PREDICTION OF HOUSING PRICE AND FOREST COVER USING MOSAIKS WITH SATELLITE IMAGERY

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Abstract:–

It is growing more expensive to estimate land use, road length, and forest cover using a plant-scaled ground-based monitoring system. Satellite imaging contains a significant amount of detailed information. Combining this with machine learning aids in the organization of these data and the estimation of each variable separately. The resources necessary to deploy Machine learning technologies for Remote sensing images, on the other hand, restrict their reachability and application. Based on satellite observations which are notably underutilised in impoverished nations, while practical competence to implement SIML might be restricted. Encoded forms of images are shared across tasks, and they will be calculated and sent to an infinite number of researchers who can achieve top-tier SIML performance by training a regression analysis onto the actual data. By separating the duties, the proposed SIML solution, MOSAIKS, shapes SIML approachable and global. A Featurization stage turns remote sensing data into concise vector representations, and a regression step makes it possible to learn the correlations which are specific to its particular task which link the obtained characteristics to the set of data.

Keywords: Satellite imagery, machine learning, image encoding, CNN, MOSAIKS, Regression, SIML.

1. INTRODUCTION

To solve comprehensive universal concerns including controlling anthropogenic climate change, demographic changes, ecological change, or sustainable growth, many experts, decision-executives demand complete access to accurate, enormous observations for multiple factors at that instant. ML is proven to be a powerful tool for converting huge quantity of disorganized imagery data into organised estimators. For example, the use of satellite imagery combined with machine learning (SIML) has allowed for more precise identification of tree cover, usage of land, poverty rates, and population density which is improving research and decision-making. A task is a term used to describe the process of predicting a single variable. The expanding need of estimate based on SIML is evidenced by huge count among private sector providers specialised in estimating either one or few projects. From the other side, the resources necessary to develop techniques of SIML constrain its application and to use. In impoverished nations, where practical ability to use SIML might be restricted although where these measures are probable to be helpful, satellite measurements are of little utility. Government agencies in impoverished communities, for example, can be curious in local river pollution, illicit land usage, or mass migration. SIML, on the other hand, is pretty much entirely out of reach for this and many other user groups, as current approaches necessitate a large-scale, organisation with substantial resources associated with the combination of domain-specific expertise, spatial analysis and engineering expert knowledge,

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image access, intricate architecture customization, and enormous machine learning computational resources.

Managing worldwide problems such as climate change, demographic changes, environmental shifts, and economic progress need the availability of large-scale, precise measurements of multiple parameters for a wide range of academics and decision-makers (hence referred to as "users"). Ground-based monitoring devices are frequently too costly for this purpose, however satellite imaging may be an alternative since there are over 700 Earth observation satellites in orbit. ML is also proven to be an effective approach for translating these large volumes of unstructured image data into organised evaluations of ground conditions. Researchers and policymakers can better understand forest area, agricultural use, poverty levels, and density of population by combining satellite data with machine learning (SIML). An individual variable is referred to as a task. Demand for SIML-based estimates is growing, as seen by the large number of private service providers that specialize in projecting one or a few of these occupations.

Installing SIML technology, on the other hand, requires significant financial and human capital. Low-income nations, whose technical expertise to use SIML may be restricted but where such measures are most likely to be helpful, underutilize satellite-based observations. Government entities in low-income regions, for example, may be interested to understand more about local river pollution, illegal land use, or massive migration.. These potential customers and many others will never have access to SIML because the current approaches require a large-scale enterprise with a high level of resource intensiveness, including domain expertise, remote sensing, engineering, imagery access and the customisation and adjusting of advanced ML architectures.

