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7. Application of Research
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9. Conclusion and Future Scope
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Note: 1. Number of slides – 15-20 slides

2. Presentation time – 5-7 mins.
3. Questions – 2-3 mins.

Dr D Y Patil Institute of Engineering Management and Research, Akurdi, Pune

Department of Artificial Intelligence and Data Science

AY 2022-23 Semester I

Third Year Engineering

Subject : Seminar and Technical Communication

Topic : **Change Detection of Amazonian Alluvial Gold Mining Using Deep Learning and Sentinel-2 Imagery**

Name of Student : Sujit M. Nirmal
Roll Number: TEB22605

Name of Guide: Mrs. Kalyani Kute.

➢ Introduction and Motivation:

- Amazonian alluvial gold mining has caused severe deforestation, environmental degradation, and pollution in the Amazon rainforest. The expansion of mining activities in the region has led to widespread destruction of ecosystems, threatening biodiversity and indigenous communities. Remote sensing technology, such as Sentinel-2 imagery, offers a non-invasive method to monitor these activities and track changes in land cover. However, manually identifying and analyzing the changes in vast regions is labor-intensive. The application of deep learning, specifically Convolutional Neural Networks (CNN), offers a powerful tool for automating the detection of land use changes, making it more efficient and accurate.

- The motivation behind this research lies in the urgent need to protect the Amazon rainforest from illegal gold mining activities. By utilizing advanced AI techniques, we can develop a system capable of detecting changes in mining activity at an early stage, enabling timely interventions and mitigation efforts

- In most cases, effective outcomes should be prioritized over important clinical events such as symptom improvement, need for treatment, and prolonged patient quality of life. Current research often ignores these important variables, leaving AI's shortcomings exposed in real-world situations. A comprehensive plan to evaluate AI in healthcare should include patient feedback, clinical trials, and longitudinal studies to determine the true impact of AI-driven approaches.

Literature Survey:

	Paper Title	JournalName, Year	Objective	Methodology /Technology/ Algorithm used	Dataset/Features	Conclusion
1	**Change Detection in Deforestation Using Sentinel-2 Satellite Images**	Remote Sensing - 2020	▪ The study aims to track deforestation activities in tropical forests using remote sensing techniques.	▪ The researchers used machine learning techniques like Support Vector Machines (SVM) and Random Forest for land cover classification from satellite imagery.	▪ Sentinel-2 satellite images with temporal data on land cover.	▪ Machine learning methods are effective for deforestation detection and change analysis.
2	**Detection of Alluvial Gold Mining Using Multi-temporal Satellite Images**	Environmental Monitoring - 2019	▪ To develop an automated system to detect alluvial gold mining activities using satellite data.	▪ The study uses multi-temporal Landsat satellite imagery and employs pixel-based image classification techniques like k-means clustering.	▪ Landsat images capturing temporal data of deforestation patterns.	▪ Remote sensing technologies are highly accurate in detecting illegal mining activities.
3	**Deep Learning for Environmental Change Detection**	MDPI - 2021	▪ To explore the application of deep learning models for environmental change detection, focusing on deforestation and mining activities.	▪ The authors used Convolutional Neural Networks (CNNs) for image segmentation and classification of environmental changes in the Amazon region.	▪ Sentinel-2 satellite images, geospatial data. .	▪ Deep learning approaches significantly improve the accuracy of change detection. .
4	**Detecting Environmental Degradation Using Remote Sensing and Deep Learning**	IEEE - 2022	▪ (CNNs), Prophet Algorithm, Long Short-Term Memory Neural Networks.	CNN and U-Net architectures were used for image segmentation, with multi-temporal satellite data for detecting environmental changes.	▪ Sentinel-2 images, time-series data for change analysis. data.	▪ Deep learning models are efficient for detecting environmental degradation.

Sr No	Paper Title	Journal Name, Year	Objective	Methodology /Technology/ Algorithm used	Dataset/Features	Conclusion
5	**The Use of Machine Learning for Monitoring Deforestation in the Amazon**	Journal of Remote Sensing - 2021	▪ To assess the effectiveness of machine learning algorithms in detecting deforestation in real-time.	▪ Implemented various ML algorithms, including Decision Trees and Random Forests.	▪ Deforestation data derived from MODIS and Landsat imagery.	▪ The study indicates that machine learning can significantly reduce detection time.
6	**Assessing the Impact of Illegal Mining on Forest Cover in the Amazon**	Environmental Science & Policy - 2020	▪ To evaluate the environmental impact of illegal mining on forest cover changes in the Amazon.	▪ Combines remote sensing data with socio-economic analysis.	▪ Remote sensing imagery and socio-economic indicators from local surveys.	▪ Illegal mining has led to significant forest cover loss, impacting local communities. .

