Land Cover Analysis with Fully Convolutional Network

Abib Raifmuaffah Ihwan
Informatics Engineering
Tadulako University
Palu, Indonesia
bitongihwan@gmail.com

Nouval Trezandy Lapatta
Informatics Engineering
Tadulako University
Palu, Indonesia
nouval@untad.ac.id

Yuri Yudhaswana Joefrie
Informatics Engineering
Tadulako University
Palu, Indonesia
yuri.yudhaswana@untad.ac.id

Yusuf Anshori
Informatics Engineering
Tadulako University
Palu, Indonesia
yusuf.anshori@untad.ac.id

Syahrullah
Informatics Engineering
Tadulako University
Palu, Indonesia
syahrullah@untad.ac.id

Abstract— This study analyses land cover in Morowali Regency using Sentinel-2 satellite imagery and the Fully Convolutional Network (FCN) algorithm. Land cover analysis in this area is crucial for monitoring rapid industrialization, especially in the mining sector. The methodology includes retrieving image data from Google Earth Engine, image processing to eliminate cloud influences, and model training using the European Space Agency (ESA) datasets. The results of the analysis show that 50% of the Morowali Regency area has the potential to be planted with trees, followed by 20% for water areas, and the rest for bushes, development land, and empty land. This study proves that FCN can be relied on to predict land potential with high accuracy with a loss value of 1.3001.

Keywords—Land Cover Analysis, European Space Agency, Google Earth Engine, Sentinel-2, Fully Convolutional Network

I. INTRODUCTION

The potential of natural resources in Morowali Regency is very large and can be utilized as efficiently as possible for the welfare of the community, especially in the mining sector. Morowali Regency is one of the targets in the development of the Mining Industrial Area in Indonesia. The industrialization process in Morowali Regency has developed rapidly, starting with mining and mineral exports in the 2000s until the establishment of IMIP in 2014 which manages nickel ore to be produced into lithium batteries for electric cars [1]. As a result, there has been a significant change in land function to land cover in the area.

Land cover changes are changes from one type of land cover to another type of land cover, for example, agricultural land to mining land, forests to settlements, and so on. The land cover always changes over time as a result of meeting human needs [2], as is the case in the Morowali Regency. Changes in land cover have an impact on geological conditions, economic conditions, and population density in Morowali Regency. In this case, an analysis of land cover changes is needed so that it can be a parameter to determine the function of land in the area.

In the era of digital transformation 4.0 now, the need for image data analysis is increasing, especially in satellite image data processing. Satellite data processing is carried out using remote sensing techniques based on the internet (cloud computing). One of the technologies used to process satellite image spatial data is Google Earth Engine (GEE). By using GEE, it will be easier to process satellite data without having to download large data. Users simply access it via a browser and use an internet connection. GEE provides complete and historical raw image data and is equipped with spatial features needed by users, as well as providing features for downloading raster data and vector data [3].

To analyze the land cover of an area, real-time big data is needed. One of the big data available on GEE is Sentinel imagery. Sentinel imagery is satellite imagery developed by the European Space Agency (ESA) to operate the Copernicus program, which includes all-weather radar imagery from Sentinel-1A and 1B, high-resolution optical imagery from Sentinel-2A and 2B, ocean and land and climate data from Sentinel-3, and air quality data from Sentinel-5P. Sentinel-2 is a high-resolution multispectral imagery with wide coverage and a global revisit frequency of 5 days.

Utilizing satellite imagery for land cover analysis is a big challenge. An analysis is needed using the right method, for example using Machine Learning. The use of the machine learning method functions so that land cover analysis is not done manually. Machine learning is a method that can determine patterns that have a relationship between 2 variables, namely the dependent variable and the independent variable [4]. Several algorithms in machine learning are often used in land cover analysis, such as random forest, support vector machine (SVM), and even the utilization of deep learning methods using convolutional neural in completing the analysis.

Several previous studies related to land cover analysis. Research conducted by (Susan E. Manakane, Philia Christi Latue, & Heinrich Lakuasa, 2023) which analyzed land cover in the Marikururu Watershed, Ternate using Landsat 4-5 TM C2 L2 imagery using Arc GIS 10.8 software resulted in that built-up land in the Marikurubu Watershed, Ternate City experienced an increase in area in the period 2003 by 44.58%, 2013 by 49.60%, and 2023 by 51.74% [5]. Research conducted by (Denny Lumban Raja, 2023) produced a random forest algorithm that has a better level of accuracy compared to the classification and regression trees algorithm in identifying mining areas using satellite imagery in Cipatat District, West Bandung Regency [3]. And research conducted by (Andrei Stoian, Vincent Poulain, Jordi Inggris, Victor Poughon, & Dawa Derksen, 2019) showed that the fully convolutional network (FCN) algorithm is present as a complement to the random forest algorithm in producing land cover maps with the ability to handle annotation data and a high level of accuracy [6].

