MITIGATING CLIMATE AND HEALTH IMPACT OF SMALL-SCALE KILN INDUSTRY USING MULTI-SPECTRAL CLASSIFIER AND DEEP LEARNING

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ABSTRACT

Industrial air pollution has a direct health impact and is a major contributor to climate change. Small scale industries particularly bull-trench brick kilns are one of the major causes of air pollution in South Asia often creating hazardous levels of smog that is injurious to human health. To mitigate the climate and health impact of the kiln industry, fine-grained kiln localization at different geographic locations is needed. Kiln localization using multi-spectral remote sensing data such as vegetation index results in a noisy estimates whereas use of high-resolution imagery is infeasible due to cost and compute complexities. This paper proposes a fusion of spatio-temporal multi-spectral data with high-resolution imagery for detection of brick kilns within the "Brick-Kiln-Belt" of South Asia. We first perform classification using low-resolution spatio-temporal multi-spectral data from Sentinel-2 imagery by combining vegetation, burn, build up and moisture indices. Then orientation aware object detector: YOLOv3 (with θ value) is implemented for removal of false detections and fine-grained localization. Our proposed technique, when compared with other benchmarks, results in a $21\times$ improvement in speed with comparable or higher accuracy when tested over multiple countries.

1 PATH TO CLIMATE IMPACT

Industrial air pollution has a direct health impact and is a major contributor to climate change. Unregulated small-scale informal industries spread across vast areas are common in resource-limited settings and can be difficult to locate and monitor. Remote identification of kilns and monitoring of their carbon production can assist air pollution surveillance, regulation, and climate mitigation efforts. The exact numbering and location of kilns is needed to understand and address the kiln sector's climate and health impacts.

2 INTRODUCTION

Vehicles and industries are considered as one of the major contributors of pollution resulting low air quality and smog Haque et al. (2022). According to an estimate 20% of global black carbon emission is from the brick kilns Maithel (2014). These kilns are also a major source of employment, however according to the Global Slavery Index of 2019, approximately 60% (24.3 millions) of the modern day slaves are within the "Brick-Kiln-Belt" of South Asia (between Afghanistan and Nepal) Landman & Silverman (2019). Keeping in view the UN's Sustainable Development Goal (SDG) 3.9 and 8.7 which specifically aims to address air pollution and forced labor respectively, mapping brick kilns in the South Asia is an essential first step.

Manual surveying of "Brick-Kiln-Belt" is infeasible due to the large area ($1,551,997\ km^2$) as well as geographic boundaries. Due to recent advancements in machine learning as well as availability

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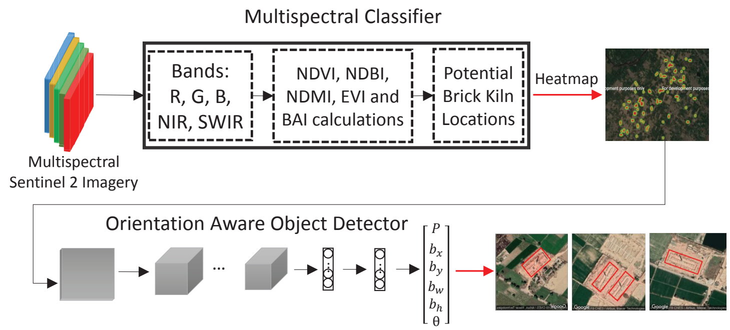

Figure 1: Illustrative example of working of the proposed approach. In the first step we apply a rule based classifier on spectral indices (NDVI, EVI, NDMI, NDBI, BAI) on regions of interest to classify brick kilns as shown in the heatmap (Satellite images courtesy Google Earth).