It is necessary to build a new SIML approach that enables non-experts to attain current performance levels without the need for specialized computer resources or the creation of a complex predictions procedure in order to address these challenges A one-time, task-agnostic encoding that transforms each satellite image into a vector of variables (hence, features) may be able to support this approach.. Unsupervised encoding may be a better fit for SIML issues than deep-learning algorithms that were originally created for natural images (e.g., photos taken from handheld cameras). There are many features of natural imaging that are inconsistent, needing complex solutions that may not be necessary when learning from satellite photos. The unsupervised encoding of satellite images has been studied in the past, but no one set of features has been proved to compete with DL algorithms across a variety of tasks and to scale globally.

2. LITERATURE SURVEY

In this proposed research prediction of land usage from satellite data is done using ML approaches. Time-series normalised difference vegetation index[1] is used to collect input features from satellite images (NDVI). The work was done entirely in Python, and the KNN method was used to achieve the highest level of accuracy. In this research, a mixture Habiganj monitoring [2] and mapping of agriculture, as well as crop growth and production prediction, is presented. Landsat-8 photos of Habiganj with multi-spectral bands have been prepared, and satellite image indicators linked to agricultural yield and production have been retrieved. Habiganj's crop yield is projected using existing parameters, and the datasets of future values are forecasted using 2 types of time-series data analysis models for improved accuracy (ARIMA and LSTM).In this paper, categorizers such as SVM , DT, RF, NB, an effort was made to better detect land cover categories from Sentinel2A[3] data (CART) are

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used. Performance measures computed in the paper also validate the findings obtained by the used models. According to the findings, the random forest classifier surpasses different classification techniques with 95.67 percent accuracy.

This proposed system, The Geographical Random Forest (GRF) [4] is indeed a localized Random Forest execution (RF) to forecast density of population using Remote Sensing with Extremely High Resolution such as VHHRS data. As a result, the GRF technique is proposed as a viable fact-finding and illustrative technique for modeling spatially heterogeneous remotely sensed relationships. This study suggests a two-step approach for using satellite images to anticipate poverty in India's rural areas. To extract images for the villages from the determined geocodes, we used the Google Static Maps API [5]. Training a multi-task fully convolutional model first, followed by training the network to predict income levels.Residential geo-objects are used as fundamental leveling units in this research, and the problem is formalised as geographical forecasting[6] model applying HSR satellite based imagery and multi-source geo-spatial data with algorithms of ML.

The Land cover analysis using fundamental pixel-based features extracted from much more sophisticated Ultra Spectral imagery is the subject of this study. Second, for pixel-based land cover analysis, an exploration of parametric and non-parametric [7] machine learning techniques. They employed SPOT-5 aerial photographs with a range of nearly 2.64m for an experimental investigation. We choose Maximum Likelihood Estimator (MLE), Support Vector Machine and Neural Networks from the techniques of machine learning collection (ANN). Higher performance of these algorithms in pattern recognition tasks led to their selection. Scant Flora, Sugar Beet, Urban Areas, Water, Roads, Tobacco and Rough Terrain are seven types in which the feature space is divided. Using satellite photos and machine learning, anticipate air heavy metal contamination. Satellite pictures from the Google Earth Engine platform and sampling data from the UNECE [8] International Cooperative Program (ICP) Vegetation Data Management System were used to train the model. The pollution and satellite pictures were correlated using the KNN technique for data modeling. To obtain some indexes, researchers collect and evaluate samples. A sampling is rarely done for objective purposes, and the size of the sampling grid might be quite large. Modeling may be a good option in this circumstance. Our plan is to train a specific statistical model using real-world data on heavy metal concentrations and indexes obtained from satellite photos. In this proposed work, to identify modifications in tropical forests during the 29-year period (1987–2015) images from remote sensing satellites are used. To reclaim multispectral [9] data that has been lost, they first suggest a spatiotemporal in painting mechanism because the original data is badly inadequate and cluttered with artefacts. The spatial filling procedure uses data from surrounding transient instances, after that, sparse encoding-based restoration. The goal of change identification is formulated like regional classification task. We produce a candidate set of bounding box recommendations that contain probable change zones by creating a multi-resolution profile of the target area.

