

# DEEP LEARNING-BASED APPROACH FOR ANNUAL CHANGE DETECTION AND OPEN PIT COAL MINE DETECTION USING SATELLITE IMAGERY

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**ABSTRACT:** This study introduces a novel deep learning-based method for detecting open pit coal mines in medium high (MH) resolution satellite imagery and analyzing annual variations in coal mining areas. The study aims to monitor and precisely identify coal mines, given their vital function as a primary energy source and a significant contributor to greenhouse gas emissions. The proposed method employs the U-Net architecture and ResNet 34 as its backbone for accurate detection and classification. The applied dataset consists of multispectral imagery from Sentinel-2 and synthetic aperture radar (SAR) imagery from Sentinel-1. Manual labelling of known coal mine locations using mining data as a reference, subdividing Sentinel image patches for training U-Net convolutional neural networks (CNNs) to classify coal mine and non-coal mine areas, and training and testing U-Net architecture and ResNet as a backbone deep learning model are the three essential steps involved in the process. The classification accuracy of the coal mining detection deep learning model is 97%, and the kappa value is 0.91. Preliminary results indicate that the investigation demonstrates the evolution of coal mining from 2016 to 2021, with an increase of over 40% in coal mining area in 2019. In 2017 and 2020, the area mined for coal will decrease. Variations in annual coal mining variations emphasize the significance of replanting efforts. The proposed method uses deep learning and satellite imagery to provide an accurate and efficient solution for detecting and monitoring open-pit coal mines. Incorporating artificial intelligence into dynamic coal mining activities yields valuable insights that aid in making informed decisions for sustainability.

## 1. INTRODUCTION

### 1.1 Background

Coal has made a great contribution to world electricity production. The International Energy Agency (IEA) estimates that global coal consumption in 2022 will be over 8 billion metric tons. Coal power accounts for 37% of the world's electricity production, or the equivalent of 44,000 terawatt-hours [1]. Coal mining in Tapin Regency, South Kalimantan, has contributed to local economic activity and 26.47% of the gross domestic product.

However, Coal mining, in particular, is one of many activities that can have significant environmental impacts [2]. One of the biggest causes of methane emissions is coal mining. According to the U.S. Environmental Protection Agency (2019), coal mines account for 11% of all global methane emissions, while the global emission inventory EDGAR v4.3.2 places the fugitive CH<sub>4</sub> emissions of coal mines at around 13% of the total anthropogenic methane budget [3]. Study from Greenpeace Indonesia, approximately 3,000 kilometers, or approximately 45 percent of South Kalimantan's rivers, travel through a coal mining area and may be contaminated by coal mine hazardous waste. Greenpeace analyzed 29 samples, 22 of which were from tailings basins and ex-mining pits in five coal mining concessions. South Kalimantan has a pH level significantly below the government's standard. Eighteen samples from the tailings storage pond have a pH below four and contain significant concentrations of nearly all metals [4]. As a result, coal is like double edge sword. Both the positive and negative effects of coal mining need to be monitored.

Monitoring coal mining is important, especially with remote sensing. Remote sensing technology is essential in monitoring mining pollution, geological disasters, and mining activities. It is also used to determine the size and location of mines [5]. Remote sensing, especially Synthetic Aperture Radar (SAR), can be used in any weather, around the clock, and at long range [6]. The developments in neural networks and deep learning techniques have proved successful in land use and land cover classification task [7] on remote sensing data. Combining deep learning with remote sensing data can increase effectiveness and reduce costs more efficiently than manual outcrop techniques [8]. Therefore, continuous monitoring of open-pit coal mining is of utmost importance and enables efficient planning and management of mining by recording environmental impacts and enforcing relevant regulations [6].

