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Application of Deep Learning Model in Brick Kiln Information Extraction

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Abstract

Developing Asian nations such as India use clay bricks as basic building blocks for construction purposes. The process of firing of bricks leads to generation of exhaust gases which in turn degrade air quality and have considerable adverse effect on the flora and fauna in the vicinity. The area in north of India, especially surrounding national capital New Delhi, is highly polluted and has an abundance of brick kilns which further worsens the situation. Thus, keeping a record of brick kilns in an area can help regulate their optimal working considering both, the production and environmental impact. Satellite imagery proves to be helpful in this case as the amount of ground work is reduced up to a large extent. The dataset was formed using images from Google Earth after appropriate pre-processing. SSD (Single Shot Detector) architecture of deep learning was used to detect brick kilns and hence regulate their impact. The approach followed was used to train and test the model with enough remotely sensed data followed by validation of results achieving an overall accuracy of 81.9% and precision of 95.06%. Furthermore, the individual brick kiln data was processed to do sub-classification in terms of location, shape and status of brick kiln. Depending upon the total number of brick kilns present in an area, the approximate amount of exhaust was estimated.

Keywords: Brick kiln, Bounding Box, Deep Learning, Single Shot Detector (SSD)

1. Introduction

The deteriorating condition of environment calls for measures to control the impact of anthropogenic activities on atmosphere. Cities lying in the Indo-Gangetic plains of South Asia have the world's worst anthropogenic air pollution (Misra et al., 2020). Natural causes of air pollution include calamities like forest fires and volcanic eruptions along with decay processes be it microbial or radioactive. But as it can be observed, these events are either rare or slow in pace. Whereas the anthropogenic causes of air pollution such as exhaust from industrial factories, fossil fuel-based power plants, vehicles, etc are far more potential.

Brick kilns manufacturing takes place

on a large scale in India. 74% of brick kiln production in India is from Bull Trench Kiln (BTK). This includes moving fire which essentially creates three zones namely - cooling zone, firing zone and pre-heating zone. The movement of air is such that it enters from the cooling zone, gets heated and hence rises along the way to the firing zone. This prevents proper combustion of the fuel on the ground in firing zone.

A large area covering parts of Delhi NCR and Uttar Pradesh have a number of brick kiln manufacturing units in close vicinity of each other. Here the choice of fuel is coal or biomass. Since the design of BTK is such that the fuel fallen on ground for firing is not ignited properly, emissions from the kiln increase notably.

Average emission factors were found to be 6.35 to 12.3 kg of CO, 0.52 to 5.9 kg of SO2 and 0.64 to 1.4 kg of particulate matter (PM) for the production of 1000 bricks. Being major causes of air pollution, sulphur dioxide (SO2), oxides of nitrogen (NOx) and suspended particulate matter (SPM) contribute to urban pollution as well as regional acid depositions. (Skinder et al., 2014).

Since significant brick kilns are in working condition at the same time except for rainy season, pollution caused by them is undeniable. Coal fired brick kiln factories generate significant amount of brick kiln bottom ash (BKBA) which contains toxic metals (Pb, Cr, Cd, Zn, Mn, and Cu) that contaminate surrounding areas. The amount of toxicity introduced into the soil from the brick kiln ashes is a reason of concern for human health and ecological risk in the surrounding area (Mondal et al., 2017). Since these sites are often not present in any records, it's difficult to monitor and control them due to lack of information and hence no one is answerable for the harm caused. Thus, in order to control the amount of emissions, development of monitoring techniques are required.

There has been significant research in this field in last 2 to 3 years where remotely sensed data was used for the detection of brick kilns in a particular area. Availability of open source remotely sensed data has made it preferable for a number of analysis and monitoring applications. The use of satellite imagery for object detection makes the process efficient and more versatile as satellite data acquisition provides continuous global coverage, even in the areas that may be inaccessible for manual visits. Also, large scale surveys and time series analysis have been made possible due to continuity and uniformity of satellite data.