This study introduces a new approach to land cover analysis in Morowali Regency, which has experienced rapid industrialization, especially in the mining sector since the establishment of IMIP in 2014. Several previous studies have applied remote sensing technology and machine learning algorithms for land cover classification. For example, a study by Putri et al. (2022) utilized Google Earth Engine (GEE) and Landsat 8 OLI imagery to produce a land cover classification map in East Belitung Regency, achieving an overall accuracy of 93% and a kappa value of 0.81 [7]. In addition, a study by Miranda (2021) utilized CNN for land cover classification using Sentinel-2 satellite imagery, which showed high potential in the application of deep learning in remote sensing [8], but did not classify objects into mining classes. However, the application of the Fully Convolutional Network (FCN) algorithm that can handle high spatial complexity in areas with significant industrialization pressure, such as Morowali, is still limited.

This study aims to fill this gap by integrating high-resolution Sentinel-2 imagery data from the European Space Agency (ESA) and the Fully Convolutional Network (FCN) algorithm, this study offers advantages in producing more accurate land cover maps compared to traditional methods such as random forest or SVM. The use of Google Earth Engine (GEE) to process data in real time is also an innovative step that allows big data processing without the need to manually download large data. In addition, this study expands the scope of analysis by including the often overlooked "water" class in the ESA WorldCover dataset, thus providing a more comprehensive representation of the Morowali region. The results of this study not only contribute to the development of land cover analysis methods but also provide a strong basis for decision-making related to sustainable land use in areas with similar industrialization pressures.

II. METHODOLOGY

This research method uses a fully convolutional network (FCN) algorithm on Sentinel-2 imagery to analyze land cover. The research flow is shown in Figure 1.

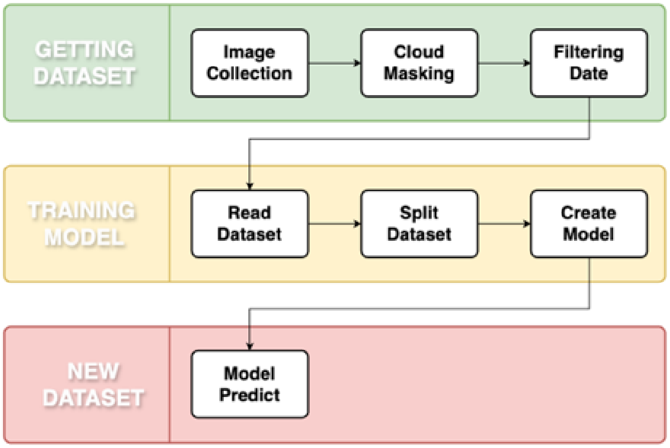

Figure 1. Research Flow

A. Getting Dataset

The initial stage of this study obtained satellite image data from Google Earth Engine (GEE). The satellite image used is Sentinel-2. Sentinel-2 is a satellite image that can be used for agricultural, maritime, and other analyses. Sentinel-2 has 2 satellites, namely Sentinel-2A and Sentinel-2B which can produce images every 5 days. In addition to being superior in terms of image production speed, Sentinel-2 is also superior in having a high resolution with a pixel size of 10m x 10m [4]. Sentinel-2 has 13 bands that can analyze accurate land cover. Here are 13 bands in the Sentinel-2 image.