Utilising remote sensing data, air pollution, field measurements, and meteorological data as predictors, a recent study [9] estimates and compares spatial empirical models based on Land Use Regression (LUR) to estimate the number of respiratory disease patients. The objective of another study [10] is to provide an up-to-date overview of URIs caused by coal mine dust in light of its medical benefits. Another study [6] concentrates on the use of SAR to monitor mining activities, particularly with the Normalised Difference Activity Index (NDAI), which can provide temporal decorrelation in coal mining. The study on LULC in coal mining areas [11] examines the impact of coal mining on LULC at the V. D. Yalevsky coal mine in Russia from 1992 to 2019.

This study aims to develop a deep learning approach for monitoring annual change in surface coal mines using a U-Net architecture and both multispectral and SAR imagery.

## 1.2 Related Work

### 1.2.1 Deep convolutional neural networks for surface coal mines determination from sentinel-2 image

The present study investigates the utilization of deep convolutional neural networks (CNNs) for the precise identification of surface coal mines in Sentinel-2 satellite imagery. The research employs the VGG19 architecture within a deep learning framework to accomplish this objective. One noteworthy discovery in this study is to the comparison between the conventional Maximum Likelihood Classification technique and the more sophisticated Deep Learning VGG19 Architecture. This comparison underscores the superior performance of the deep learning methodology in successfully identifying surface coal mines from the Sentinel-2 dataset, which has 13 spectral bands. This paper provides significant contributions to the understanding of the effectiveness of deep learning techniques, particularly the VGG19 architecture, in improving the precision and efficiency of surface coal mine detection in remote sensing applications [12].

### 1.2.2 Understanding deep learning in land use classification based on Sentinel- 2 time series

The present literature review examines the application of deep learning methods in the classification of land use, specifically focusing on the usage of Sentinel-2 time series data. The aforementioned statement highlights the importance of interpretability in prediction, especially in domains such as public budget management and policy compliance. The authors emphasize that the absence of interpretability in deep learning models hinders their acceptance, as the justification for model decisions remains unverifiable. This research focuses on the utilization of a recurrent neural network to classify land usage within the framework of the European Common Agricultural Policy. The primary aim of this study is to improve the understanding of network activity and discover crucial factors that can predict outcomes in the classification process. The findings indicate that the utilization of red and near-infrared bands from the Sentinel-2 satellite is of utmost importance in obtaining essential data. Moreover, it is seen that features derived from acquisitions during the summer season exert the greatest influence. The authors of this study admit that deep learning plays a significant role in supporting the Resource-efficient Europe program. However, they also recognize that there are issues associated with interpretability in this context. Deep learning models are frequently perceived as opaque systems that exhibit great levels of accuracy but lack transparency. This research posits the importance of not only providing accurate reports but also elucidating the internal workings of classifiers in order to facilitate informed decision-making. The enhancement of interpretability in algorithms, such as BiLSTMs, is a topic of discussion in relation to memory utilization. In summary, this study provides a thorough examination of the application of deep learning techniques in the classification of land use using Sentinel-2 data. This statement underscores the significance of interpretability and the difficulties that deep learning encounters within this particular framework. The alignment of deep learning with sustainability objectives underscores its significance, but, the effective deployment of this technology necessitates substantial improvements in interpretability [13].

## 2. METHODOLOGY

### 2.1 Deep Learning Approach

Deep learning is a subset of machine learning techniques based on artificial neural networks and representation learning. LeCun (2015) states that learning can be supervised, semi-supervised, or unsupervised. U-Net is a semantic segmentation architecture. It comprises of a path that contracts and a path that expands. The path of contraction conforms to the standard architecture of a convolutional network [14].

As shown in Figure 1, the deep learning architecture for this research employs the U-Net model and ResNet-34 as the backbone model. ResNet, or Deep Residual Network, is an artificial neural network (ANN). This architecture was devised to address issues with deep learning training, which typically takes a long time and is restricted to a certain number of layers. The complexity of ResNet is due to the use of skip connections or shortcuts. The ResNet model is implemented by omitting connections to two to three architecture-specific layers containing ReLU and batch normalisation.

