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Sand Mining Prediction Using Satellite Images

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ABSTRACT

This research paper focuses on the prediction of sand mining in different areas using satellite images. Illegal sand mining has emerged as a major environmental issue, affecting numerous regions worldwide. Sand mining nowadays has become a curse for society. It should be stopped before it creates a drastic problem for the universe. Some areas are widely affected by illegal sand mining resulting in floods and scarcity of resources. In this paper, YOLOv5(you only look once) is used to train the model. The collection of data is a major problem one is going to face at the start of the project, in the case of a satellite-based image. To feed the algorithm, a dataset is taken that clearly demonstrates the difference between legal and illegal sand mining. After collecting the data, the next step is to label the data and for labelling, several platforms can be used. In this research paper, LabelImg is used for the labelling part. A total of 5 classes were taken to identify the object which includes images of several objects that are used in sand mining. During the training of the model, several batches and a limited quantity of epochs are given for a good learning rate. Despite the limited size of the dataset, reaching an accuracy of 0.7 illustrates YOLOv5's outstanding efficacy. This result demonstrates the model's capacity to produce meaningful predictions while being trained on relatively small amount of data.. This study contributes to the growing research on remote sensing techniques and their application in stating environmental issues.

***Index Terms*— Sand mining, Yolov5, Labelimg, Classes, Batch, Epoch**

INTRODUCTION

Sand, a natural resource, is widely used in construction, manufacturing, and other industrial activities. However, the extensive extraction of sand from rivers, lakes, and coastal areas has become a universal problem, leading to severe environmental issues like degradation, ecological imbalance, and social conflicts. Illegal sand mining, driven by high demand and its lucrative profits, has Intensified these issues, causing irreparable damage to ecosystems and impacting livelihoods. Traditionally, monitoring mining activities have been challenging due to factors such as limited resources, vast mining areas, and lack of real-time data. However, innovations in satellite imagery nowadays offer promising solutions for identifying and tracking illicit sand mining activities. High-resolution satellite images provide detailed geospatial information that can be utilized to detect and monitor illegal activities with advanced accuracy and efficiency.

This research paper aims to present a thorough analysis of satellite imagery in combating illegal sand mining. By utilizing state-of-the-art satellite images and spatial analysis methods, one can identify illegal mining activities, and monitor changes in land over time. The integration of satellite imagery with the SAS-Planet and Yolo model enables the automatic detection of various equipment which are in use of sand mining and can site whether that's legal mining or not. The objectives of this study are as follows:

- To identify the areas vulnerable to illegal sand mining using satellite imagery.
- To develop an algorithm for the detection and monitoring of illegal sand mining activities.
- To quantify the volume of sand extracted illegally through remote sensing techniques.
- To assess the impact of illegal sand mining on the environment and surrounding ecosystems.
- To provide valuable insights for policymakers in formulating effective strategies to combat illegal sand mining.

By achieving these objectives, the main aim is to contribute to curb illegal sand mining and promote sustainable resource management. The findings of this research will provide valuable information to governments and environmental agencies involved in the conservation and regulation of sand mining activities.

LITERATURE REVIEW

Hongtao et al. [1] address the widespread issue of sand mining activity and its effects on water quality, ecosystem health, and dam safety. The researchers work on VIIRS DNB data to monitor the operations in the nighttime for illegal sand dredging vessels. The findings in the research clearly demonstrate a strong correlation between the results obtained from the VIIRS DNB data and those derived from daytime Landsat series data. The research also conducted an evaluation of government policies and proposed a method that evaluates both daytime and nighttime remote data to assess the intensity of sand mining. These findings provide valuable insights and management support for governments dealing with similar issues in water bodies worldwide. Addo1 et al. [2] demonstrate a study that aimed to assess the reliability of medium-resolution satellite images in mapping shoreline positions and estimating rates of change. Both manual and semi-automatic methods are used using multi-spectral satellite images. The data is taken over 25 years, in which shoreline positions were extracted for five-time points from 1986 to 2011. Ambiguity in shoreline positions ranges from ±4.1m to ±5.5m. Results showed that the Keta shoreline in Ghana is highly dynamic, with an average erosion rate of approximately 2m/year ±0.44m. This study demonstrates the potential of medium-resolution satellite images for estimation in shoreline change. Asokan and Anitha [3] present a comprehensive technique for processing satellite images. Satellite imaging is frequently used in real-time applications like navigation, geographic information systems, and the detection of agricultural land. This paper conducts a detailed comparison of machine learning-based image processing approaches and gives an extensive analysis of those techniques. Due to their big size, undesirable artefacts, and background information, these photographs do present some difficulties. This study examines various image processing methods, algorithms, and improved algorithms designed to get over their drawbacks. It also offers many indicators for assessing the effectiveness of image processing methods.