➢OBJECTIVES:

- Develop a deep learning model using satellite imagery to detect changes in alluvial gold mining activities in the Amazon region. The model should leverage the capabilities of Convolutional Neural Networks (CNNs) and other advanced techniques to identify mining sites and track their progression over time.

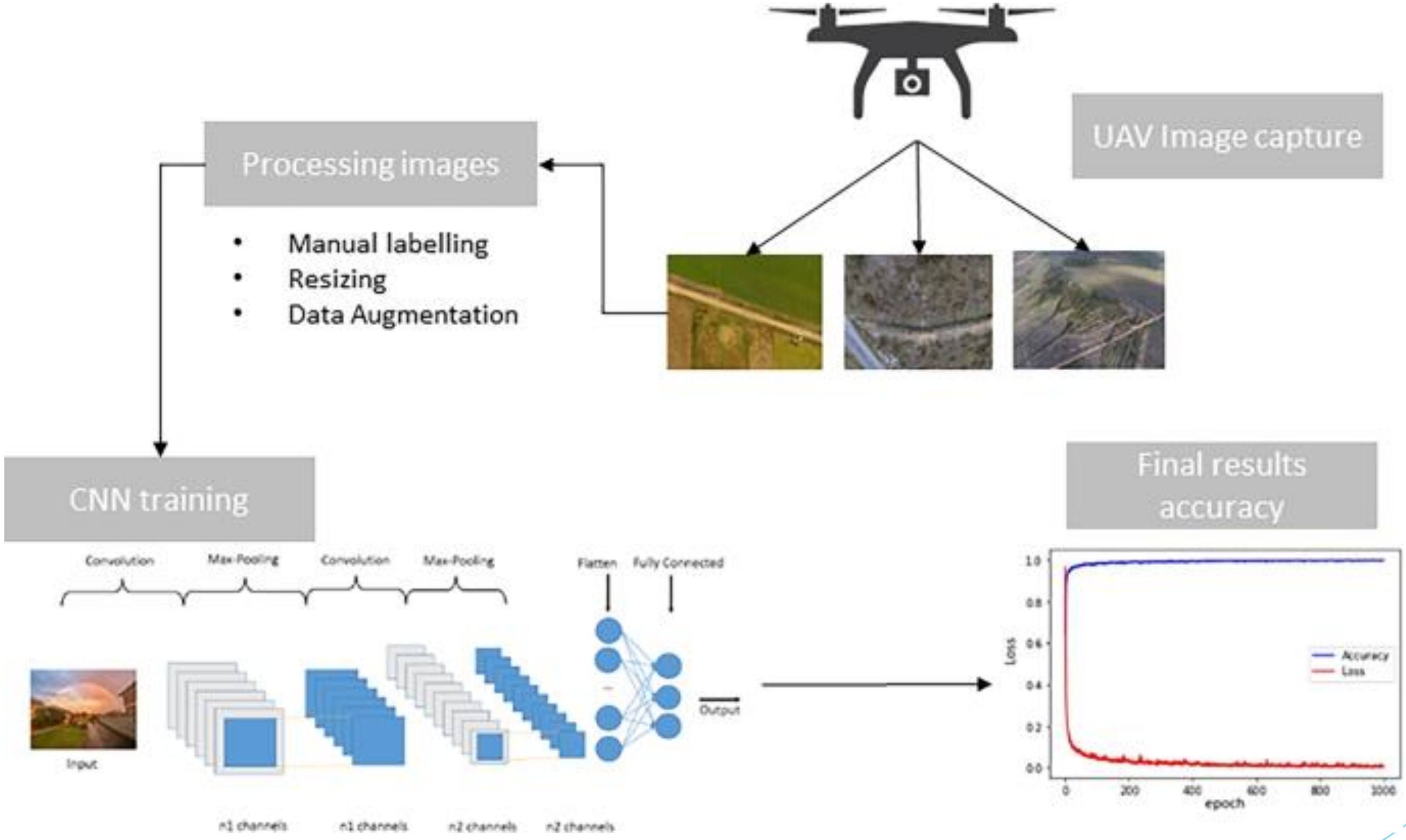
- Evaluate the accuracy and performance of the proposed deep learning model by comparing its results with traditional change detection methods (e.g., manual interpretation, thresholding techniques, or unsupervised classification). This analysis will demonstrate the model's effectiveness in detecting mining-induced changes in land cover.