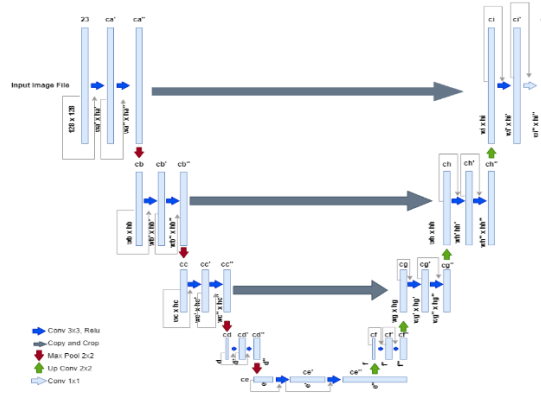


Figure 1. U-Net with ResNet Deep Learning Architecture

## 2.2 Pre-Processing Satellite Imagery

### 2.2.1 SAR Pre Processing Workflow

The pre-processing workflow of SAR from Sentinel-1 GRD data. The figure 2 shown SAR consists of 7 processing steps explained in a distinct part below and intended to minimize error propagation in the following operations [15]. The proposed pre-processing workflow for Sentinel-1 SAR data involves several essential steps. It starts by applying accurate orbit data to improve geolocation. Thermal noise removal reduces distortion, while border noise removal corrects artifacts at image edges. Calibration converts pixel values to calibrated backscatter. Speckle filtering enhances image quality, and Range Doppler terrain correction compensates for viewing angle distortions. Finally, conversion to dB provides a more intuitive backscatter representation. This workflow enhances image accuracy, clarity, and geolocation, enabling better analysis and interpretation of Sentinel-1 SAR data. Sigma dB from VV Polarization process to make the Gray Level Co-Occurrence Matrix (GLCM).

GLCM determines the likelihood that, inside a specified window, a pixel with grey value  $i$  will be located a specific distance and angle from a pixel with grey value  $j$ . For each of the eight directions, GLCM matrices were made and averaged to create the omnidirectional textures [16].

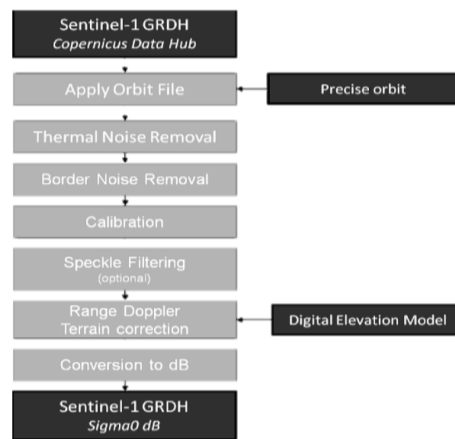


Figure 2. Sentinel-1 Ground Range Detected (GRD) pre-processing workflow. [15]

### 2.2.2 Gray Level Co-occurrence Matrix (GLCM)

The Gray-Level Co-occurrence Matrix (GLCM) offers second-order statistical measures for the purpose of extracting texture features. The algorithm computes the likelihood of a pixel with a gray value  $i$  appearing at a specific distance and angle from another pixel with a gray value  $j$  within a defined window. In order to generate omnidirectional textures, the process involved the creation of GLCM matrices for each of the eight directions, which were afterwards averaged [16].

The averaged GLCM retains the presence of directional structures, albeit with less impact due to the process of averaging. The inclusion of the specific orientation of structures is no longer a component of the average Gray-Level Co-occurrence Matrix (GLCM). The remaining parameters are often chosen by manual selection or optimized for a particular study and afterwards held constant. The calculation of individual scalar texture features can be derived from the GLCM using the following formula.