To assess the accuracy of available census numbers, we comparing the results from the ARIMA models with the Regression models for predicting. We provide a method for obtaining cost-effective and timely information regarding poverty, which may be used to help establish monetary policy, provide foreign aid, or channel other types of assistance [10].

By using pixel-based classification, the LISS-III satellite image has been categorized into distinct areas enclosed with water, jungle, mangroves, and improvements. Following an evaluation, the innovative features set of data is fed into an ANN to examine what influence the optimal training data has on prediction performance. [11].

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First, parameters with instability standardized ridgeline regression coefficients or stable coefficients with moderate actual numbers are omitted from the analysis. For the remaining attributes, a new SVM dataset is created and utilised for the input values. As a second step, the new dataset is divided into two parts: one for training and the other for testing. Finally, the model's correctness is examined in light of the results. The method's experimental findings show that it is capable of accurately predicting fire regions [12].

The study's innovative preprocessing method improves picture clarity and reduces blur and noise in low-contrast or degraded satellite images by integrating several independent processing stages that remove noise, enhance contrast, and enhance image clarity. Finally, PSNR parameters are used to compare the output of each step [13].

As a result of the drawbacks of conventional manual feature extraction and the shortcomings of single-layer convolutional neural networks (CNN), a multilayer convolutional neural network (MCNN) has been developed. Head size variations due to different factors, such as the penetration impact, will not alter the properties of CNN learning images in this article [14].

Evaluation of estimation methods is done via a Monte Carlo method. Our suggested estimators outperform conventional ridge estimators based on the mean square error criteria. A programme is also provided to demonstrate the simulation findings [15].

The key advantage of the ridgeline models over the PRMSE of the CHLS-MECI models was a 65 percent reduction in the estimation error of new leaves. Despite this, the CHLS evaluation of water-stressed leaves indicated no improvements. [16].

The proposed method makes use of an MPP model with interconnected tubes and a post-tracking mechanism. Our approach for detecting roads in remotely-sensed images is shown using data from the Massachusetts roads dataset [17].

For this purpose, we compared the urban growth patterns of the cities of Adelaide (Australia), Tokyo (Japan), and other cities throughout the world using NTL. In both Adelaide ($r = 00.90$) and Tokyo ($r = 00.81$), researchers found a strong correlation among densely populated metropolitan areas and density of population. [18].

SLIC segmentation process has an effect on the consistency of changing regions, whereas CNN characteristics have an effect on the integrity of change regions and SCAE features have an effect on the performance of SVM classifiers, according to the findings. Furthermore, characteristics collected from structures improve the capacity to retrieve information from ground objects. The results of the comparison reveal that it outperforms other change detection approaches [19].

Overall, this study contributes to a better knowledge of the relationship among Sustainable improvement, earth examination, and ML, as well as how they might help nations achieve sustainable development and how to uncover connections between them. Given the importance and expanding quantity of data created by Earth Observation in achieving the Sustainable Development Goals, it is decided that new methodologies and techniques are required, strongly recommending the employment of new Machine Learning techniques [20].

We are attempting to map the villages around the Bulgarian city of Plovdiv using textual assessment of a Corona photograph taken in 1968. Data from Sentinel-2B and Landsat-8 images taken recently are compared to the results. Here, we look at the Corona image's ability to distinguish between different settlement types and the possible application of textural analysis to historic land use and land cover mapping based on images. Analysis of one early satellite mission's picture and discussion of the ability to extract characteristics from these primitive images are presented in general. [21].

Today's satellite and information methods are discussed in detail in this report. Using CNNs to analyze data from man-made Earth satellites is not an uncommon occurrence. Using data, CNN can learn and identify the best possible functions on its own. [22].

To begin, we propose a thorough comparison of these techniques using a single structure and a shared collection of photos. We discovered that Geographical changes on the geographical axis of poverty measurements affect all of the approaches' prediction ability. As a result, we describe a novel approach that enhances poverty prediction by combining grid-cell selection with ensembling to tackle coordinate displacement [23].