Due to significant development in neural networks, especially deep learning, visual recognition systems such as image classification, localization and detection have attained remarkable performance. Deep learning techniques are being preferred for state-of-the-art object detection systems (Pathak et al., 2018). The reason lies in the complex design which is capable of keeping up with the increasing dataset size. One of the main reasons for the success of Deep learning techniques is the large amounts of annotated data (Zhao et al., 2019).

Since the number of different types of remotely sensed data that can be utilized for training and testing purpose is large, it is important to pay attention to the need of type of data so as fit the algorithm and methodology. Hence the selection of dataset is done considering the quality of imagery in terms of spatial resolution, number of pixels and the computational load on the system according to the algorithm/model implemented.

A study on Dhaka identified kilns with 94.2% accuracy and 88.7% precision and extracted the precise GPS coordinates of every brick kiln across Bangladesh. This was done with the help of machine learning on satellite imagery. Using these estimates, it was concluded that at least 12% of the population of Bangladesh (>18 million people) lives within 1 km of a kiln. Also, 77% and 9% of kilns are (illegally) within 1 km of schools and health facilities, respectively. Under the influence of an unfavourable wind direction, brick kilns contribute up to 20.4 μg/m3 of PM2.5 (particulate matter of a diameter less than 2.5 μm) in Dhaka (Lee et al., 2021).

Brick kilns similar to Bull Trench Kilns were identified using the Sentinel-2 imagery around the state of Delhi in India. Transfer learning was employed to avoid the requirement of huge training dataset, along with random forest classification technique. This method achieved a recall of 0.72, precision of 0.99 and F1 score of 0.83 (Misra et al., 2020). Use of NDVI was done for determining the age of brick kiln i.e., whether or not they are in working condition. Whereas in our work, SSD300 model architecture was used for deep learning. Also, in order to detect active and abandoned brick kilns, the model itself was used with an addition of classification on the basis of shape of brick kiln (circular, elliptical and rectangular). This serves as a more holistic approach towards mapping of brick kilns as various purposes are met at a single shot.

Remote sensing is also being used an evidence for backing up various kinds of studies which involve detection of objects on a large scale for further analysis to support a cause. Brick kilns are known sites of modern-day slavery. Thus, to calculate the impact of slavery, the number of brick kilns across the 'Brick Belt' that runs across south Asia was estimated using high resolution satellite imagery from Google Earth (Boyd et al., 2018).

Another study proposed a two-stage gated neural network architecture called Kiln-Net where at the first stage, 99% of irrelevant data was filtered out using the ResNet-152 model followed by application of YOLOv3-based object detector to find the precise location of each brick kiln (Nazir et al., 2020).

The brick kilns can be easily identified from the satellite imagery. The active brick kilns appear bright while the abandoned ones look greenish in colour. Figure (1) shows different types of brick kilns with respect to shape as well as their operating status.

(a) Active Elliptical Brick Kiln

(b) Abandoned Elliptical Brick Kiln

(c)Active Rectangular Brick Kiln

(d) Active Circular Brick Kiln

(e) Abandoned Circular Brick Kiln

Figure 1: Different types of brick kilns as visible in satellite imagery

In this research work, objective was to study a deep learning based approach for brick kiln detection at different levels using satellite imagery. SSD (Single Shot Detector) model architecture was implemented with Keras and TensorFlow at the backend to generate a deep learning model. The images were pre-processed accordingly for training of the model followed by validation. Once the weights were generated after training, the model was tested using satellite images of varied sizes and zoom level. The point locations and geographic coordinates of individual brick kilns present in the input image were retrieved. This was followed by detecting brick kilns along with the sub-classes that they belong to. The sub-classification was done with respect to the shape (rectangular, circular and elliptical) and status of brick kiln (active or abandoned). Furthermore, based on the number of brick kilns present in an area, the environmental impact in the form of total pollution contributed by them can be estimated.

2. SSD Model Description

SSD, i.e., Single Shot Multibox Detector is a method for object detection using single deep neural network. It discretizes the output space of bounding boxes into a set of default boxes (or anchor boxes) over different aspect ratios and scales per feature map location. The layer architecture is such that they keep decreasing in size so as to perform detection at different scales (Liu et al., 2016). Figure (2) shows the model architecture of SSD.