- Analyze the spatial and temporal dynamics of alluvial gold mining activities in the Amazon basin. This involves studying the geographical expansion of mining operations, deforestation rates, and the environmental impact of such activities over different time periods using Sentinel-2 imagery.
- Propose a scalable and automated framework for continuous monitoring of environmental changes caused by illegal mining. This framework should be easily adaptable to other geographic regions and environmental issues and offer real-time monitoring capabilities using satellite data and AI-driven change detection models.

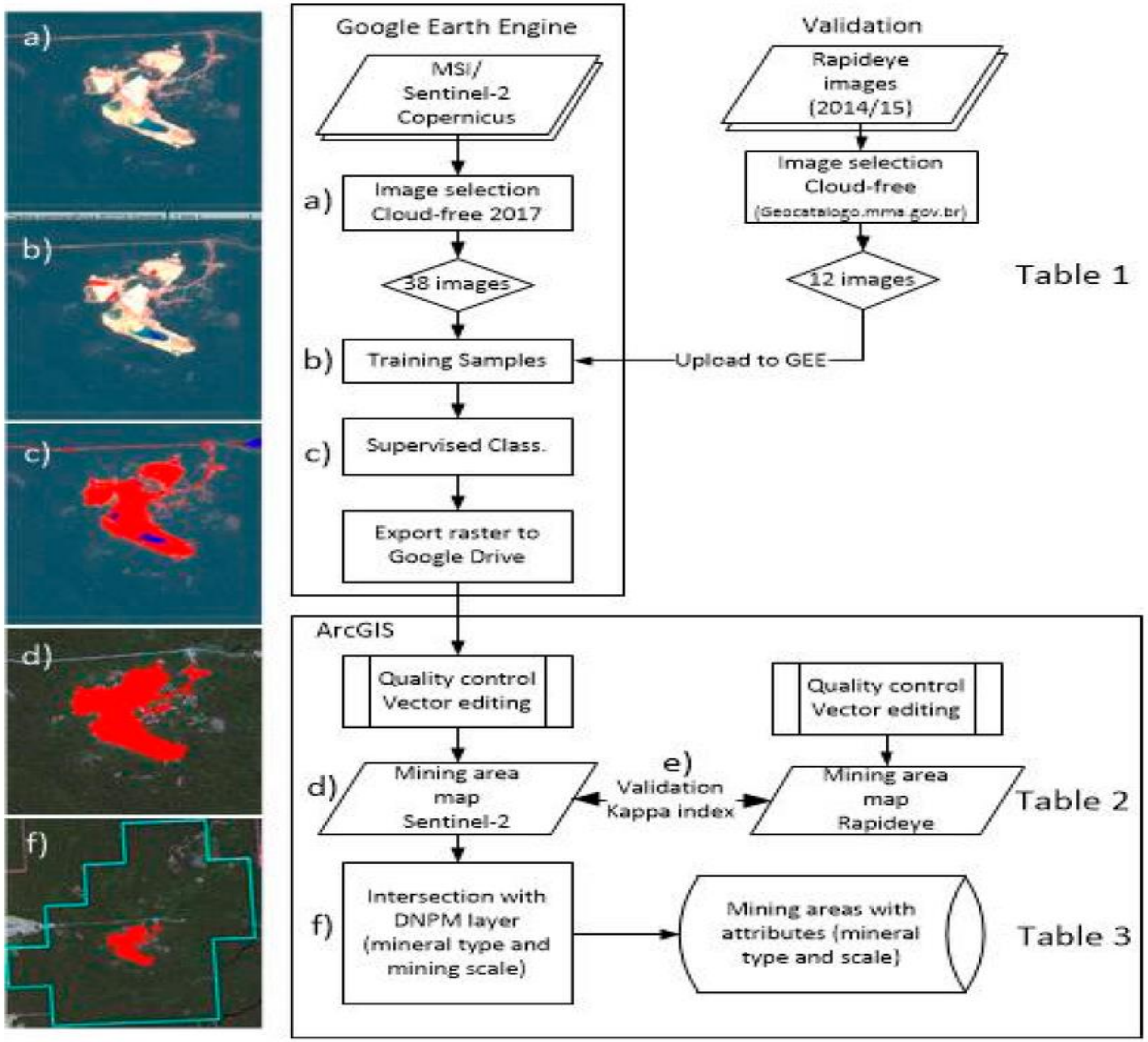
- Identify potential environmental consequences of alluvial gold mining in terms of deforestation, habitat loss, and soil degradation. This will involve correlating mining activities with environmental metrics to highlight the broader impacts on Amazonian ecosystems.