Remi Cresson's [4] study presents a framework that uses deep learning methods on geographical data and remote sensing photos. The Orfeo ToolBox and Tensor Flow, a high-performance numerical calculation library, both are widely known as open-source libraries. The framework displays computational efficiency independent of the hardware setup and permits the use of deep neural networks with no restrictions on picture size. This gives remote sensing professionals a useful tool to use deep learning techniques for image processing and geospatial data applications. Lior and Ivan [5] state that machine learning plays a crucial role in addressing the issue of deforestation, which results in the loss of forest areas equal to football fields every second. In this context, a competition focused on developing algorithms capable of analysing satellite images of the Amazon forest. This article details our participation in the SCCON and Planet Labs multi-label picture categorization competition. The approach in this paper involves the use of various Convolutional Neural Network (CNN) models to learn relevant features from the training images. ResNet50, our top-performing model, received an F2 score of 92.886%, whereas other models received an F2 score of 93.008%. Napiorkowska et. al [6] state that in computer vision, object identification in pictures has been extensively used, especially in industries like robotics and surveillance. With the development of deep convolutional neural networks (CNNs) and the availability of potent GPU processing capabilities, substantial advancements have been achieved in this area in recent years. This study shows how one of the networks created for the ImageNet competition may be modified and used for object recognition on satellite data. The research specifically focuses on finding things of interest in satellite photos, such as highways, palm trees, and vehicles.

Mark and Garry [7] state that applications including disaster response, law enforcement, and environmental monitoring heavily rely on satellite images. The use of conventional object identification and classification techniques to address this issue could be more effective and reliable. In this study, the data used is the IARPA Functional Map of the World (fMoW) dataset to apply deep learning approaches to the problem of object and facility detection in high-resolution, multi-spectral satellite images.

Arsalan et al. [8] present a study that demonstrates that agriculture, urban planning, and defence are not only the sectors that use computer vision applications for satellite images where object detection is critical. However, due to issues including poor pixel resolution, tiny item recognition in large-scale pictures, class changes, different object postures, object size variance, lighting, and thick backgrounds, object detection in satellite imagery presents a number of difficulties. According to the results, SIMRDWN obtains 97% accuracy on high-resolution pictures, whereas Faster R-CNN achieves 95.31% accuracy on images with standard resolution (1000*600). On a conventional resolution of 300 x 300, YOLOv3 obtains an accuracy of 94.20%, and SSD achieves an accuracy of 84.61%.

Jacob and Adam [9] developed an algorithm that explores the use of super-resolution methods on satellite images and assesses their effects on object detection algorithm performance. Creating enhancement levels of 2, 4, and 8 over five different resolutions ranging from 30 cm to 4.8 metres by using the Very Deep Super-Resolution (VDSR) architecture and a specially designed Random Forest Super-Resolution (RFSR) framework. Using the SIMRDWN object detection framework, which incorporates well-known methods like SSD and YOLO into a unified framework for effective object recognition in big satellite pictures, several unique detection models use both the original and super-resolved data. Results show that performance drops from a mean average precision (mAP) of 0.53 at a resolution of 30 cm to 0.11 at a resolution of 4.8 m. The best results are obtained by super-resolving the original 30 cm imaging to 15 cm, which increases mAP by 13–36%.

Austen et al. [10] developed a study that compares several state-of-the-art algorithms' detection accuracies and speeds when it comes to finding tiny automobiles and fracking wells for oil and gas in commercial electro-optical satellite images. The results show that single-stage detectors offer improved prediction speed than two-stage and multi-stage. However, two-stage and multi-stage versions show noticeably improved accuracies when it comes to identifying little autos, at the cost of some speed. As a benchmark for comparison, the paper also offers time statistics for the sliding window object identification technique.