Multiple regression (LR) analysis, on the other hand, has its own set of qualities or constraints, like lengthy calculation times, sparse, unstructured information, and so on. Here, researchers provide a more computation-efficient technique for achieving an optimal solution that may help the solution avoid slipping into the local minimum trap based on ridge regression using the glowworm swarm optimization method with t-distribution parameters [24].

There are several uses for land cover categorization data, such as tracking land use and changes and identifying deforestation, desertification and water scarcity. As a side benefit, land cover classification assists in the identification of changes in land cover. Pixel-by-pixel data is sent by most satellites, as well as high-tech sensors.. In order to investigate a tiny area in high quality, the No. of pixels generated is in the millions. As a consequence, the task's run time and accuracy must be balanced. To detect land cover using multi-spectral temporal data, we compared the Multi CNN model to industry standard models. This study makes use of data from the Landsat-8 satellite.

3. PROPOSED WORK

MOSAIKS' design lends itself to two additional characteristics: the capacity to fuse combine information from various sensors with photo forecasts and assign sub-image scale locations to image-scale predictions. SIML predictions can be improved with the help of available satellites that have a variety of characteristics (for example, sample timing and wavelength). As the step of regression in the attributes is linear, MOSAIKS' design enables for incorporation of information seamlessly from various satellites.

3.1 FEATURIZATION STEP

This phase is used to convert satellite imagery (images x) into concise vector representations. The way images are represented as characteristics determine how generalizable they are. The featurization function is based on MOSAIKS, which we utilize to construct RCFs from satellite images and is theoretically supported. RCFs quantify the measure of correlation among each sub-image in each and every set of pictures without utilising task-specific information or contextual information. As shown in the diagram, the properties of x are then used by MOSAIKS as an over fitted means of determining any y that might be an image objects non-linear function in figure 1.

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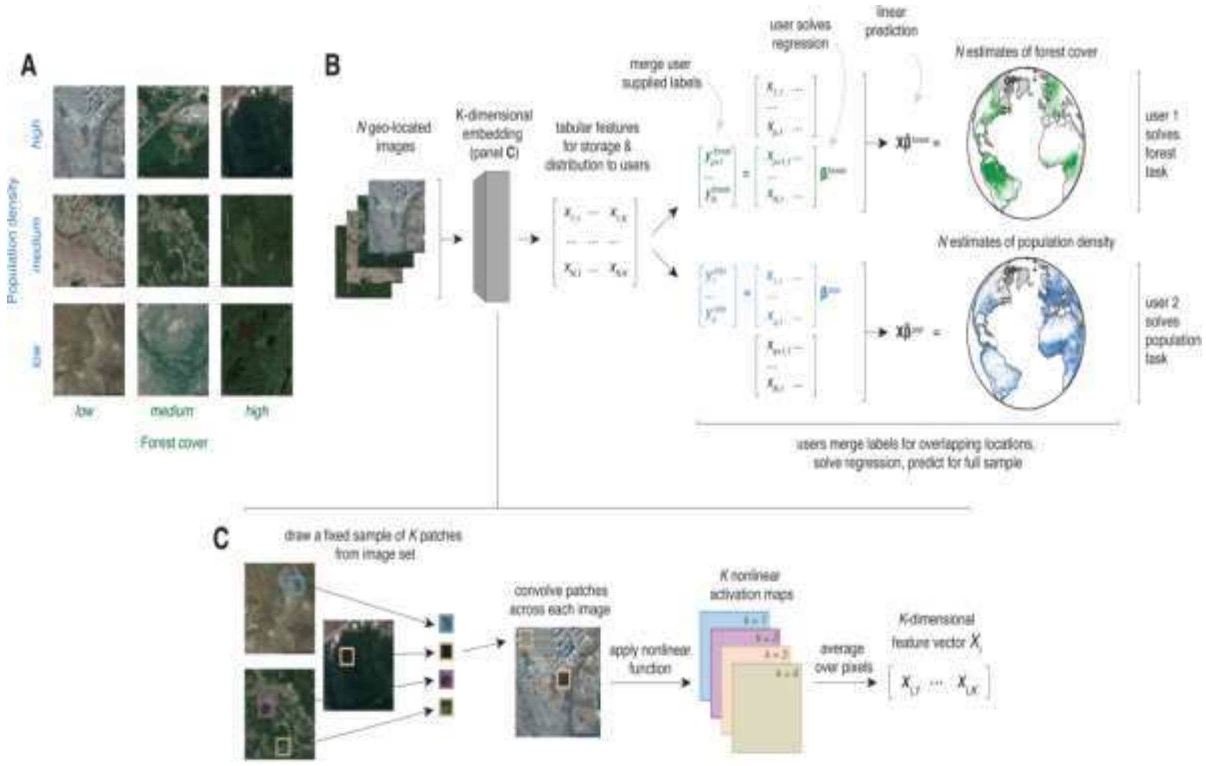