Tabel 1. 13 Sentinel-2 Bands

Name	Scale	Pixel Size	Wavelength	Description
B1	0,0001	60 m	443.9nm (S2A) / 442.3nm (S2B)	Aerosols
B2	0,0001	10 m	496.6nm (S2A) / 492.1nm (S2B)	Blue
B3	0,0001	10 m	560nm (S2A) / 559nm (S2B)	Green
B4	0,0001	10 m	664.5nm (S2A) / 665nm (S2B)	Red
B5	0,0001	20 m	703.9nm (S2A) / 703.8nm (S2B)	Red Edge 1
B6	0,0001	20 m	740.2nm (S2A) / 739.1nm (S2B)	Red Edge 2
B7	0,0001	20 m	782.5nm (S2A) / 779.7nm (S2B)	Red Edge 3
B8	0,0001	10 m	835.1nm (S2A) / 833nm (S2B)	NIR
B8A	0,0001	20 m	864.8nm (S2A) / 864nm (S2B	Red Edge 4
B9	0,0001	60 m	945nm (S2A) / 943.2nm (S2B)	Water Vapor
B10	0,0001	60 m	1373.5nm (S2A) / 1376.9nm (S2B)	Cirrus
B11	0,0001	20 m	1613.7nm (S2A) / 1610.4nm (S2B)	SWIR 1
B12	0,0001	20 m	2202.4nm (S2A) / 2185.7nm (S2B)	SWIR 2

This study uses Sentinel-2 as its image input. Then apply the QA60 band which has information related to image quality to detect cloud cover or cirrus clouds in its image. The training data used is the dataset from The European Space Agency (ESA) WorldCover in 2020 with a resolution of 10m on Sentinel-1 and Sentinel-2. This dataset is equipped with 1 band for the LandCover class (land cover) which has 11 land cover classes. However, this ESA

WorldCover only consists of land cover classes and ignores values in water areas such as rivers, lakes, seas, and others [9]. Therefore, this study labels water areas with the "water" class. This study uses 9 land cover classes to analyze land cover in the Morowali district. Here are the 9 classes.

Tabel 2. 9 Land Cover Classes

Value	Color	Description
80	#0064c8	Water
10	#006400	Trees
30	#ffff4c	Grass
90	#0096a0	Water Vegetation
40	#f096ff	Plantations
20	#ffbb22	Shrubs
50	#fa0000	Development Areas
95	#00cf75	Mining
60	#b4b4b4	Bare Soils

After Sentinel-2 has been de-clouded and cirrus clouds, the imagery will be time-filtered for use in the training dataset. ESA's de-clouded Sentinel-2 imagery will be captured from January 1, 2020, to December 31, 2020. This dataset will be used as training data to train the model to obtain the desired analysis results.

Figure 2. Masking and Filtering Process on Training Data

B. Training Model

The Sentinel-2 image dataset that has been obtained and has gone through the pre-processing stage, will go through the next process, namely the read dataset. At this stage, the collected images will be inputted into Google Colab and then read to obtain information related to the image, such as image size, image dimensions, and number of images.

```
inputs : float32 (128, 128, 13)
labels : uint8 (128, 128, 1)
```

Figure 3. Size and Number of Channels in Training Data

The data used as input is Sentinel-2 imagery with a pixel size of 128 x 128, meaning that the spatial dimension size of the image is 128 pixels wide and 128 pixels high with several channels or features of 13 for each pixel. The number of features of 13 refers to the number of bands in the Sentinel-2 image. After the data is read, a label will be given for each pixel. The result of the labeling process is 128 pixels wide and 128 pixels high with the number of features per pixel being 1. Pixel 1 indicates the land cover at that pixel, for example, agricultural land, water, mining, grass areas, and so on.

After the labeling process, the Sentinel-2 image data from ESA will be divided into 2 parts, namely training data and testing data. This data division is 90:10, where 90% is for training data and 10% is for testing data. This dataset division aims to ensure that the model created produces accurate analysis. The training data is used to train intelligent models for land cover analysis and the testing data is used to measure the quality of the analysis results using evaluation metrics [6]. The following are the results of the training process from Sentinel-2 ESA WorldCover imagery.