of remote sensing data, automated surveys are now more commonly used for such large scale analysis Redmon & Farhadi (2018); He et al. (2017); Li et al. (2018); Xie et al. (2016); You et al. (2017); Cotrufo et al. (2018). Recently, remote sensing images have also been used to analyze the extent of modern slavery Boyd et al. (2018); Jackson et al. (2018); Misra et al. (2019); Foody et al. (2019). The "Slavery from Space" project Boyd et al. (2018) proposed a crowd-sourced procedure to manually detect brick kilns from satellite imagery. They randomly sampled the potential kiln areas into 320 cells of 100 km^2 each. However, they were only able to manually annotate 30 geographic cells (i.e. only 2% of the entire Brick-Kiln-Belt). As a result, the manual crowd-sourced method lacks generalization and scalability as is evident from the resulting annotated maps that are extremely sparse. On the other hand, low-resolution multi-spectral satellite data has also been used to classify brick kilns in the region surrounding the Delhi state in India Misra et al. (2019). The analysis in this work was based on normalized difference vegetation index (NDVI) and transfer learning, which unfortunately is prone to generate a large number of false detections. In contrast, high-resolution satellite imagery has also been used to detect brick kilns to the east of Jaipur, which is the capital city of India's Rajasthan state Foody et al. (2019). This work used Faster R-CNNs to automate the process of brick kiln identification in the given tile of images. However, owing to the large computational complexity, this approach is difficult to apply at a large scale. Moreover, it yields a very high false positive rate for which they proposed to train a two-staged R-CNN classifier to achieve acceptable performance which further increased the processing time. A more recent approach called KilnNet Nazir et al. (2020) combined inexpensive classifier with object detector in a two-stage strategy to address the issue of time complexity. This approach too is only based on high resolution satellite imagery and is infeasible due to data acquisition and processing costs.

We also propose a two-stage strategy for automated detection of brick kilns, our approach is over 21× faster than SOTA benchmarks and mostly relies on freely available low resolution remote sensing data. Most existing object detection techniques in low resolution satellite imagery are significantly less accurate whereas computation is very costly for high resolution satellite imagery. To overcome this our proposed methodology decouples classification and localization. Classification is performed using spectral properties while localization is accomplished using orientation adapted detector. This results in a coarse-to-fine search in which fine-grained orientation aware localization via object detection is performed as a second stage only on less than 10% of the total region. This results in a 21× improvement in speed in addition to improvement in accuracy. We tested our approach on three countries (Pakistan, India and Afghanistan) and showed that it is scalable as well as generalizable to varying structural, environmental and terrain conditions.

This paper has the following four technical contributions: **(i) Fusion of spectral Indices**: Classification is performed using mixture of spectral indices as shown by equation 1 in the paper. **(ii) Fusion of low resolution and high resolution imagery**: Our proposed approach processes input from low-resolution sensors for the generation of potential candidates for kilns which are then filtered via high-resolution input via Orietation-aware YOLOv3. **(iii) Processing large datasets**: The proposed strategy reduces the computational burden associated with processing of large datasets by fusion of low resolution and high resolution imagery. SOTA benchmarks take on average 674 seconds to process three datasets in Table 1 of the paper. Our proposed approach on the other hand reduces this compute time to 38 seconds only. **(iv) Detection of other objects**: Our multi-sensor and multi-stage strategy can also be used to detect other objects that have differentiable spectral signatures and well defined shapes e.g. industrial units, oil tanks, warehouses, tennis courts, parking lots etc. Here we have only demonstrated its application for geo-localization of brick kilns.

3 Proposed Methodology

Brick Kilns are typically identifiable through a visual inspection of satellite imagery. However, while considering a large geographic area, several inherent complexities in satellite imagery make automated detection of brick kilns a challenging task. This include, but are not limited to, i) variations in imaging sensors, ii) differences in kilns' structure across the countries, iii) dynamic kilns' surroundings and iv) variations in luminosity, seasonal changes, and pollution levels etc. Specifically, It is very challenging task to identify brick kilns in low resolution imagery ($\frac{10\ meters}{pixel}$). Existing pixel classification along with transfer learning approach Misra et al. (2019; 2020) for detection of brick kilns is not scalable as well as generalizable at large scale due to cost complexities. In our proposed multi-spectral approach brick kilns are classified using spectral indices (without transfer learning) due to the fact that reflectance spectra of different land covers are different. The indices are designed to exploit these differences to accentuate particular land cover types. The land covers are separable at one or more wavelengths due to spectral reflectance of different materials (see Fig. 3 and Fig. 4 in Appendix A). Brick kilns being man-made structures have a high built-up index. Unlike other man-made structures and due to the specific nature of work, the kiln surrounding has a low vegetation index. Furthermore the baking process and smoke from chimneys also result in a high burn index. Thus in this work we classify brick kilns using mixture of spectral indices namely NDVI, EVI, NDBI, NDMI and BAI (see Appendix A). The proposed architecture is shown in Fig. 1.

Table 1: Table showing quantitative evaluation of the proposed approach with state-of-the-art methods. Top-3 ranking methods are in bold and, in particular, red (1st), violet (2nd) and black (3rd).