Figure 1: Process flow diagram

The above figure represents about the process of featurization.

3.2 REGRESSION STEP

The unsupervised factorization stage can be performed once for each image, resulting in a single collection of results which can be utilized to resolve a variety of problems by numerous independent users applying the regression step repeatedly. Ridge Regression was employed in this case. It is of the form Y=XB+e in this Ridge Regression. For 1 to q locations, Y is the user-supplied labels, such as population density, poverty, and elevation. The K-dimensional feature vector is denoted by X. Then, for B, each user runs a single linear regression. The whole MOSAIKS feature set as well as linear prediction with e. After that, X generates the for all locations, SIML forecasts regarding label elements.

3.3 MULTI TASK PERFOMANCE OF MOSAIKS

We begin by featurizing the photos by running them via MOSAIKS' feature extraction method, which produces 8,192 features for each image. We then repeat to perform a cross-validated ridge regression for every job to forecast forest cover (R2 = 0.91) , road length (R2 = 00.53), & average cost of house (R2 = 00.52) using generated feature matrices (X) in the regression procedure. The figure represents the prediction of Road Length in the US continent with 1km x 1km resolution daytime images.

Algorithm:

Featurization:
Gridcreation();
Featurization();
Regression();

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```
Gridcreation()
{
    latmin = 25
    latmax = 50
    lonmin = -125
    lonmax = -66
  gridvals <- makegrid(zoom, pixels, lonmin, lonmax, latmin, latmax)
  latVals <- gridvals[[2]]
  lonVals <- gridvals[[1]]
 save(file.path(data_dir, "int/grids", paste0(filename, ".npz")), lon = lonVals, lat = latVals,
zoom = zoom, pixels = pixels)
}
Featurization()
{
subgrid_files = Path(c.grid_dir).glob("[!grid_]*.npz")
area = grid_name_lst[0]
sample = grid_name_lst[3]
image_folder = base_image_dir / f"{area}_{sample}"
outfpath = Path(c.features_dir) / f"{image_folder.name}.pkl"
featurize_and_save(image_folder, out_fpath, c);
}

featurize_and_save(image_folder, out_fpath, c)
{
X_lift, names, net = featurize(image_folder, c)
  latlon = np.array([i.split("_")[:2] for i in names], dtype=np.float64)
  lon = latlon[:, 1]
  lat = latlon[:, 0]
  zoom_level, n_pixels = [int(i) for i in names[0].split("_")[2:4]]
  ij = spatial.ll_to_ij(
     lon,
     lat,
     c.grid_dir,
     c.grid["area"],
     zoom_level,
     n_pixels,
  )
  ij = ij.astype(str)
  ids = np.char.add(np.char.add(ij[:, 0], ","), ij[:, 1])
}
Regression()
{
subset_n = slice(None)
subset_feat = slice(None)
solver = solve.ridge_regression
(
     this_X,
     this_X_test,
     this_Y,
     this_Y_test,
```