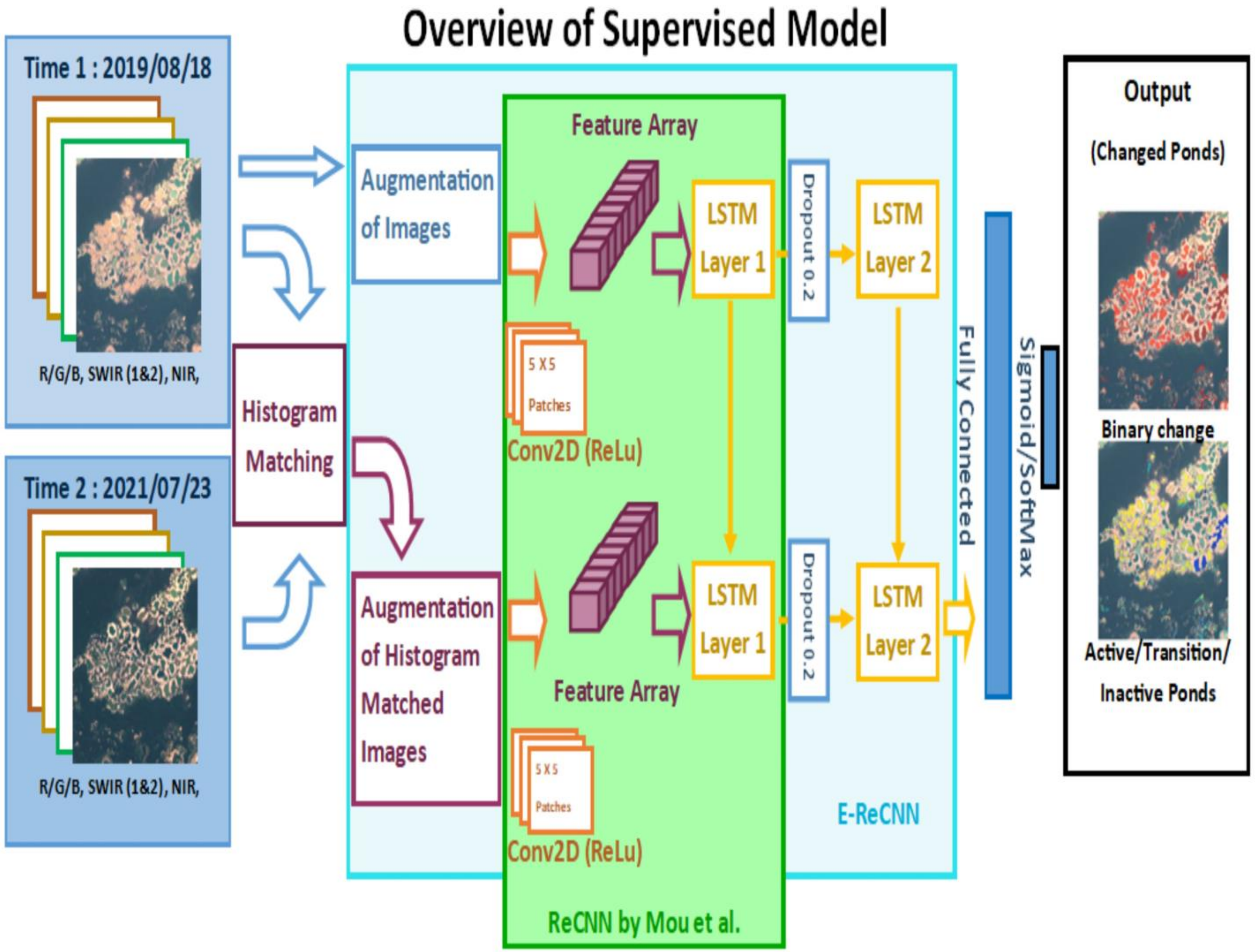
- Provide policy recommendations and insights for conservation efforts and sustainable management of the Amazon rainforest by utilizing the deep learning model's outputs. The goal is to help governments, NGOs, and local communities respond more effectively to illegal mining activities.