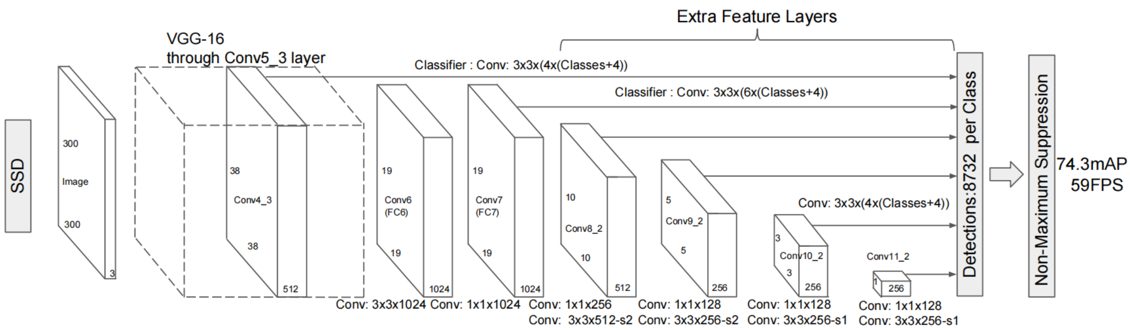

Figure 2: Single Shot Detector Model (Liu et al., 2016)

3. Proposed Methodology

In this research study, the data was downloaded from Google Earth while maintaining the latitude and longitude extent. The images were then divided into three parts for training, validation and testing. The training and validation dataset required pre-processing in the form of image cropping. Therefore, the images were cropped into 300 X 300 pixel size due to the requirement of SSD300. Also, annotations and sequencing text files were created for the testing and validation dataset. This included marking the ground truth in them so that their coordinates are recorded according to the bounding boxes.

Once all the six input files were ready, the model was created in training mode along with other necessary settings as mentioned further in detail. The paths to input files were specified and model was trained for detecting brick kilns in the area including parts of the Ghaziabad, Uttar Pradesh. The weights generated were saved in a file for testing and further analysis.

The model was subsequently created in inference mode for testing where the weight file was loaded into it and path to the test images was specified. The prediction was carried out on test images followed by extraction of their geographic coordinates and impact on environmental. Figure 3 shows the methodology in form of a flow chart.