Remis et al. [11] study explores how deep learning, open-source software, and free cloud computing can be used to solve a significant issue: automatically identifying and categorising surface mines and mining tailings dams in Brazil. The locations of mines and dams that were formally registered were made available by the Brazilian government's open data resource, and deep neural networks were trained and tested using TensorFlow 2 and Google Colaboratory on Multispectral Sentinel-2 satellite imagery. This study shows the potential of these publicly available technologies by proving their efficacy in creating cost-effective data science tools with significant social benefits.

Vaishnnave et al [12] describes how satellite imagery and remote sensing techniques have attracted a lot of interest with their usage in a variety of applications and scene classification. Deep learning's quick development has accelerated its adoption in industries like computer vision and natural language processing. Comprehensive assessments of datasets and techniques intended for classifying scenes in satellite photography are still lacking in reviews. By describing the idea and development of deep learning and giving a complete analysis of current advancements in this field, this paper is moving a step ahead to fill this gap. In conclusion, the paper identifies some research gaps in deep learning techniques and satellite imagery algorithms, highlighting areas requiring more exploration and development.

Anupama et al [13] demonstrate that the expansion of illegal landfills, particularly in developing nations, has become a pervasive problem that necessitates novel solutions. The use of remote sensing, deep learning, and computer vision techniques is required, but traditional manual detection methods are insufficient. This research proposes a highly detailed Landfill dataset collected from satellite images to meet this criterion. The work illustrates that adequate deep learning systems may locate landfills even with limited and constrained information. Waytehad et al [14] presents an overview of deep learning (DL) applications in making Satellite Image Time Series (SITS) predictions.

SITS uses satellite picture sequences to capture a region over time and has applications such as classification, segmentation, anomaly detection, and prediction. The research divides DL-based models into three types: recurrent neural network (RNN)-based models, hybrid models, and feed-forward models (convolutional neural networks and multi-layer perceptrons). The paper also discusses satellite image properties and significant SITS prediction applications such as weather forecasting, precipitation nowcasting, spatiotemporal analysis, and missing data restoration. The work intends to contribute to the knowledge and progress of DL approaches in SITS prediction by offering a complete assessment, supporting further research and practical applications in the field.

PROPOSED METHODOLOGY

A. Data Collection

The availability of high-quality data is critical for solving any object detection challenge, especially for satellite images. Many datasets obtained from satellite photos including the UC Merced land use dataset (Newsam & Yang, 2010), DeepSat (Basu et al., 2015), Urban Atlas, and BigEarthNet (Charfuelan et al., 2019) are employed in remote sensing applications. However, these datasets largely cover generic land categories, they are insufficient for training a YOLO algorithm to detect sand mining. As a result, the sole choice is to acquire a different dataset. Collecting a dataset of satellite images is a herculean task, especially when working on a specific task. Collecting a task desired dataset is a tedious task until and unless one has the satellite login credentials or working on a joint mission with the space agencies. As a preliminary step, a few significant mining areas were taken in Asia and Europe.

Several methods and tools are there, on the basis of which one can manually find and collect a dataset of satellite images. Some of them are USGS(United States Geological Survey), SAS Planet, ISCGM Global Map (International Steering Committee for Global Mapping) and Sentinel Satellite Data. Also, collecting datasets from these sources is still not easy, as one needs the exact latitude and longitude coordinates for satellite images. In the Asian region, talking about India especially, there is no particular distinction between legal and illegal sand mining items. So, the dataset taken into consideration for this paper is mostly collected for the European region. Also, most of the data is from seashore regions where legal sand mining takes place. A limited set of data is collected to train and test the detection of sand mining in different areas.