```
        this_latlons,
        this_latlons_test,
    ) = parse.merge_dropna_transform_split_train_test(
        c, label, X[sampling_type], latlons[sampling_type]
    )
    this_X = this_X[subset_n, subset_feat]
    this_X_test = this_X_test[:, subset_feat]
    this_Y = this_Y[subset_n]
    this_latlons = this_latlons[subset_n]
kfold_results = solve.kfold_solve(
        this_X,
        this_Y,
        solve_function=solver,
        num_folds=c.ml_model["n_folds"],
        return_model=True,
        return_preds=True,
        svd_solve=False,
        clip_bounds=bounds,
    )
    preds = np.vstack([solve.y_to_matrix(i) for i in best_preds.squeeze()]).squeeze()
    truth = np.vstack(
        [solve.y_to_matrix(i) for i in kfold_results["y_true_test"].squeeze()]
    ).squeeze()
ll = this_latlons[
        np.hstack([test for train, test in kfold_results["cv"].split(this_latlons)])
    ]

    data = {
        "truth": truth,
        "preds": preds,
        "lon": ll[:, 1],
        "lat": ll[:, 0],
        "best_lambda": best_lambda,
    }
with open(save_path_validation, "wb") as f:
        pickle.dump(data, f)
    results_dict = r2_score(truth, preds)
}
```

4. IMPLEMENTATION

The below figures shows the bar plots of the labels forest cover in each states of India and across each districts of Andhra Pradesh. Where X-axis represents states and Y-axis represents forest cover Area in figure 2.

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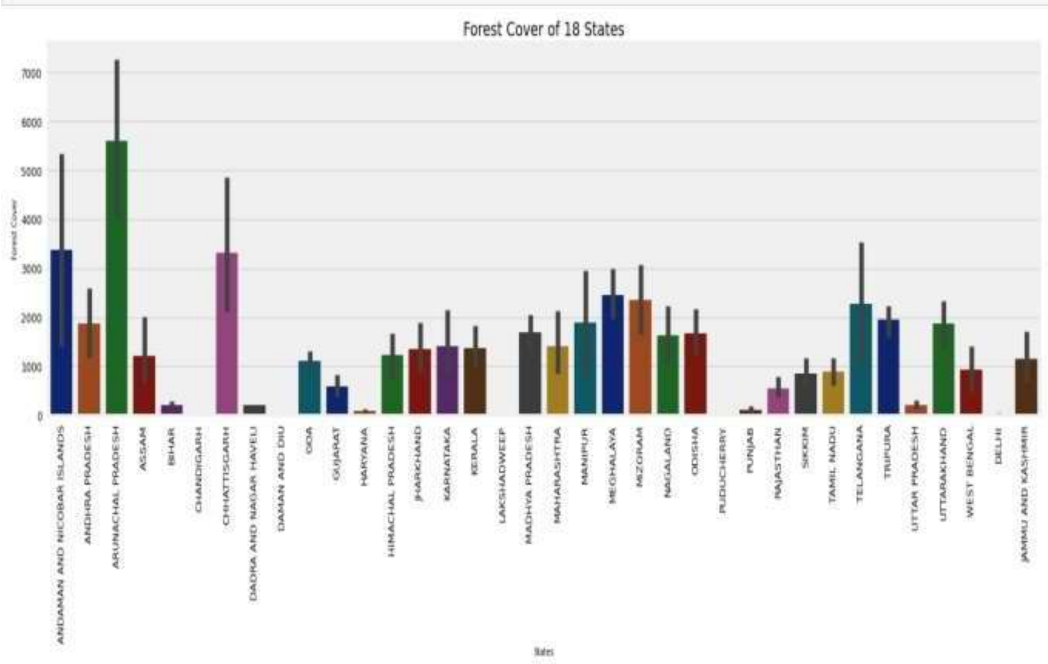

Figure 2: Representation of Forest Cover in different states across India.

The lowest forest cover is in the state of Haryana followed by Punjab while the highest forest cover is in the state of Arunachal Pradesh. The above data is taken from 2015 forest cover dataset in figure 3.

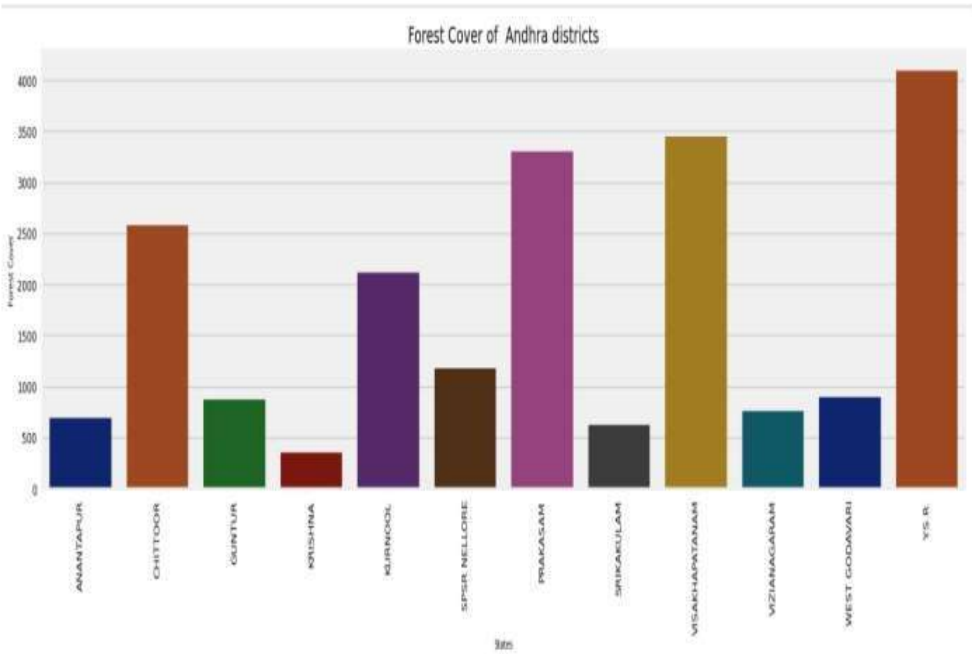

Figure 3: Representing Forest Cover in different districts of Andhra Pradesh

The lowest forest cover is in the district of Krishna while highest forest cover is in the district of Y.S.R Kadapa in figure 4.

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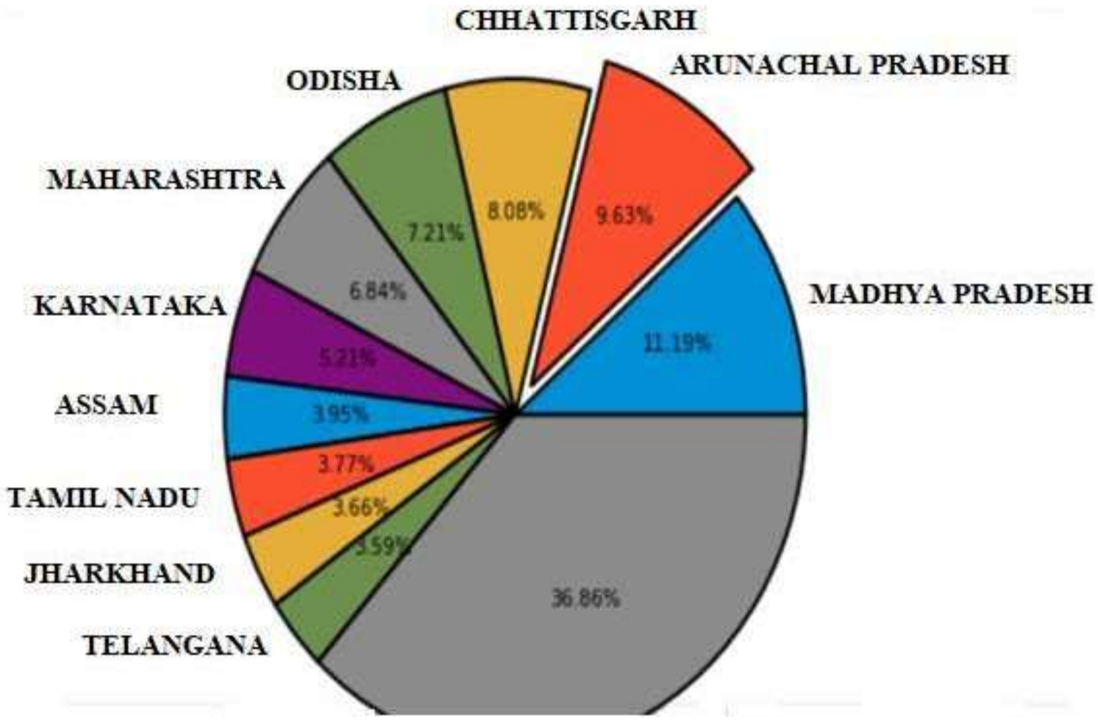

Figure 4: Representing Total share of top 10 states in India