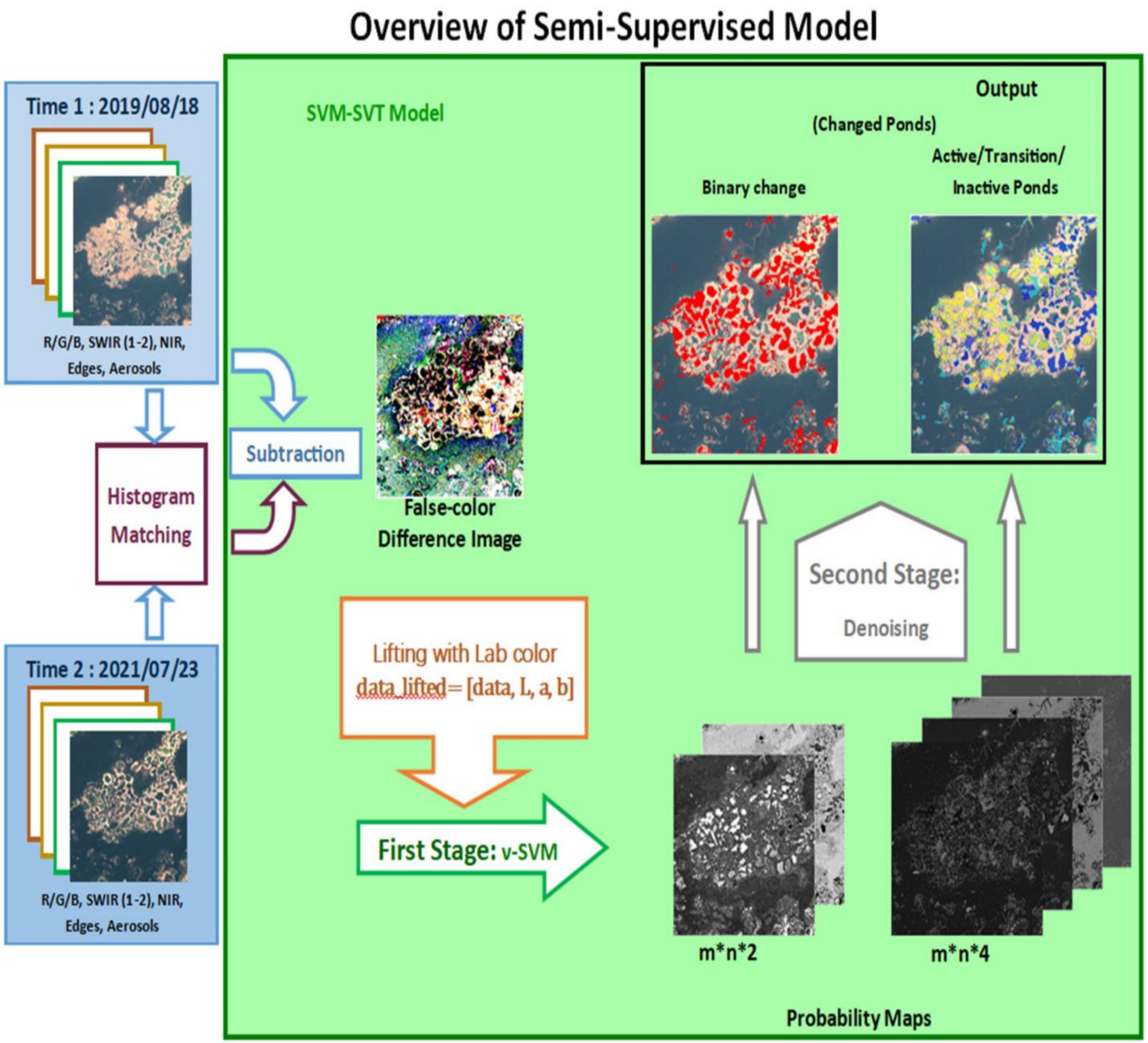
➢ System Architecture



➢ **Methodology (Algorithms/Flowcharts):**




Overview of Supervised Model
Time 1 : 2019/08/18
R/G/B, SWIR (1&2), NIR,
Time 2 : 2021/07/23
R/G/B, SWIR (1&2), NIR,
Histogram Matching
Augmentation of Images
Augmentation of Histogram Matched Images
Feature Array
5 X 5 Patches
Conv2D (ReLu)
LSTM Layer 1
Dropout 0.2
LSTM Layer 2
Feature Array
5 X 5 Patches
Conv2D (ReLu)
LSTM Layer 1
Dropout 0.2
LSTM Layer 2
ReCNN by Mou et al.
E-ReCNN
Fully Connected
Sigmoid/SoftMax
Output
(Changed Ponds)
Binary change
Active/Transition/
Inactive Ponds