Fig 1. High-resolution satellite images showing sea-shore legal mining

B. Data Preparation

i) Image Processing Step

USGS and SAS Planet satellite images are present in many forms, where USGS gives historical satellite images, on the other hand, SAS Planet allows one to go live and capture images according to their specific requirement. Image processing steps involve resizing the images, converting images into greyscale images, and also enhancing the quality of the images. In this paper, a few or very minimal preprocessing steps were done, as the data required for the paper requires high-resolution satellite images and also this paper requires coloured images, to identify different sand mining equipment.

ii) Labelling Methodology

In order to label different objects in satellite images, several tools are there to label an image. Lableme, LabelImg, Hasty.ai and Labelbox are the name of some tools which can be used for labelling images. In this research paper, LabelImg is used for labelling images. A total of 5 classes were declared that include the labelling of both machines and equipment used in sand mining that can be seen in fig 2.

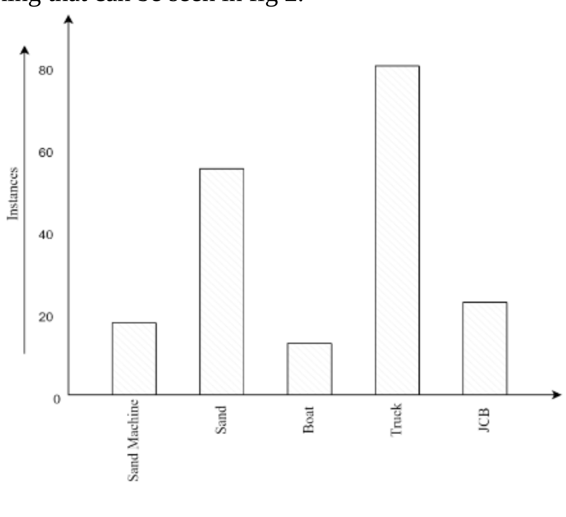

Fig 2. Number of instances per label

iii) Dataset Specifications

As the satellite images downloaded from different sources are very large. Also, large images were required to detect certain objects in images, i.e. to satisfy the criteria. So, there is no need of resizing the image. In fact, resizing can be done during training time so that model will take less time to train according to the number of epochs.

C. Machine learning model

In order to detect sand mining in the dataset, a pre-trained model is used named YOLO(You Only Look Once). A dataset of several high-resolution images was taken as clear from Fig 1. To perform the object detection model on the custom dataset, YOLO model is used for this research paper. This is an algorithm that detects and recognizes various objects in a picture (in real time). Object detection in YOLO is done as a regression problem and provides the class probabilities of the detected images. YOLO algorithm employs convolutional neural networks (CNN) to detect objects in real-time. As the name suggests, the algorithm requires only a single forward propagation through a neural network to detect objects. This means that prediction in the entire image is done in a single algorithm run. CNN is used to predict various class probabilities and bounding boxes simultaneously. YOLO algorithm improves the speed of detection as it can predict objects in real-time. YOLO is a predictive technique that provides accurate results with minimal background errors and has excellent learning capabilities that enable it to learn the representations of objects and apply them in object detection. The YOLO algorithm consists of various variants. Some of the common ones include tiny YOLO, YOLOv3 and YOLOv5.

In this research paper, YOLOv5 is used for detecting objects in satellite images. The principal task in an object detection model is to do the labelling. Several platforms are there to do labelling which are discussed in labelling methodology. Most annotation platforms support export at YOLO labelling format, providing one annotation text file per image. Each text file contains one bounding box (BBox) annotation for each of the objects in the image. The annotations are normalized to the image size and lie within the range of 0 to 1.

They are represented in the following format: < object-class-ID> <X center> <Y center> <Box width> <Box height>.

Several configuration files are created to run the YOLOv5 model which includes data configuration and model configuration files. The data configuration file contains the path regarding the train and validation data and also includes the count of the number of classes and names of the classes as well. This is a .yaml file and the model configuration file also includes a .yaml file which tells about the number of classes. Ultralytics supports several YOLOv5 architectures, named P5 models, which vary mainly by their parameters size: YOLOv5n (nano), YOLOv5s (small), YOLOv5m (medium), YOLOv5l (large), YOLOv5x (extra large). These architectures are suitable for training with an image size of 640*640 pixels. Additional series, that is optimized for training with a larger image size of 1280*1280, called P6 (YOLOv5n6, YOLOv5s6, YOLOv5m6, YOLOv5l6, YOLOv5x6). P6 models include an extra output layer for the detection of larger objects. They benefit the most from training at higher resolution and produce better results. After creating of all the configuration files and their execution, the next step is to train the model. In this paper, the epoch is set to more than the average amount required to train the data as the data required to train a YOLO model is very small and as an output, the main aim is to get the best prediction.