The highest forest cover share is contributes by Madhya Pradesh followed by Arunachal Pradesh.

The below figure represents the scatter plot of labels Housing price in each states of India.

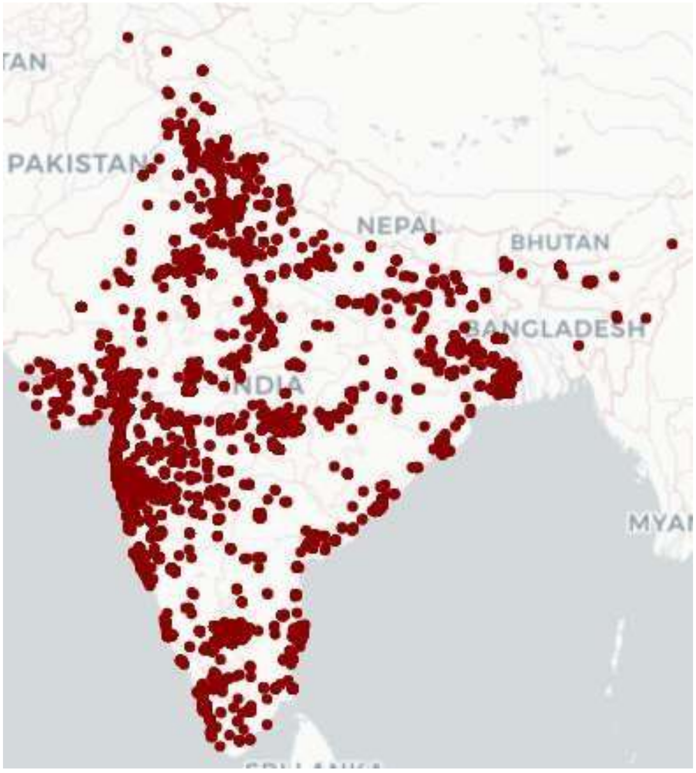

Figure 5: Representing Housing Price in different states in India

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5. ADVANTAGES

This particular system has following advantages:

i. The photographing of the ground surface is a constant operation.Having a duration of 4 days.
ii. As a result, the most appropriate image was selected.
iii. The formalities of aerial photography and flight planning are omitted in this case.
iv. The cost of using satellite images is far less than that of using aerial photographs.

6. CONCLUSION

The MOSAIKS platform as a whole, which includes linear prediction and featurization. It can be thought as a double layered Convolutional Neural Network with a massive private intermediate layer created with filters which are not trained, or a computationally practical kernel ridge regression approximation for a fully convolutional network.

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