 4. Prediction of Population Density for Indian maps

The above figure 4 is taken after the prediction of population density analyzing the final estimates. The Map is presented with different colors on the basis of density scale which is ranging from 0-4. When mouse hovers it displays the density, density scale and id of that particular state in India [26].

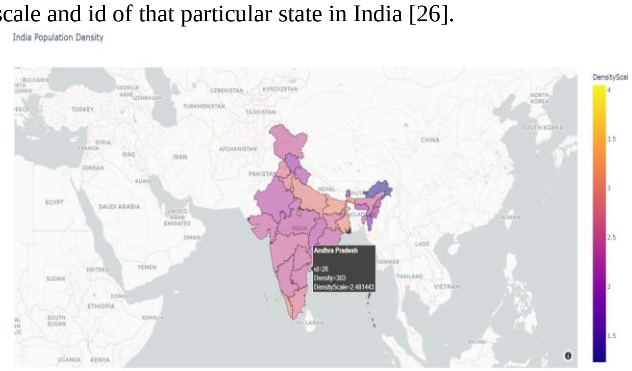

Figure. 5. Prediction of Population Density for Indian maps representing in world maps

The above figure 5 represents the prediction of population density for Indian maps which is plotted in world maps. Similarly, it also shows the density, density scale and id of each state. The density is obtained by dividing population with area. The density scale ranges from 0-4 [27].

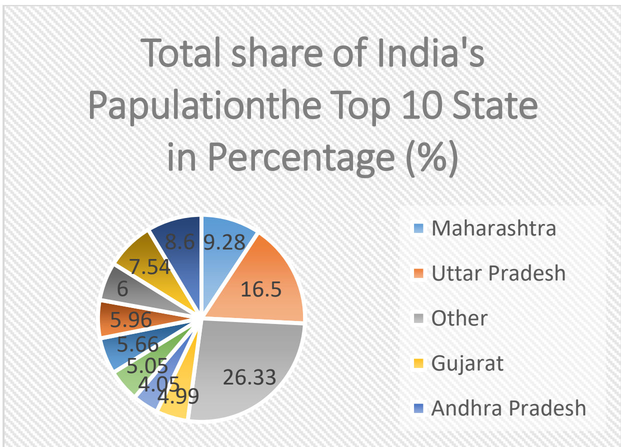

Figure. 6. Pie Chart representation of India’s Population

The above Figure 6 represents the India’s population in top 10 states which indicates Uttar Pradesh has Highest Population density. It also replicates the Highest and Lowest Population Density states [28] [29].

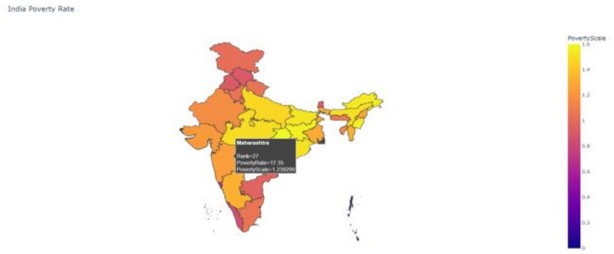

Figure. 7. Poverty Rate of Indian states

The above figure 7 represents the predictions of Poverty rate of Indian states. The Poverty scale ranges from 0-1.6. When mouse hovers to particular state then Rank, Poverty Rate and Poverty Scale of that state will appear

Figure. 8. Poverty Rate of Indian states represented in world map

The above figure 8 represents the prediction of population density for Indian maps which is plotted in world maps. Similarly, It also shows the density, density scale and id of each state. The density is obtained by dividing population with area. The density scale ranges from 0-4 [30][31].

Table :1 performance measure

Method	accuracy	recall	throughput	sensitivity	efficiency
SVM	89.34	89.45	79.34	89.34	89.23
X-boost	94.34	95.28	87.34	93.24	91.87
KNN	92.47	91.59	96.34	95.35	92.89
RFO-GIS (proposed)	98.78	97.34	97.75	98.45	96.25

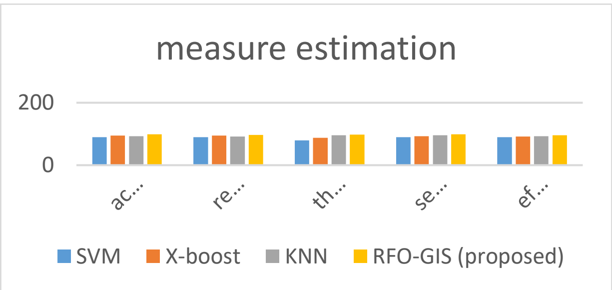

Figure: 9. performance measure

The above figure 9 and table 1 are explains about various models' comparison analysis of GIS based poverty and population density estimation [32][33]. In this analysis proposed RFO-GIS model attains more improvement compared to existed methods [34][35].

6. Conclusion

The total mosaic estimation can be hold through Linear prediction and Featurization techniques, the RFO based GIS related paths are used to getting population density. Especially, this work can be elucidated as practicable estimation to kernel-ridge-regression for complete convolution between GIS image and kernel. On the other hand, two layered CNN with a phenomenal broad layer have been used to detect hidden features. As mosaic has been inspired from enabling theorize and adept SIML forecast technology. It will be fulfilled through nesting images that want to be descriptive (models which are trained on unity basis large skill) as well as efficient (skill accomplished by taking moderately less dimensions). The path of nesting depends on concept of RFO, which is a process to generate features and qualify Linear estimation of chosen tasks. The polynomial features with distinct Fourier changes have to be estimate 1-dimension functions. The user puts in these features on linear regression, to recognize the linear outputs on vector key to predict particular set of labels. By high dimension inputs, the satellite images show tentatively over-all basis for prediction problems. This proposed model generates accuracy 98.78%, recall 97.34%, throughput 97.75% sensitivity 98.45% and efficiency 96.25% on uncertain data-set.

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