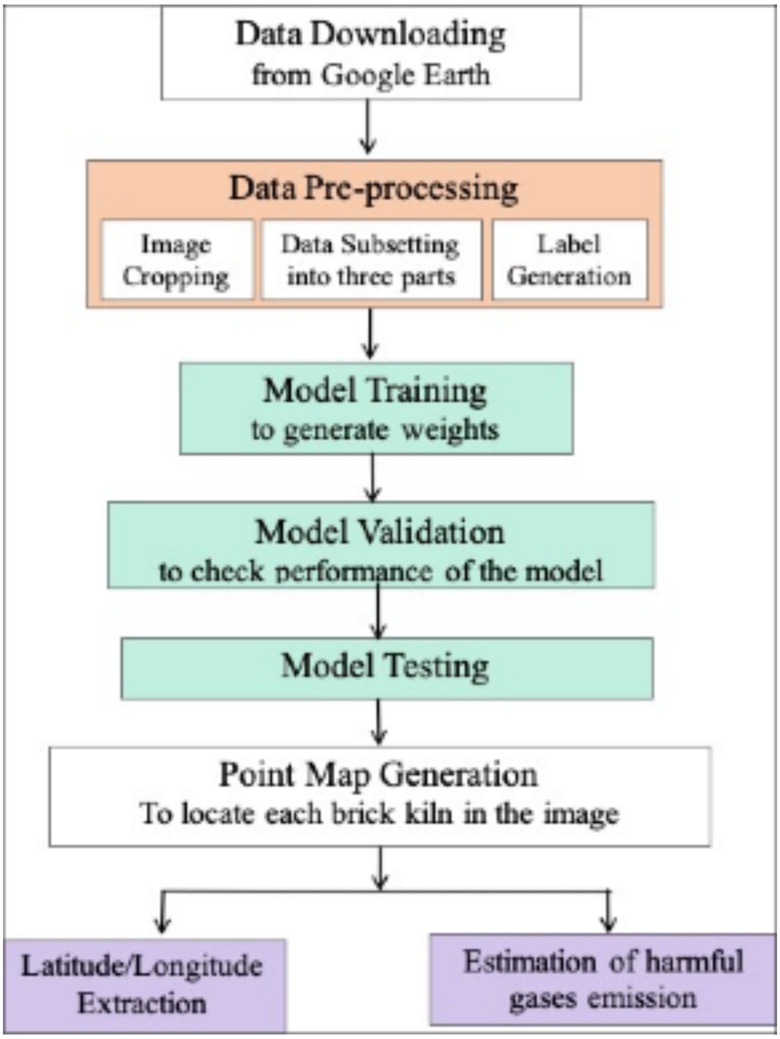

Figure 3: Methodology adopted for the study

3.1 Data Description and Study Area

For the detection of brick kilns, multi-band data was required as color information plays an important role in determination of presence of brick kilns. As per the requirement of model architecture of choice (SSD), satellite imagery was download form Google Earth. The area under study is that of Ghaziabad, Uttar Pradesh, which is known to have an abundance of brick kilns. The latitude extent of study area is from 28.7443° N to

28.8179° N. The longitude extent is from 77.3065° E to 77.3770° E.

The data was downloaded from Google Earth. It provides optical multispectral data with resolution 30 cm and derived resolution 15cm. The dates of acquisition of data used in this work are 23rd February 2019 and 4th May 2021. While capturing data it was taken care that monitoring of the Lat/Lon extent done precisely and retaining the coordinate information associated with the images. This information further helps in demarcating individual brick kilns along with their geographical coordinates for construction of an appropriate database. This gives as a result, a set of remotely sensed images containing three bands namely Red, Blue and Green which forms the basis of identification of brick kilns taking into account their reflectance in the visible region of the electromagnetic spectrum.

3.2 Stages

3.2.1 Pre-processing

The data was downloaded from Google Earth. It was divided into three parts, one for each, training, validation and testing. For training dataset, images were cropped made into size 300x300, which is requirement of SSD300. Annotations files were generated for the training and validation dataset. These annotations were holding labels such as class, bounding box coordinates, format, etc which was formed by marking brick kilns in the test imagery with the help of makesense.ai. They were exported in xml file format for the training further.

3.2.2 Training

The training and validation dataset was prepared along with the respective annotations. Two text files were prepared which held the names of images in the order of processing required. All these files were given as input to the model. Weights hence generated were saved in hierarchical data format (.h5) for further use. Table (1) shows the parameters while training the model.

Epochs play an important role in getting a good accuracy for the model. The model calculates the errors on both the training and validation set. Training stops when the validation error is the minimum. Basically, validation set is used to lower the overfitting as much as possible (Afaq et al., 2020).

Table 1: Model Parameters for Training

S. No.	Parameter	Value/Status
1	Mode	Training
2	Image height, Image width	300
3	Image channels	3
4	Mean Color (for mean subtraction)	[68, 48, 122]

5	Number of classes	1: Brick Kiln classification 6: Brick Kiln sub-classification
12	Normalize Coordinates	True
13	Batch size	8
14	Epochs	300
16	Classes	
	Classification	['background', ' brick_kiln']
	Sub-classification	['background','Active Rectangular Brick Kiln', 'Active Elliptical Brick Kiln', 'Active Circular Brick Kiln', 'Abandoned Rectangular Brick Kiln', 'Abandoned Elliptical Brick Kiln', 'Abandoned Circular Brick Kiln']

3.2.3 Testing

Here the model was created in Inference Mode. The weights generated after training were loaded into the model. Various parameters were initialized within the model such as the number of positive classes, their names for display, mode, thresholds. The confidence threshold and IoU threshold were kept as 0.8 and 0.4 respectively and they decided whether or not the classification should be carried out. As testing was completed, each brick kiln with the bounding boxes, their predicted class and the confidence level should be assigned. The model thus generated was then used for processing the testing dataset consisting of images of varied sizes and zoom level. The outputs were recorded and used for further analysis.