$$ASM = \sum_{i=1}^k \sum_{j=1}^k S_{(i,j)}^2 \quad (1)$$

$$Contrast = \sum_{i=1}^k \sum_{j=1}^k (i-j)^2 S_{(i,j)} \quad (2)$$

$$Correlation = \frac{\sum_{i=1}^k \sum_{j=1}^k (i - \mu_x)(i - \mu_y) S_{(i,j)}}{\sigma_x \sigma_y} \quad (3)$$

$$Dissimilarity = \sum_{i=1}^k \sum_{j=1}^k [i-j] S_{(i,j)} \quad (4)$$

$$Energy = \sqrt{ASM} \quad (5)$$

$$Entropy = - \sum_{i=1}^k \sum_{j=1}^k S_{(i,j)} \log_{10} [S_{(i,j)}] \quad (6)$$

$$Homogeneity = \sum_{i=1}^k \sum_{j=1}^k \frac{S_{(i,j)}}{1 + (i-j)^2} \quad (7)$$

$$Mean = \sum_{i=1}^k i(S_{(i,j)}) \quad (8)$$

$$Variance = \sum_{i=1}^k S_{(i,j)} (i - Mea)^2 \quad (9)$$

$$Maximum Probability = Max(S) \quad (10)$$

### 2.2.3 Spectral Indices Calculation

In this research, three spectral indices were derived to characterize the spectrum features of coal mining areas for all segmented objects. These indices are essential for analysing and monitoring environmental changes associated with coal mining activities. The three indices are the normalized difference coal index (NDCI), the normalized difference vegetation index (NDVI), and the built-up area index (BAI).

By utilizing these spectral indices, researchers can gain valuable insights into the distribution of coal mining areas. This information is vital for monitoring the coal mining change. The formula for NDVI, NDCI, and BAI is as follows:

$$NDVI = (NIR - Red) / (NIR + Red) \quad (11)$$

$$NDCI = (NIR - SWIR1) / (NIR + SWIR1). \quad (12)$$

$$BAI = (Blue - NIR) / (Blue + NIR). \quad (13)$$

## 2.3 Dataset

### 2.3.1 Area of Interest

The study area used in this study was three coal mining area on Tapin Regency in South Borneo, Indonesia, Tapin Regency is located between 2°32'.43" and 3°00'.43" south latitude and between 114°46'.13" - 115°30'33" east longitude (BPS, 2021). Tapin is one of the biggest coal producing areas on South Borneo, the coal mining area are Lokpaikat Coal Mining Area, South Tapin Coal Mining Area, and Binnang Coal Mining Area as shown in figure 3.

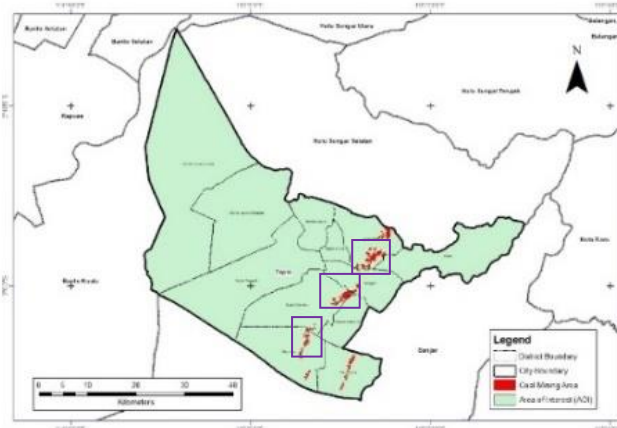


Figure 3. Tapin Regency area of interest

### 2.3.2 Annual Imagery Collection Dataset\



Figure 4. Annual Dataset with 23 bands from Sentinel 2 and Sentinel 1

The annual imagery dataset from 2016 to 2021 for deep learning uses 23 bands from multispectral imagery that contains RGB, NIR, VNIR, and SWIR with three indices like NDVI, NDCI, BAI (12 bands), and SAR from composite polarization  $\sigma_{VV}$  with GLCM (total of 11 bands) as shown in figure 4.

## 3. RESULT AND DISCUSSION

### 3.1 Deep Learning Classification

The result from the U-Net deep learning model trained for identifying two classes, coal mine and no coal mine, The model took 2 hours and 20 minutes for training with a system of NVIDIA RTX 2060 GPUs with a 6 GB memory capacity. The U-Net deep learning model depicted in Figure 5 was constructed using 205 tiles with 128 x 128 pixels per image and 200 epochs. On a validation dataset containing two classes and 23-band imagery.