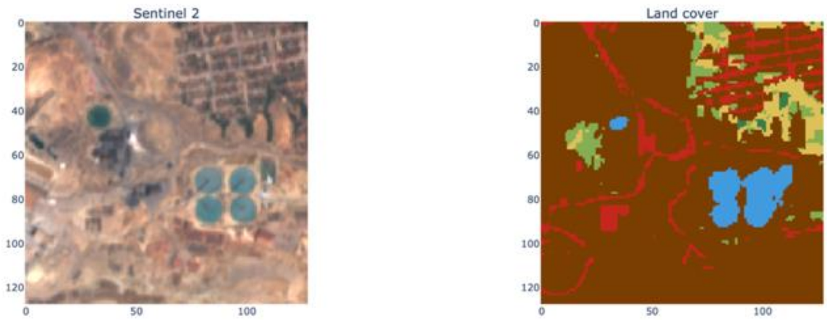

Figure 4. ESA WorldCover LandCover Sentinel-2 Training Results

The learning model used in this study is a fully convolutional network (FCN). In the case of remote sensing research, fully convolutional network is a suitable architectural model because the fully convolutional network architecture can handle per-pixel classification for images with arbitrary sizes and complex textures [10]. The FCN model is a CNN that consists only of locally connected layers such as convolution, pooling, and upsampling, which means that they can natively handle inputs with different shapes [11]. The FCN model allows the final output of the network to remain a two-dimensional matrix, thus preserving spatial information between pixels and facilitating feature extraction [12]. To make the network output the same size as the input, the original FCN simply upsamples the output of the last convolutional layer to the same size as the input image [13]. A fully convolutional network (FCN) is a dense matrix multiplication of the input vector with a trainable weight vector (weight) with the addition of a trainable bias vector at the output [14]. The output of each layer in the FCN is represented in Equation 1.

$$output = a(Wx + b) \qquad (1)$$

Where W is the weight matrix, b is the bias vector, and a is the non-linear activation function.

In this study, the TensorFlow Keras Python library is used to design and implement the FCN model. This library contains various pre-built patterns for neural networks and machine learning [15]. The final model structure contains an input layer, a normalization or preprocessing layer, a convolutional layer with deconvolution, and an output layer. All layers in the FCN model are fully connected. This means that the layer connects all neurons or parameters from the previous layer to the next layer, which facilitates complex relationships [9]. This study uses a fully convolutional network (FCN) in analyzing land cover in the Morowali district, because this architecture is considered superior to other architectures, namely more memory efficient, efficient in processing large data, and more accurate. FCN involves substituting a fully connected layer with its convolutional layer. Finally, the FCN network can input image patches of various sizes into the convolution layer [16].

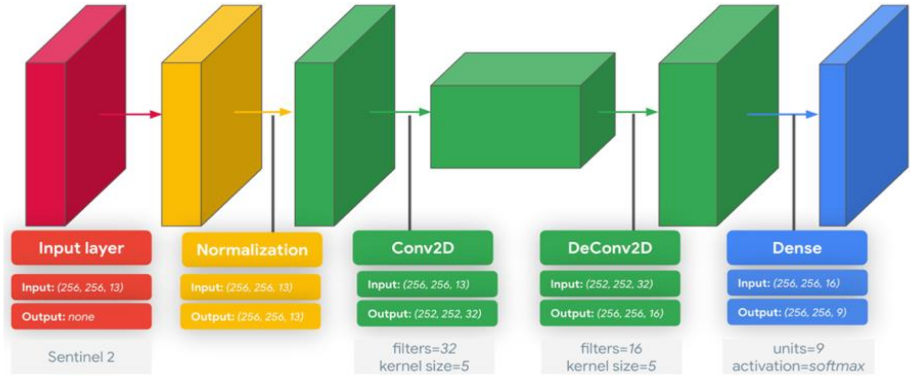

Figure 5. Fully Convolutional Network (FCN) Model Architecture

The image above shows the learning process on the fully convolutional network (FCN) architecture. The process begins with the input layer as an image input with the image input dimensions being (256, 256, 13). This shows that the input image has a size of 256 pixels wide, 256 pixels high, and 13 channels (features) which means 13 bands in the Sentinel-2 image. The input image will be normalized to standardize the data scale to make it more stable during the learning process (train). In the normalization process, the input image is sized (256, 256, 13) and maintains its size in the output image results. In the Conv2D layer, the input image with a size of (256, 256, 13) will be processed using 35 filters with a size of 5 x 5. The Conv2D layer will use 32 filters (kernels) to extract features from the Sentinel-2 image. The result is an output tensor with size (252, 252, 32), where each channel represents a feature map that has been extracted by the filters. The output from the Conv2D layer with size (252, 252, 32) will be input to the DeConv2D layer. In the DeConv2D layer, it will be projected back to a higher dimension with size (256, 256, 16). The goal is to restore a more detailed spatial representation of the previous features. The Deconv2D layer will use 16 filters or kernels to project the features back to a higher dimension. This number of filters is usually less than the previous Conv2D layer [17]. The output from the DeConv2D layer with size (256, 256, 16) will be input to the dense layer. In the Dense result, the input with size (256 x 256 x 16) will be projected to an output vector with size (256 x 256 x 9). Each element in this output vector represents the probability of a class. This Dense result will have 9 units or nodes. The number of units determines the output dimension of this dense. The softmax activation function is used in the Dense result because the output of this model is a multiclass classification [18]. Softmax will produce the probability of each class, where the sum of these probabilities will be equal to 1 [19]. The softmax function converts a vector of numbers (an array of K (z) values) into a vector of probabilities, where the probability of each value is proportional to the relative scale of each value in the vector. Thus, this function converts some numbers into quantities that can be interpreted as probabilities [18]:

$$softmax(z)_k = \frac{e^{Z_k}}{\sum_{k=1}^{K} e^{Z_k}} \qquad (2)$$

Z is the raw output vector of the neural network, the value of e≈2.718, and the kth entry in the softmax(z) output vector can be considered as the predicted probability of the test input belonging to class k. And for the value of K will refer to the number of classes used in the model.

This study uses the Adam optimizer (Adaptive Moment Estimation) to improve the model weights based on the gradient. The Adam Optimization Algorithm is a first-order gradient-based optimization of a stochastic function. This is a method that is very suitable to be implemented directly for any model in terms of large data sets and parameters [20]. In terms of hardware resources, it requires less memory and is very computationally efficient. Adam is also a combination of RMSprop and Stochastic Gradient Descent because Adam estimates the first and second moments of the gradient to balance the learning rate for each weight of the model network. To measure how well the FCN model performs land potential classification in the Morowali district, a loss function is used. The loss function used in this study is Categorical Crossentropy. This loss function is suitable for multiclass classification problems [21].

```
Epoch 1/10
2/2 ━━━━━━━━━━━━━━━━━━━━ 1s 215ms/step - loss: 1.5249 - one_hot_io_u: 0.2370
Epoch 2/10
2/2 ━━━━━━━━━━━━━━━━━━━━ 2s 355ms/step - loss: 1.4673 - one_hot_io_u: 0.2471
Epoch 3/10
2/2 ━━━━━━━━━━━━━━━━━━━━ 1s 350ms/step - loss: 1.4444 - one_hot_io_u: 0.2428
Epoch 4/10
2/2 ━━━━━━━━━━━━━━━━━━━━ 3s 337ms/step - loss: 1.3892 - one_hot_io_u: 0.2663
Epoch 5/10
2/2 ━━━━━━━━━━━━━━━━━━━━ 2s 511ms/step - loss: 1.4139 - one_hot_io_u: 0.2664
Epoch 6/10
2/2 ━━━━━━━━━━━━━━━━━━━━ 1s 209ms/step - loss: 1.3603 - one_hot_io_u: 0.2950
Epoch 7/10
2/2 ━━━━━━━━━━━━━━━━━━━━ 2s 199ms/step - loss: 1.3855 - one_hot_io_u: 0.2960
Epoch 8/10
2/2 ━━━━━━━━━━━━━━━━━━━━ 1s 211ms/step - loss: 1.3670 - one_hot_io_u: 0.2986
Epoch 9/10
2/2 ━━━━━━━━━━━━━━━━━━━━ 1s 219ms/step - loss: 1.3840 - one_hot_io_u: 0.2844
Epoch 10/10
2/2 ━━━━━━━━━━━━━━━━━━━━ 1s 207ms/step - loss: 1.3001 - one_hot_io_u: 0.3096
```

Figure 6. FCNN Model Training Process

The FCN model in this study uses the OneHotIoU metric, which is a metric for measuring Intersection over Union (IoU) for predictions represented in a one-hot format. Intersection over Union (IoU), commonly known as the Jaccard index, is the overlap area between the predicted segmentation divided by the combined area between the predicted segmentation and the ground truth [22]. IoU is a metric often used for image segmentation problems, which measures how well the prediction of the relevant area is with the actual area. Based on Figure 6 above, shows that during the training process, the loss and one_hot_io_u values changed from epoch 1 to epoch 10. The loss value shows a decrease from epoch 1 with a value of 1.5249 to epoch 10 with a value of 1.3001, this shows that the model is getting better at predicting land potential in the Morowali district. While the one_hot_io_u value fluctuates, it generally shows a trend of improving model performance.

C. New Dataset

The test data used in the FCN model is the Morowali district area which is divided into 9 sub-districts. First, by creating a polygon from the Morowali district area to determine the test data for the model.