3.2.4 Post-processing

The coordinates of bounding boxes of each brick kiln detected were used to find out the centre for generating a point map locating different brick kilns in the test image. This was followed by extracting the latitude and longitude of each brick kiln with the help of geographical coordinates of the corners of input image. As the number of brick kilns are finalized in an image, the amount of emissions from them was calculated using the values for average emissions per day. The total number of brick kilns in an image were recorded along with the geographic coordinates and environmental impact of the same in a text file.

4. Results and Discussion

4.1 Brick Klin Detection

The weights generated after training were loaded further in the model for testing to obtain results. Using matplotlib library, the bounding boxes predicted were plotted on the respected test imagery along with the confidence level. This followed calculating the centre point of each bounding box to plot a point map. The latitude and longitude information were retrieved using the geographical coordinates of the corners of input image. The total number of brick kilns and their respective coordinated were saved in a text file. The training and validation loss plots in Figure (4) show negative slope and represent good learning rate.

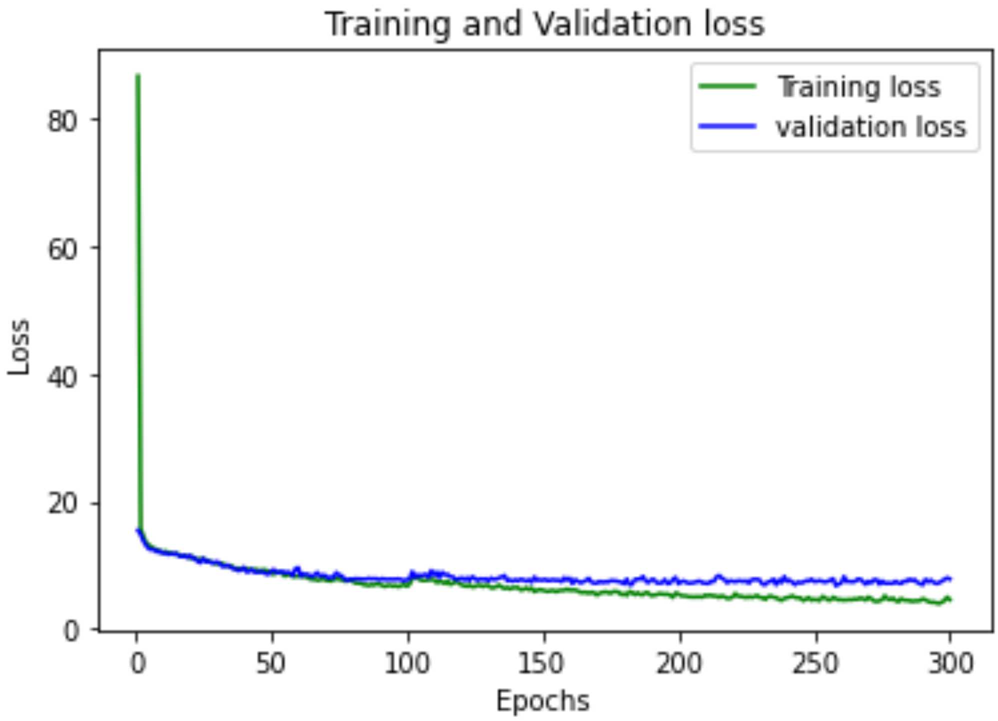

Figure 4: Training and Validation Plot against Epochs

4.2 Impact on Atmosphere

Since most of the brick kilns are of BTK type and use mostly coal (sometimes biomass) as fuel, the amount of emissions is huge. Brick kilns work throughout the year except for rainy season which makes the operational period around 9 months. The amount of emissions corresponding to one brick kiln for a continuous period of seven days were taken from the literature (Table 2) and averaged to obtain approximate emission values per day. The average value of emissions per day, when considered over the total operational period of a brick kiln, gives estimated emissions from a brick kiln per year. This was subsequently used to estimate the contribution of brick kilns present in a test image according to the total number of brick kilns detected in it.