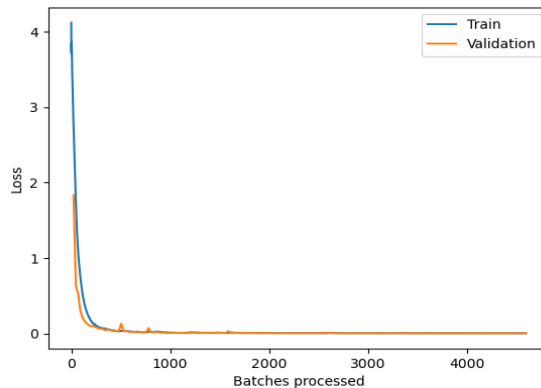

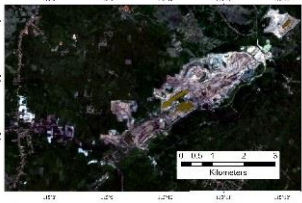

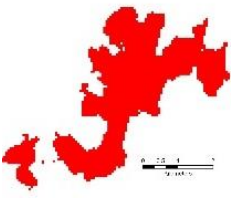
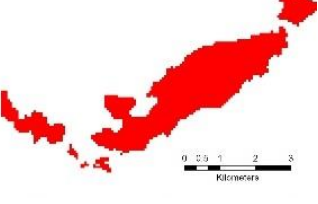

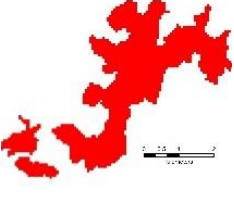
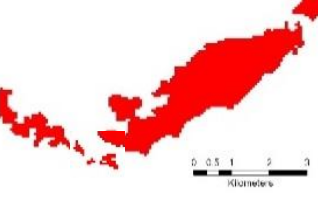
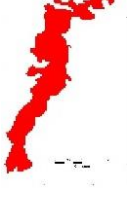


Figure 5. U-Net Model Training and validation loss

As can be seen in Table 1, the classification results are similar to the reference based on the topographic map and visual interpretation. Labels for coal mining included open cuts, tailings dams, waste rock dumps, trees inside the coal mining area, and water ponds.

Table 1. Coal Mining Area Deep Learning Classification

Category	Lokpaikat, Indonesia	South Tapin, Indonesia	Binuang, Indonesia
Imagery			
Result			
Reference			

As ground truth, the topographic map and the coal mines that can be seen are used to evaluate how well the model classifies. The overall accuracy of a deep learning model based on the confusion matrix shown in Table 2 is 97.4%, with a Kappa value of 0.91. The deep learning model has greater accuracy in non-coal mining areas. Usually the area of interest is covered by cloud, which can be a disturbance to the classification. A deep learning model in another area has an overall accuracy of 95%.

Table 2. Confusion Matrix

Tapin, Indonesia	Reference (Pixels)		
	Coal	No Coal	User
Coal Mine	4190	326	4516
No Coal Mine	378	21786	22164
Producer	4568	22112	26680

Overall Accuracy = 97.4%, Coal Mine User Accuracy = 92.8%, No Coal Mine User Accuracy = 98.3%, Coal Mine Producer Accuracy = 91.7%, No Coal Mine Producer Accuracy = 98.5%, Kappa = 0.91