Testing Datasets	Network Architectures	Classification Score TP	TN	FP	FN	Duplicates	Precision	Recall	F1 score	Time (seconds)
Pakistan (Kasur)	Multi-spectral Approach	21	-	303	0	2	0.065	1	0.12	3
	Two-Stage Faster R-CNN	13	3090	1	6	0	0.93	0.68	**0.79**	195.5
	Two-Stage SSD	12	3090	1	7	0	0.92	0.63	0.75	179.5
	Kiln-Net (Two-Stage YOLOv3) Nazir et al. (2020)	19	3091	0	0	0	1	1	**1**	**162.5**
	Proposed (Multispectral Two-Stage Strategy)	21	-	1	1	2	0.95	1	**0.97**	**7.04**
India (New Delhi)	**Multi-spectral Approach**	52	-	636	0	12	0.076	1	0.14	**4**
	Two-Stage Faster R-CNN	37	4441	1	3	0	0.97	0.93	0.95	276.1
	Two-Stage SSD	38	4442	0	2	0	1	0.95	**0.97**	255.3
	Kiln-Net (Two-Stage YOLOv3) Nazir et al. (2020)	40	4442	0	0	0	1	1	**1**	**232.8**
	Proposed (Multispectral Two-Stage Strategy)	52	-	1	0	12	0.98	1	**0.99**	**8.16**
Afghanistan (Deh Sabz)	**Multi-spectral Approach**	406	-	1940	0	142	0.17	1	0.29	**8**
	Two-Stage Faster R-CNN	100	4097	5	22	0	0.95	0.82	**0.88**	553.2
	Two-Stage SSD	90	4094	8	32	0	0.92	0.74	**0.82**	416.4
	Kiln-Net (Two-Stage YOLOv3) Nazir et al. (2020)	85	4073	29	37	0	0.75	0.70	0.72	**279.6**
	Proposed (Multispectral Two-Stage Strategy)	198	-	17	66	142	0.92	0.75	**0.83**	**23.1**

3.1 Kiln Candidates via Multi-Spectral Classification

Based on the observation, kiln locations have low vegetation and moisture index whereas high build-up and burn area index, small or negative values of NDVI, EVI and NDMI with positive values of NDBI and BAI are classified as brick kilns (see Fig. 2 (i)). Thus our classification rule is defined as:

$$f(x,y) = \begin{cases} 1 & if\ NDVI < 0.2 \,\&\, EVI < 0.2 \,\&\, NDMI < 0 \,\&\, NDBI > 0 \,\&\, BAI > 5e^{-8} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where (x, y) is a location in latitude and longitude and function $f(\cdot)$ gives the classification decision. We set the threshold of 0.2 for NDVI and EVI as values > 0.2 are considered as healthy vegetation Huete et al. (2002). In second stage we apply orientation aware detector (YOLOv3 with θ value) for false removal and kilns bounding boxes.

3.2 Orientation aware detector: YOLOv3

Although the unique spectral characteristics of brick kilns distinguish them from other classes, however they are still confused with other small industries' chimneys as they exhibits similar spectral properties particularly NDVI and NDBI. We eliminates the resulting false detection via object detector. Unlike, urban housing, kilns in South Asia are usually build at sparse locations which is mostly surrounding by agriculture land. Instead they are usually built at arbitrary orientations. Thus

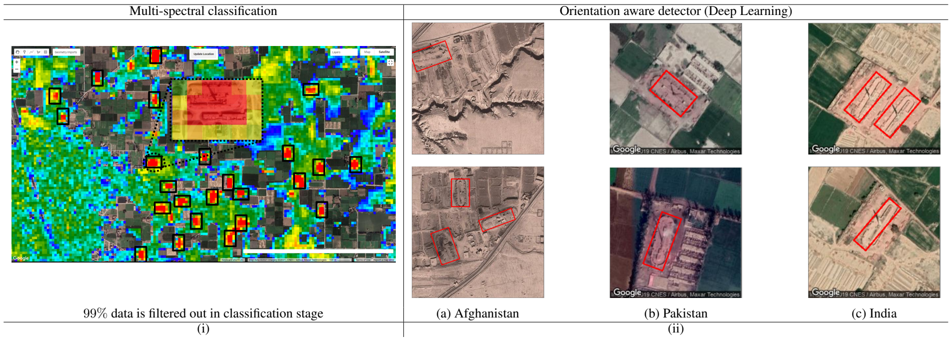

Figure 2: (i) Qualitative evaluation of our proposed Multi-spectral approach on region of Punjab, Pakistan. In first stage of our proposed two stage strategy, around $> 99\%$ data is filtered out and only positive potential candidates (red pixels images) are passed to second stage for localization. (ii) Qualitative evaluation of Orientation aware YOLOv3. (Satellite images courtesy Google Earth).