The quantities thus obtained show the graveness of situation. These exhausts further degrade the air quality of the area and have potential to cause harm to the workers as well as the flora and fauna in vicinity.

Figure 5 shows two of the outputs obtained for detection of brick kilns. The bounding boxes can be seen along with their respective confidence level, followed by point map generation using bounding box coordinates. Lastly, the information extracted, i.e., geo-locations and yearly emissions can be observed from the text file saved after the execution which is shown in Table (3).

Table 2: Stack Gas Emission (Le et al., 2010)

Day	Stack Gas Emission (kg/day)		
	CO	**SO_2**	**PM**
1	3	2	9
2	1266	16	24
3	997	6	61
4	624	3	51
5	1033	91	95
6	850	140	257
7	306	162	15
Yearly (tonne/year)	195.90	1.62	19.75

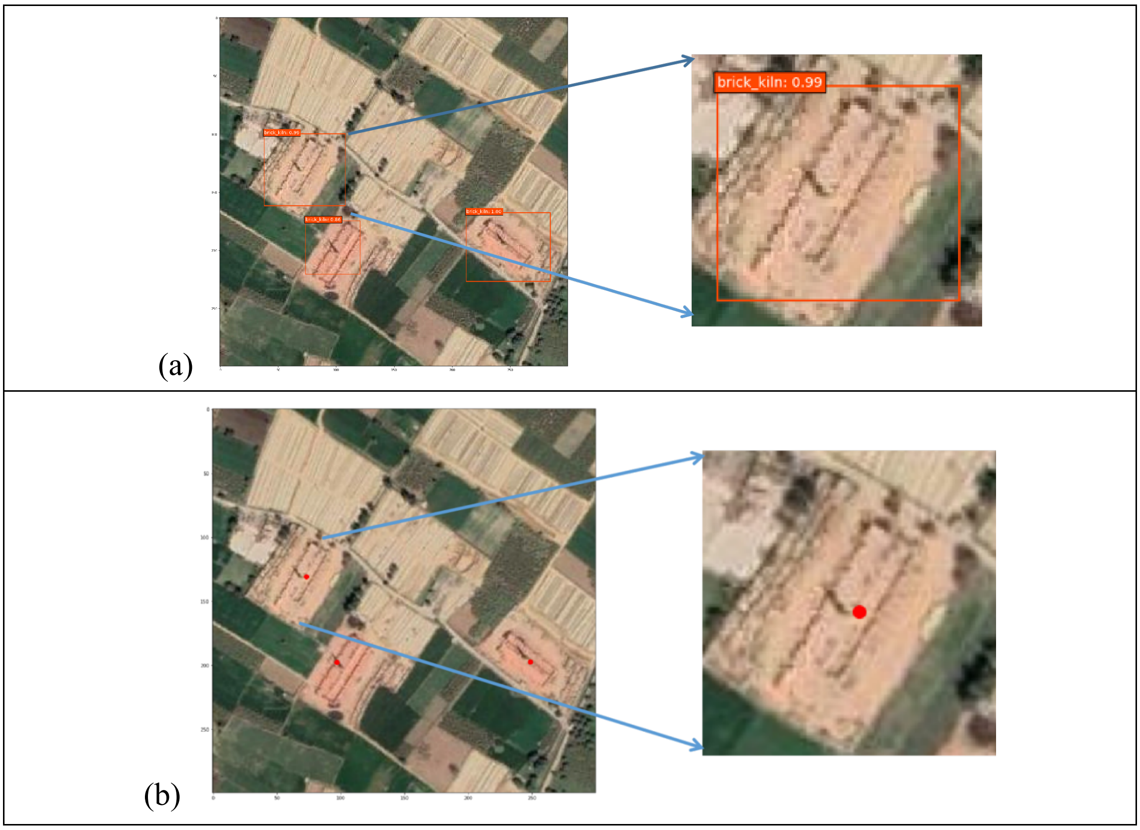

Figure 5: Output for Brick Kiln Classification. (a) Brick kilns identified, represented using the bounding boxes along with confidence level of each. (b) Point Map generated using centre of each brick kiln's bounding box.