In order to train the models, the pan-sharpened mining dataset was split into 80% training and 10% validation set in a stratified manner. 10% of images were earmarked as the test set on which the performance of the models was evaluated. A draft of both the training and evaluation images can be seen below in fig 3.

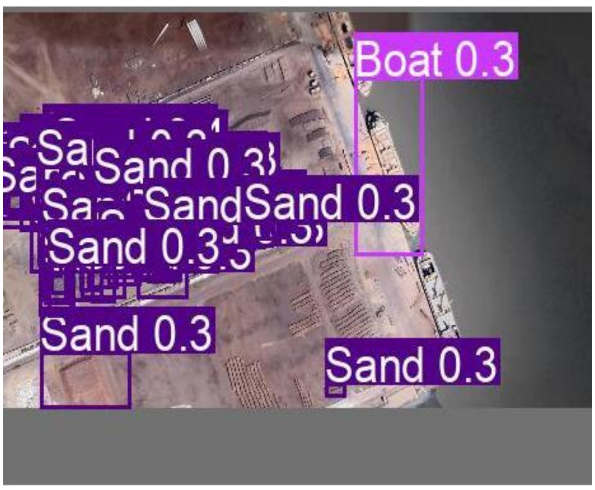

Fig 3. Trained images with labels

RESULTS

The performance of model is calculated using the metrics that are typical for a object detection problem. Several metrics are there for the evaluation of the model which includes class loss, box loss and object loss as well. All these metrics are calculated to check the performance of YOLO model on training dataset. Box_loss is a metrics which determines the bounding box regression loss (Mean Squared Error). A loss metric that measures how "tight" the predicted bounding boxes are to the ground truth objects (the labels on your dataset's images). A lower value indicates that model is improving for generalization and creating better bounding boxes around the objects the dataset has been labeled to identify. In Fig 4 that can be clearly seen that the value of box loss goes on decreasing as the number of epochs increases, which means model learning rate is improving with increase in the number of epochs. The blue line in the graph indicates the results accordion to the data where as the orange line shows the smooth transition that need to be according to data. Class loss also known as the classification loss is a loss metric, based on a specific loss function, that measures the correctness of the classification of all predicted bounding boxes. Each individual bounding box may contain an object class, or a background label. As seen in fig 4, during training there is difference between result and smooth line where as during validation there is hardly difference between result and smooth line which shows that all the classes are predicted clearly.