the detection of axis aligned kilns Misra et al. (2020); Nazir et al. (2020) is not applicable and results in increased missed detections. To address this problem, bounding box with orientation can be used Zhang et al. (2019). We then modified the YOLOv3 detector and added the neuron for regressing orientation with each bounding box. We only provided filtered images (potential candidates for kilns), obtained after classification stage, to the orientation-aware YOLOv3 model and obtained brick kiln bounding boxes as output results.

4 Quatitative and Qualitative Evaluation

For detailed experimentation of our proposed procedure, we choose evaluation dataset of three cities named Deh Sabz, New Delhi and Kasur from three different South Asian countries namely Afghanistan, India and Pakistan. For fair comparison we use the same geographical regions in these cities as defined in KilnNet paper Nazir et al. (2020). In addition, in order to generate training data for our object detector, we also manually annotated bounding boxes for each one of the 1300 brick kiln images from the 'Asia14' dataset Nazir et al. (2020).

We evaluated our proposed multispectral two-stage strategy with comparison to ResNet-152 He et al. (2016) classifier followed by the SOTA detector: Faster R-CNN Ren et al. (2015), SSD Liu et al. (2016) and YOLOv3 Redmon & Farhadi (2018). A coarse-to-fine strategy is proposed that aims to filter the bulk of the data using spectral properties while the detector is only applied on a small amount of positive detections to generate localization information while filtering false positives.

It can be seen from Table 1 that the overall F1-score of our proposed strategy is comparable with all the SOTA two-stage architectures. Simple multi-spectral approach is $54\times$ faster as compared to other strategies but results in many false positives and less F1-score. On the other hand our proposed approach is $21\times$ faster while retaining high F1-Score. Testing dataset images are 256×256 pixels for quantitative evaluation, If the image size is larger than 256×256 pixels, it is detected in two image patches. To deal with this issue, we describe the duplicates in Table 1. Our proposed architecture also outperforms in region of Afghanistan where kiln and non-kiln regions exhibit extremely low contrast as illustrated in our qualitative evaluation in Fig. 2 (ii) (see training parameters, Kiln-Net vs. proposed approach and compute cost comparison in Appendix B, C & D respectively).

5 Conclusion and Future Work

This paper proposes a fusion of spatio-temporal multi-spectral data with high-resolution imagery for detection of brick kilns within the "Brick-Kiln-Belt" of South Asia. To achieve this, we first perform classification using low-resolution spatio-temporal multi-spectral data from Sentinel-2 imagery utilizing spectral indices. Then orientation aware object detector: modified YOLOv3 (with θ value) is implemented for removal of false detections and fine-grained localization. Our proposed technique results in a $21\times$ improvement in speed with comparable or higher accuracy when tested over multiple countries. In future, we also aim to evaluate our proposed strategy and detection of illegal brick kiln activity during winter smog period on all over the "Brick-Kiln-Belt" of South Asia.

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Appendices

Appendix A Multi-spectral Indices

We use following five spectral indices to classify potential brick kilns on Google Earth Engine:

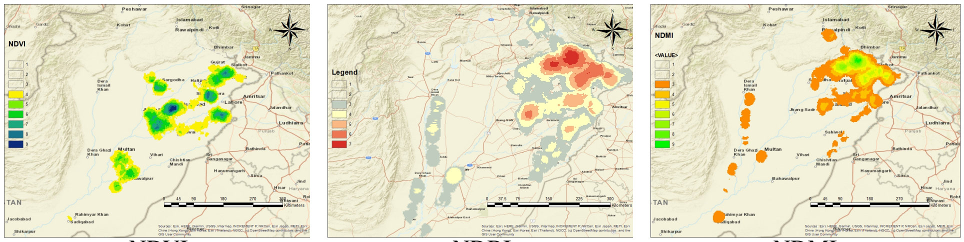
NDVI: Normalized Difference Vegetation Index (NDVI) quantifies vegetation from remote sensing imagery and is used in various applications such as tracking population changes Gillespie et al. (2019) and spatial changes of a region Ranagalage et al. (2018). Near Infra-Red (NIR) and Red bands of remote sensing images are used by the index. NDVI always ranges from -1 to 1. The equation to find NDVI is given in Eq. 2. Fig. 3 shows NDVI image at brick kiln locations in region of Punjab, Pakistan and Fig. 5 shows the zoomed version at one kiln location.