### 3.2 Annual Coal Mining Change

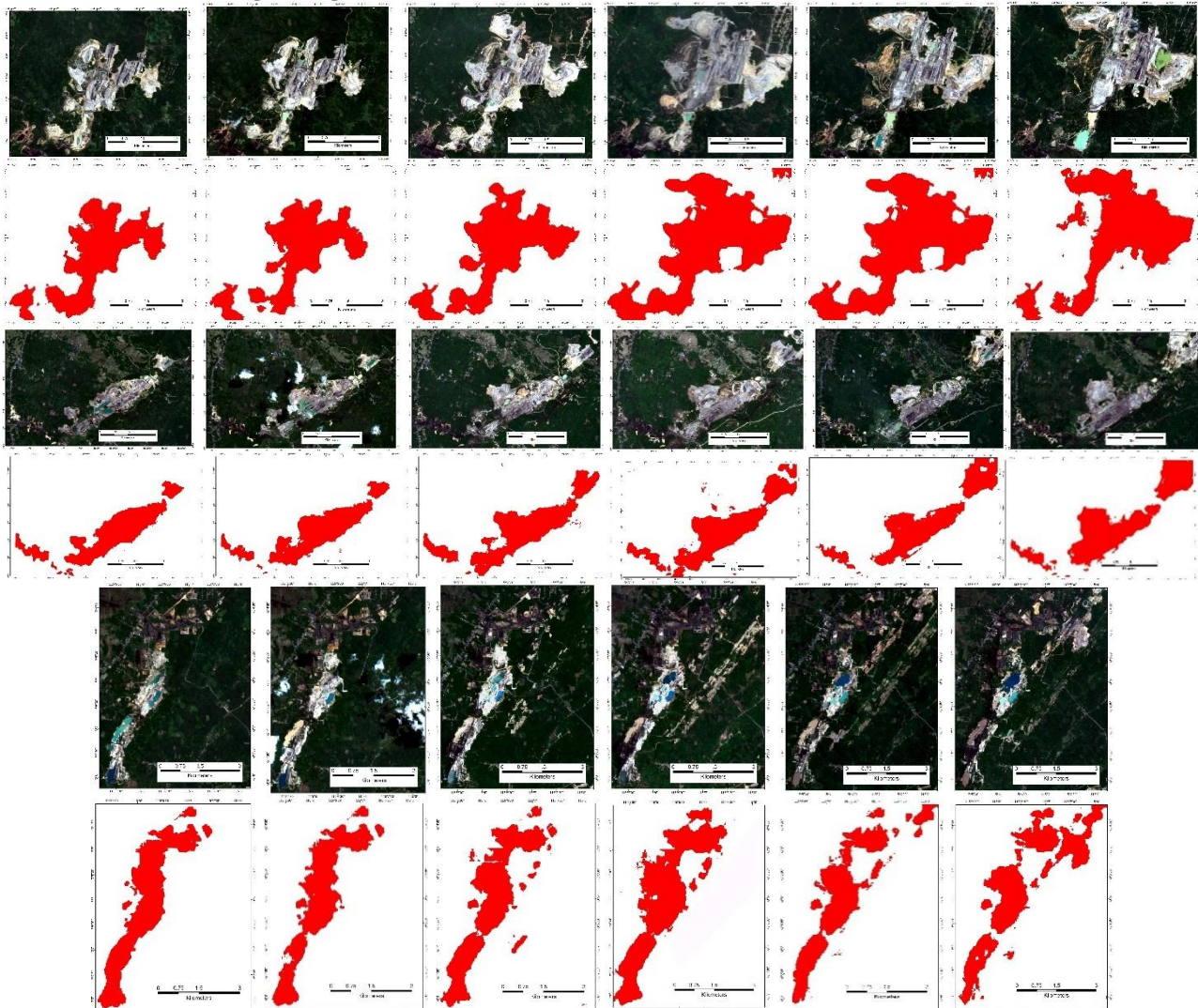


Figure 6. Annual Imagery (Top) and Classification (Bottom) of Coal Mining Area Change from 2016 to 2021(left to right) on Lokpaikat, South Tapin, and Binuang Coal Mining

During the time span between 2016 and 2021, notable transformations have been documented in the coal mining regions of Lokpaikat, South Tapin, and Binuang, as depicted in Figure 6. Significantly, the year 2019 represented a pivotal stage in coal mining operations, as shown by figure 7. It is noteworthy that Binuang stood out as the region with the most extensive mining activity, including around 1033.72 hectares. The region of South Tapin demonstrated a close adherence to the coal mining industry, encompassing an approximate land area of 1391.36 hectares. In contrast, Lokpaikat showcased the most expansive coverage of coal mining activities, spanning an estimated land area of 1793.28 hectares.