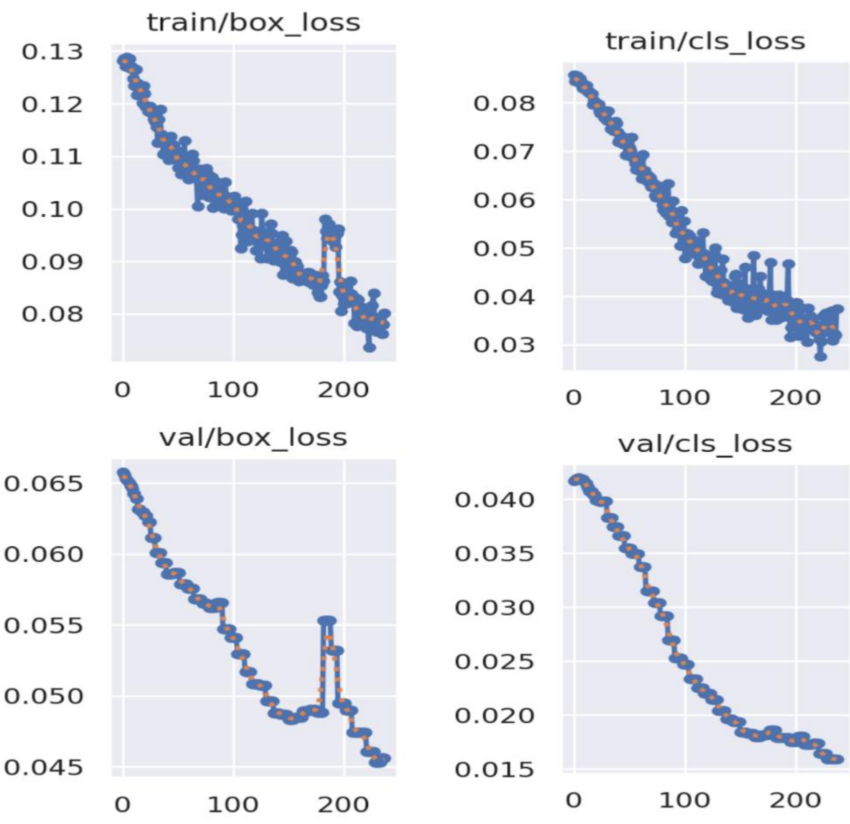

Fig 4. Graph of Box_loss and Class_loss trained model

CONCLUSION

The result demonstrates the potential for YOLOv5 to be a beneficial tool for jobs where collecting large datasets is difficult or time-consuming. Through the results that are obtained from the model, it can be shown that with remote sensing and appropriate models and methods, even a small dataset can be used to effectively detect mining with a considerable accuracy. A very useful finding of this research paper is that the model trained on very high-resolution images predicting the mining with a fair accuracy with low spatial resolution images. This transferability proves useful since most of the satellite images available have low spatial resolution. While this is suitable to detect mining that crop up legally or illegally and contains several types of equipment's, it would be useful to have datasets that help identify specific types of waste.

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REFERENCES

[1]. Hongtao Duan, Zhigang Cao, Ming Shen, Dong Liu, Qitao Xiao. Detection of illicit sand mining and the associated environmental effects in China's fourth largest freshwater lake using daytime and nighttime satellite images. https://doi.org/10.1016/j.scitotenv.2018.07.359

[2]. K. Appeaning Addo1, P.N. Jayson-Quashigah, K. S. Kufogbe. Quantitative Analysis of Shoreline Change Using Medium Resolution Satellite Imagery in Keta, Ghana. 10.5923/j.ms.20110101.01.

[3]. Anju Asokan, J Anitha. Machine Learning-based Image Processing Techniques for Satellite Image Analysis. 10.1109/COMITCon.2019.8862452.

[4]. Remi Cresson. A Framework for Remote Sensing Images Processing Using Deep Learning Techniques. 10.1109/LGRS.2018.2867949.

[5]. Lior Bragilevsky, Ivan V. Bajić. Deep learning for Amazon satellite image analysis. 10.1109/PACRIM.2017.8121895

[6]. Milena Napiorkowska, David Petit, Paula Marti. Three Applications of Deep Learning Algorithms for Object Detection in Satellite Imagery. 10.1109/IGARSS.2018.8518102

[7]. Mark Pritt, Gary Chern. Satellite Image Classification with Deep Learning. 10.1109/AIPR.2017.8457969.

[8]. Arsalan Tahir, Hafiz Suliman Munawar, Junaid Akram, Muhammad Adil, Shehryar Ali, Abbas Z. Kouzani, M. A. Parvez Mahmud. Automatic Target Detection from Satellite Imagery Using Machine Learning. https://doi.org/10.3390/s22031147.

[9]. Jacob Shermeyer, Adam Van Etten. The Effects of Super-Resolution on Object Detection Performance in Satellite Imagery.

[10]. Austen Groener, Gary Chern, Mark Pritt. A Comparison of Deep Learning Object Detection Models for Satellite Imagery. 10.1109/AIPR47015.2019.9174593

[11]. Remis Balaniuk, Olga Isupova, Steven Reece. Mining and Tailings Dam Detection in Satellite Imagery Using Deep Learning. https://doi.org/10.3390/s20236936.

[12]. M. P. Vaishnnave, K. Suganya Devi, P. Srinivasan. A Study on Deep Learning Models for Satellite Imagery.

[13]. Anupama Rajkumar, Tamas Sziranyi & Andras Majdik. Detecting landfills using multi-spectral satellite images and deep learning methods.

[14]. Waytehad Rose Moskolaï, Wahabou Abdou, Albert Dipanda, Kolyang. Application of Deep Learning Architectures for Satellite Image Time Series Prediction. https://doi.org/10.3390/rs13234822.