Overview of Semi-Supervised Model
Time 1 : 2019/08/18
R/G/B, SWIR (1-2), NIR, Edges, Aerosols
Histogram Matching
Time 2 : 2021/07/23
R/G/B, SWIR (1-2), NIR, Edges, Aerosols
SVM-SVT Model
Subtraction
False-color Difference Image
Lifting with Lab color
data_lifted= [data, L, a, b]
First Stage: ν-SVM
Output
(Changed Ponds)
Binary change
Active/Transition/ Inactive Ponds
Second Stage: Denoising
m*n*2
m*n*4
Probability Maps

Results and Discussion:

- In the context of land-use change, particularly change associated with ASGM, understanding how features across a landscape change in size and reflectance can provide critically important information for conservation and environmental policy enforcement.

- We show that the extension of an existing ReCNN detects multi-temporal change across landscape features when compared to an existing semi-supervised model (SVM-STV). E-ReCNN outperformed SVM-STV and unsupervised methods considerably for both the focal region in Madre de Dios as well as out-of-sample test regions with respect to F1, precision, and recall. Notably, E-ReCNN generated greater F1, precision, and recall values for the detection of water occurrence and the multi-temporal change in spectral response for each pond feature. Estimates of precision and recall for pond sediment decreased (82.8% and 86.1%) and increased (70.6% and 87.3%) within the MDD, showing that this method is capable of generating multi-temporal feature-based change maps. These results provide evidence that this method has wide applicability to the field of environmental change detection and monitoring.

- One ongoing challenge in the use of satellite data for change detection related to how atmospheric conditions can cause complications when attempting to document finescale feature-oriented change. Although the major remote-sensing platforms, such as Landsat, Sentinel, and MODIS, are routinely processed and corrected via well-established and formalized techniques [54–57], persistent variability in surface reflectance from image to image requires careful consideration when monitoring temporal trends. We tested a number of data preprocessing approaches to understand how these challenges could be addressed and to understand how steps can be taken to improve machine learning model results. We found that histogram matching, which has primarily been used in remote sensing to denoise atmospheric effects on image mosaics [58,59] and recently in change detection [60–62], improved outcomes for the supervised model

Application of Research:

1. Environmental Monitoring and Conservation.

2. Real-Time Surveillance and Early Detection.

3. Regulatory Enforcement and Policy Implementation.

4. Geospatial Analysis and Land Use Planning.

5. Enhancing Community Engagement and Awareness.

6. Mining Impact Assessment and Damage Quantification.

➢ Limitations:

1. Data Availability and Quality.
2. Model Generalization.
3. False Positives and False Negatives.
4. Scalability and Computational Costs.
5. Environmental Factors
6. Interpretability and Trustworthiness of Models

➢ Conclusion and Future Scope:

❑ Conclusion:

- ❖ The use of **deep learning techniques** for detecting **illegal gold mining** offers a transformative solution to one of the most pressing environmental and socio-economic challenges, particularly in sensitive regions like the **Amazon rainforest**. By leveraging the power of **remote sensing**, **satellite imagery**, and advanced **deep learning models**, such systems can automate the identification and monitoring of illegal mining activities, providing a more efficient and scalable alternative to traditional manual methods.

- ❖ Deep learning models, especially those based on **Convolutional Neural Networks (CNNs)** and other neural architectures, demonstrate strong performance in extracting patterns from high-resolution satellite data.

❑ Future Scope:

- ❖ **Real-Time Detection and Monitoring:** Future research should focus on enhancing **real-time detection** capabilities through the integration of **satellite data** and **drone surveillance**. Developing systems that can monitor illegal mining activities continuously, with minimal delays, would allow for quicker responses from law enforcement agencies. Cloud-penetrating satellite technology and more frequent data collection (e.g., via drones) could improve the timeliness of these detections.

- ❖ **2 . Enhanced Data Sources:** Future work could explore **multi-modal data fusion**, combining satellite imagery with other sources like **LiDAR** (for forest canopy penetration), **thermal imaging** (to detect machinery heat signatures), or even **ground sensors**. This would provide a more comprehensive dataset to improve detection accuracy and reduce false positives and false negatives.

➢ Plagiarism report of Seminar report:

Plagiarism Detector.net

Sep 28, 2024

Plagiarism Scan Report

0% Plagiarized

100% Unique

Characters:7384	Words:987
Sentences:28	Speak Time: 8 Min

Excluded URL	None

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Thank You!