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{2}$$

EVI: The Enhanced Vegetation Index (EVI) is designed to minimize saturation and background effects in NDVI Huete et al. (2002). Since it is not a normalized difference index, compute it with this expression:

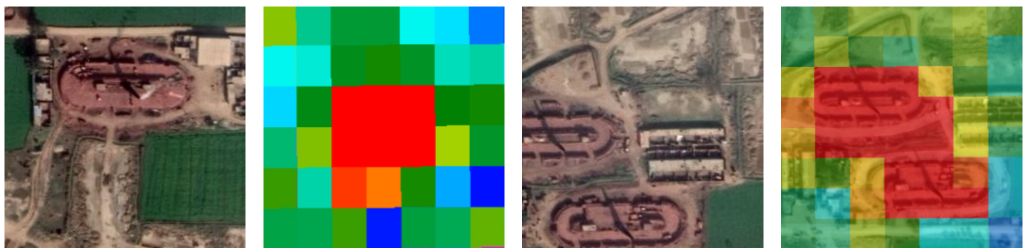
$$EVI = \frac{2.5 * (NIR - Red)}{NIR + 6 * RED - 7.5 * BLUE + 1} \tag{3}$$

NDBI: Normalized Difference Built-up Index (NDBI) is utilized to extract built-up features using remote sensing imagery. Its other applications include tracking spatial changes of a region Ranagalage et al. (2018) and to find relation between urban heat islands and land cover Ogashawara & Bastos (2012). Short Wave Infra-Red (SWIR) and Near Infra-Red (NIR) bands of remote sensing



NDVI NDBI NDMI

Figure 3: Spectral Indices of kiln locations of Punjab, Pakistan (Darker colour shows more index value).



(a) (b) (c) (d)

Figure 4: Exemplary brick kiln images as seen in the reference high resolution ($\frac{0.5\ meter}{pixel}$) imagery (a, c) [Courtesy: Digital Globe, Google Earth] and the low resolution ($\frac{10\ meters}{pixel}$) Sentinel-2 imagery (b, d) with Mean NDVI values with $Opacity = 1$ & 0.5 resp. [Image courtesy: Google Earth Engine].

images are used by the index. NDBI ranges from -1 to 1. The equation to find NDBI is given in Eq. 4 (see also Fig. 5).

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \tag{4}$$

NDMI: Normalized Difference Moisture Index (NDMI) is an index which is utilized to extricate water bodies from satellite imagery. Green and Short Wave Infra-Red (SWIR) bands of remote sensing images are used by the index. NDMI ranges from -1 to 1. The equation to find NDMI is given in Eq. 5. Fig. 5 shows NDMI image at a brick kiln location. NDMI is used to find relation between urban heat islands and land cover Ogashawara & Bastos (2012) as well as several other applications.

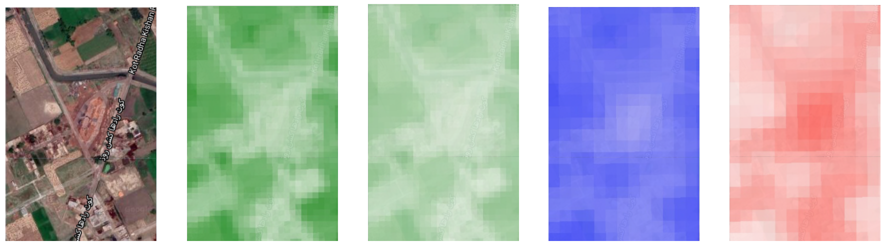
$$NDMI = \frac{Green - SWIR}{Green + SWIR} \tag{5}$$

BAI: The Burned Area Index (BAI) was developed by Chuvieco et al. (2002) to assist in the delineation of burn scars and assessment of burn severity. It is based on the spectral distance to charcoal reflectance. We used following expression to compute BAI.

$$BAI = \frac{1.0}{(0.1 - RED)^2 + (0.06 - NIR)^2)} \tag{6}$$

A.1 Qualitative analysis of spectral indices

The kiln surrounding has a low vegetation index (EVI, NDVI), low moisture index (NDMI) and a high built-up index (NDBI) (see Fig. 4 and Fig 5). Thus in this work we classify brick kilns using mixture of spectral indices namely Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Normalized Difference Built-up Index (NDBI), Normalized Difference Moisture Index (NDMI) and Burned Area Index (BAI).