Table 3: Information deduced containing brick kilns, their geographic coordinates and estimated emission per year

Total Brick Kilns detected: 3	
Latitude	Longitude
28.76580262039425	77.44493516963857
28.76698298925177	77.4414009606231
28765799489875796	77.44188740294082
Estimated Emission (tonnes/year)	
CO	587.71
SO_2	468.00
PM	59.25

4.3 Accuracy Assessment

The predicted outputs were compared with the ground truth with the help of confusion matrix to evaluate the overall accuracy as well as other metrics (Maxwell et al., 2021) Table (4) shows the confusion matrix and assessment metrics of the model.

4.4 Sub-classification

The application was improved by detecting different kinds of brick kilns on the basis of their shape and status. In terms of shape, brick kilns were classified as rectangular, elliptical and circular. Whereas classification on the basis of status of brick kiln basically worked to differentiate between abandoned brick kilns from those which were active at the time of acquisition of image. Abandoned brick kilns appear dull or dark in optical imagery as they get covered by vegetation due to course of time of inactivity. The trained weights when loaded in model, worked successfully to detect different classes of brick kilns on images with varying zoom level and sizes which proves to be of great advantage as there is no restriction on the size of testing data unlike that in training.

Table 4: Binary Assessment Metrics

		Reference Data	
		Positive	Negative
Classification Result	Positive	77	4
	Negative	13	-

Binary Assessment Metrics

Metric	Equation	Calculated Value
Overall Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	0.819
Sensitivity or Recall	$\frac{TP}{TP+FN}$	0.856
Precision	$\frac{TP}{TP+FP}$	0.951

Figure 6 and 7 show two of the outputs obtained for sub-classification of brick kilns. The bounding boxes can be seen along with their respective confidence level, followed by point map generation using bounding box coordinates. In the pop up images, different categories of brick kilns can be observed, viz.: Active rectangular Brick Kiln, Active Elliptical Brick Kiln, Active Circular Brick Kiln, Abandoned Elliptical Brick kiln and Abandoned Circular Brick Kiln. Figure 6 and 7 also show brick kilns that were not detected (highlighted in red). This may be due to slight difference in the appearance of these brick kilns in comparison with those used for training. It can further be rectified by including more training images.

5. Conclusion

Implementation of Brick Kiln Detection using Deep Learning with SSD architecture worked successfully with the overall accuracy of 81.9%. This method proved useful for test images of different sizes and zoom level as the algorithm works on anchor boxes of varying sizes. The sub-classification of brick kilns on the basis of their shape and status of working was also performed and evaluated to obtain adequate results. The advantages associated with use of this technique is the faster implementation, which includes training and testing, reduction in computational load as well as fair accuracy. This method can be applied to satellite imagery of a particular area to find the number of brick kilns, their type as well as to estimate their atmospheric impact. The results obtained clearly demonstrate the implications of emissions from the brick kilns on the environment. This indicates the need of reforms in the sector. With the help of more orderly data about the brick kilns, regulation measures such as use of efficient technology and improvement in fuel feeding can be designed and employed to reduce the environmental impact and carbon footprint.