Between the years 2016 and 2021, significant changes occurred within the coal mining regions, resulting in a state of dynamic transformation. These modifications involve a range of elements, such as changes in land cover, differences in terrain shape, and overall transformations in landscape characteristics. It is probable that the coal mining operations have resulted in alterations to the land's surface, which may have caused surface disruptions, alterations in topography, and shifts in vegetation patterns. The potential modifications may give rise to various implications for the environment, ecosystems, and nearby communities.

The significance of monitoring and assessing the observed discrepancies in coal mining regions, namely Lokpaikat, South Tapin, and Binuang, is emphasized. Comprehensive evaluations of land cover modifications and topography changes are essential in order to comprehend the effects of coal mining operations on these particular areas. The aforementioned trend in the most prominent coal mining region in Binuang during the year 2019 underscores the imperative of ongoing surveillance and conscientious administration of mining operations in order to uphold sustainable practices and avoid detrimental environmental impacts.

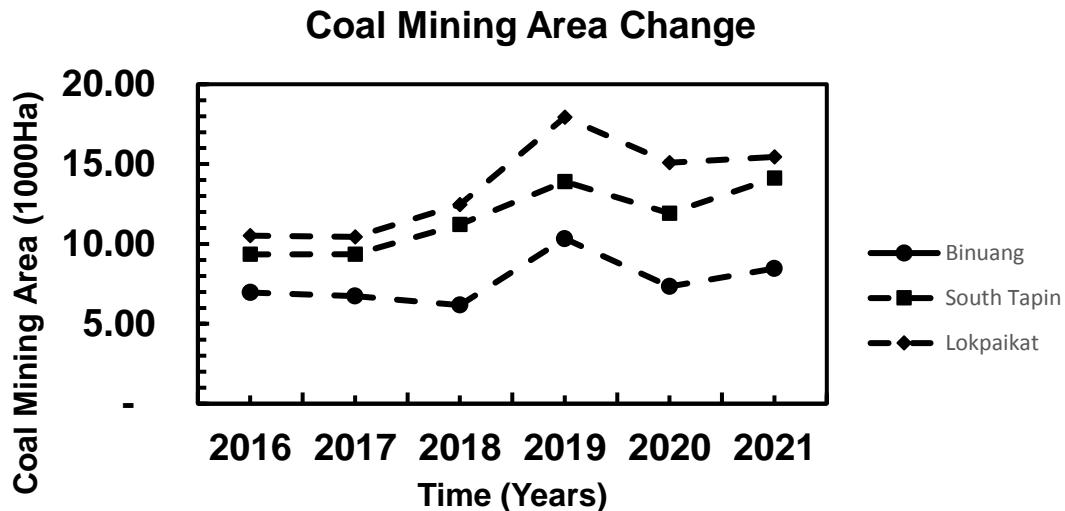


Figure 7 Annual Quantitative Coal Mining Area Change on Lokpaikat, South Tapin, and Binuang Coal Mining

This research focus on annual coal mining change from 2016 to 2021 on three different coal mining area on Tapin Regency as shown in figure 6. Cummulative of three coal mining area on Tapin Regency as shown in figure 8 the highest coal mining area on 2019 with total 4,218 Ha and it has fluctuative trend due to replantation activity of coal mining industry.