Satellite Image EVI NDVI NDMI NDBI

Figure 5: Kiln surrounding has a low vegetation index (EVI, NDVI), low moisture Index (NDMI) and a high built-up index (NDBI); (Darker colour shows more index value) [Image courtesy: Google Earth Engine].

APPENDIX B HYPERPARAMETERS FOR THE TRAINING OF ORIENTATION-AWARE YOLOV3

Optimization method is Adam with an initial learning rate of 0.001. The learning rate increases by 0.1 if validation loss does not decline for 20 epochs. Instead of using fixed number of epochs, we used early stopping criteria which terminates the training process in case there is no improvement for 50 consecutive epochs.Unlike Zhang et al. (2019), in our work instead of regressing out the value of θ directly, the methodology of Vanilla YOLOv3 Redmon & Farhadi (2018) was retained but instead of using only one class for the detection of brick kilns, the following 5 classes were used: Kiln-0^o, Kiln-20^o, Kiln-40^o, Kiln-140^o, and Kiln-160^o which rotated the un-oriented bounding box (predicted by vanilla YOLOv3) by 0, 20, 40, 140 and 160 degrees respectively based on their orientation. Using quantized values of θ rather than regression reduces the search space and time taken in the training and testing/prediction stages.

APPENDIX C KILNNET NAZIR ET AL. (2020) VS. PROPOSED APPROACH

The Key differences between KilnNet Nazir et al. (2020) and our proposed approach are as follows (see Fig. 2):

- In the prior approach Nazir et al. (2020), high resolution DigitalGlobe imagery is used. Although use of high-resolution imagery improves the accuracy, as mentioned in Fig. 10 of Nazir et al. (2020), it requires 93 days to process the entire brick kiln belt (1551997 km^2) of South Asia. In this work we addressed this concern and proposed an improved approach that results in a $21\times$ improvement in speed with comparable or higher accuracy when tested over multiple countries. We achieved this by a strategy that uses low-resolution multi-spectral imagery as well as high-resolution imagery. The low-resolution multi-spectral pre-filter bulk of data without introducing missed detections. Thus the detailed analysis is only applied on a very small chunk of high-resolution imagery.
- In the prior methodology, two-stage gated neural network architecture consisting of a ResNet-152 classifier and a YOLOv3 detector is proposed. Our proposed coarse-to-fine strategy is also a two-staged approach with two major differences. In the first stage we replace CNN based classification on high-resolution (0.149 $\frac{meter}{pixel}$) data with fusion of low-resolution (10 $\frac{meter}{pixel}$) spectral indices to pre-filter bulk of the date followed by orientation-aware YOLOv3 detector on the filtered data. Furthermore, in this work we proposed a modified object detector that along with bounding boxes also produces the orientation information.
- In the previous methodology, classifier is selected by considering the class imbalance issues using F-Beta measure. In the proposed approach we select a classifier based on the observation that kiln locations have low vegetation and moisture index whereas high build-up and burn area index.
- The prior methodology takes 674 seconds to process three datasets in Table 1 of the paper. As a result of the above mentioned differences the proposed approach on the other hand reduces this compute time to 38 seconds only.

In nutshell, our coarse-to-fine strategy aims to filter the bulk of the data using spectral properties on Google Earth Engine while the detector is only applied on small amount of positive detections as to generate localization information while filtering false positives on Google Colab (Tesla T4). We evaluated our trained network on unseen dataset consisting of Kasur (Pakistan), New Delhi (India) and Deh Sabz (Afghanistan) for quantitative analysis. (see Table 1. If the brick kiln is larger than 256 x 256 it is detected in two image patches. To deal with this issue we describes the duplicates in Table 1.

APPENDIX D COMPUTE COST COMPARISON WITH STATE-OF-THE-ART

The detection of brick kilns by analyzing the spectral properties on Google Earth Engine takes approximately 3, 4 and 8 seconds to process Kasur (Pakistan), New Delhi (India) and Deh Sabz (Afghanistan), respectively. Then the orientation aware detector: YOLOv3 is ran on potential brick kiln locations including false positives on Google Colab Tesla T4 GPU. Each experiment is repeated 5 times to find the the average time on Google Colab which is 4.04, 4.16 and 15.1 to localize potential kilns in Kasur (Pakistan), New Delhi (India) and Deh Sabz (Afghanistan), respectively (see Table 1).