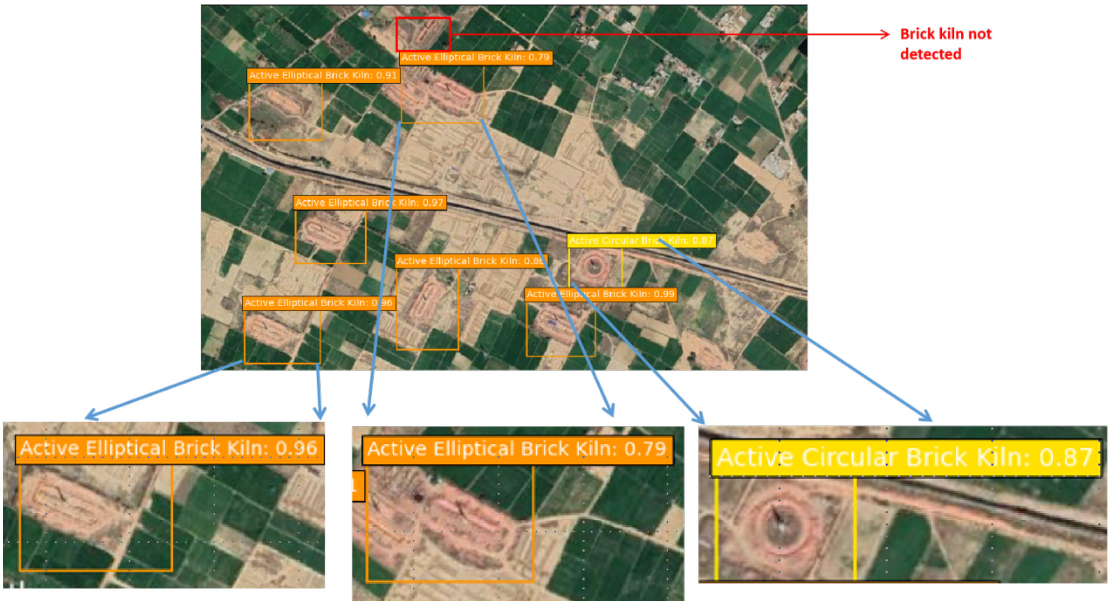

Figure 6: Sub-classification of Brick kilns with respect to shape as rectangular, elliptical, and circular

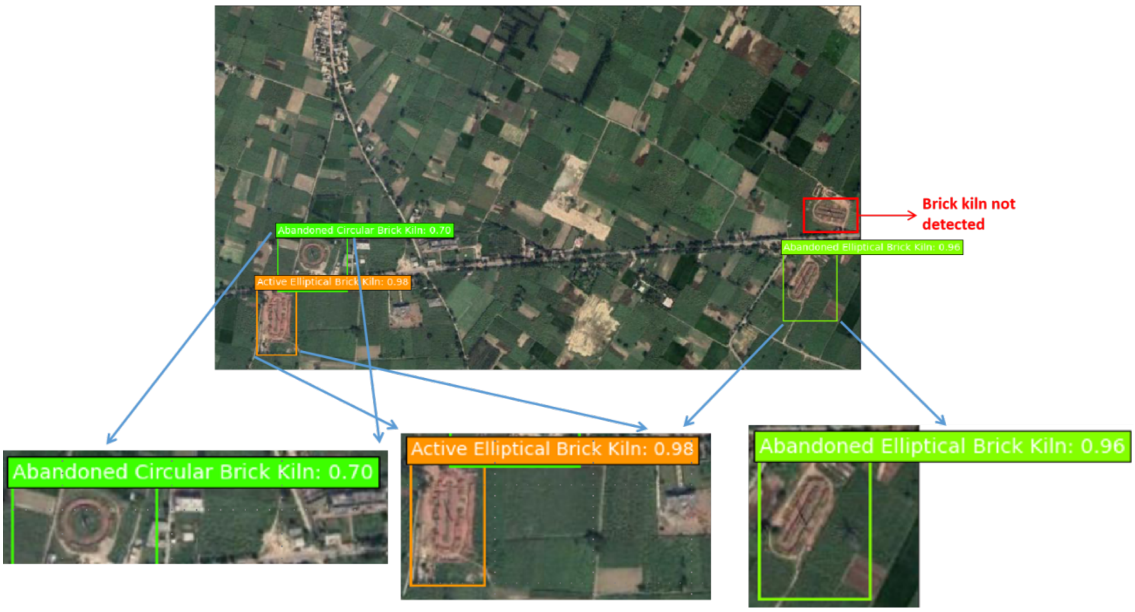

Figure 7: Sub-classification of Brick kilns with respect to active or abandoned

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