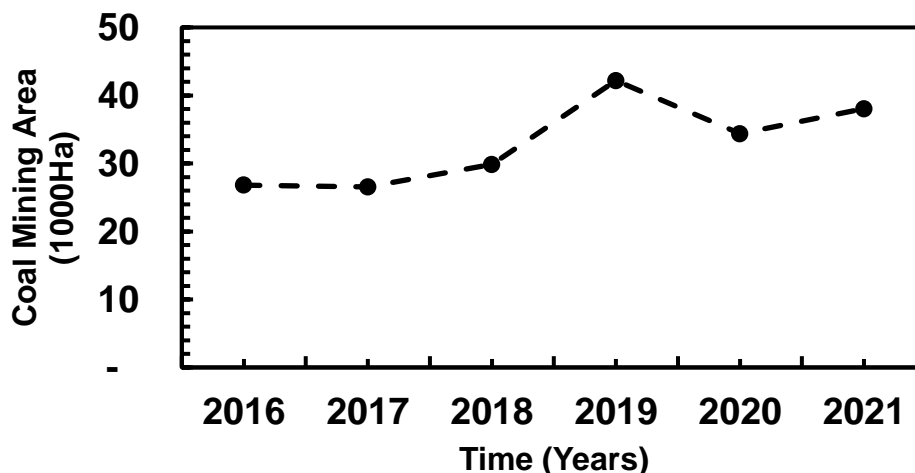


Figure 8 Annual Overall Quantitative Coal Mining Area Change

#### 4. DISCUSSION AND CONCLUSION

##### 4.1 Discussion

The implementation of a deep learning-based technique for the yearly identification of changes in open-pit coal mines presents a revolutionary method for optimizing analysis procedures. This methodology effectively reduces the time-consuming elements of manual analysis, resulting in increased productivity and significant cost savings. This study presents a detailed portrayal of the evolutionary trajectory of the coal mining region in Tapin Regency, covering the period from 2016 to 2021. Of particular significance is the huge increase of 40% in coal mining observed during the key year of 2019. This significant increase highlights the ever-changing character of the coal mining sector and reveals the various aspects of the industry. Upon further examination of the fluctuations in yearly coal extraction, a notable revelation emerges: the urgent importance of reforestation efforts in the context of coal mining. The culmination of this study's contributions is intricately interwoven throughout these insights.

The utilization of a deep learning approach enhances the research's analytical strength and introduces a unique element of novelty to the study of annual coal mining area fluctuations in Tapin Regency. This work uses deep learning techniques to explore the annual changes in coal mining in the region, going beyond conventional methodologies. It presents a novel and data driven approach that sheds light on the intricate details of these alterations. This fosters a more



comprehensive comprehension of the interaction of industrial activities, environmental concerns, and the application of advanced technology in order to promote sustainable mining methods.

## 4.2 Conclusion

In summary, the initial findings derived from the implementation of a deep learning model in the context of coal mining operations offer captivating observations. In contrast to prevailing assumptions, the region characterized by coal mining has exhibited a rather unforeseen pattern, characterized by intermittent growth but primarily by a gradual decline. The aforementioned findings redirect the discourse towards the noteworthy influence of reforestation initiatives undertaken by the coal mining industry. The consequences of these findings are significant, not just for the coal mining industry but also for the wider context of resource management and policy development. This research provides a unique viewpoint on sustainable practices that aim to reconcile economic operations with ecological balance by examining the complex dynamics of fluctuations in coal mining areas.

Therefore, these findings provide a basis for making well-informed decisions and implementing flexible strategies in the mining sector, thereby enhancing the possibility of responsible utilization of resources. The possible areas for future investigation are really intriguing. In order to enhance the progression of information, future studies on coal mining can incorporate an examination of interconnected variables. The examination of the relationship between coal mining activities and environmental factors, such as water quality, offers a potentially fruitful avenue for uncovering significant connections between industrial operations and the health of ecosystems.

Furthermore, doing an in-depth analysis of the relationship between coal mining activities and illness patterns has the potential to shed light on the possible health consequences, thereby enhancing our understanding of the complex effects of mining operations.

As we conclude, the journey undertaken through this research not only underscores the multidimensional aspects of coal mining dynamics but also underscores the potential for generating transformative insights that resonate across environmental, industrial, and societal domains.

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