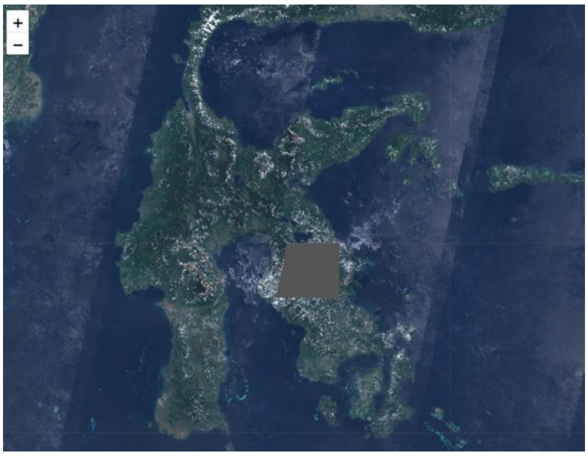

Figure 7. Polygon Morowali Regency

After successfully creating a polygon of the Morowali district, then take the coordinate points (latitude and longitude) of 9 sub-districts in the Morowali district area. The coordinate points will be used as test data to predict land potential in the area.

Tabel 3. Coordinate Points of 9 Sub-districts in Morowali Regency

No	Subdistrict	Longitude	Latitude
1	Witaponda	121.55605499522677	-2.4229756126964914
2	Bumi Raya	121.71192866824357	-2.2246035522065775
3	Bungku Barat	121.7368144528994	-2.3245725975311085
4	Bungku Tengah	121.9322349952271	-2.5120704714018545
5	Bungku Timur	121.78254572406448	-2.761253669653638
6	Bungku Selatan	122.37435051443957	-3.156387175826376
7	Bahodopi	122.18255170871882	-2.8458415382571824
8	Menui Kepulauan	123.11528572406847	-3.585786592805417
9	Bungku Pesisir	122.28808599522873	-2.95043627554088

III. RESULT AND DISCUSSION

As previously mentioned, for the test data on the fully convolutional network (FCN) model, the coordinate points from 9 sub-districts in Morowali Regency will be used. The coordinate points include the longitude and latitude of each sub-district. This study uses Tensorflow to create the FCN model architecture, divide train data and test data, and train the model, to evaluate and predict the output results, namely the land potential of each sub-district in Morowali Regency. Sentinel-2 images from Morowali Regency will be processed with cloud masking to remove the influence of clouds and cirrus clouds, thereby increasing the accuracy of predictions.

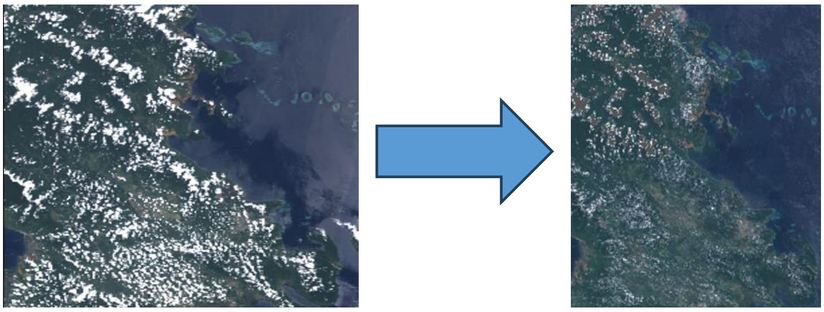

Figure 8. Cloud Masking Process in Morowali Regency

Sentinel-2 images from 9 sub-districts in Morowali district will be the input images in the FCN model that will predict land potential. The input image has a shape (512, 512, 13) which means the input image is 512 wide, 512 high, and 13 features adjusted to the number of bands in the Sentinel-2 image. After being processed through the FCN architecture, the model will produce a probability value based on the number of land cover classes. The output of the model is with the shape (512, 512, 9) which means the output image has a size of 512 wide, 512 high, and a probability value of 9 land cover classes.

```
inputs : float32 (512, 512, 13)
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 964ms/step
probabilities : float32 (512, 512, 9)
```

Figure 9. Input Image and Output Image Size Description

This study takes 9 coordinate points as sample points that will be used in the fully convolutional network (FCN) architecture to predict the land potential of each sample point. The coordinate points taken are the longitude and latitude coordinate points of 9 sub-districts in Morowali Regency. The following are the conditions of 9 sub-districts in Morowali Regency from Sentinel-2 satellite imagery as shown in Figure 10 below.

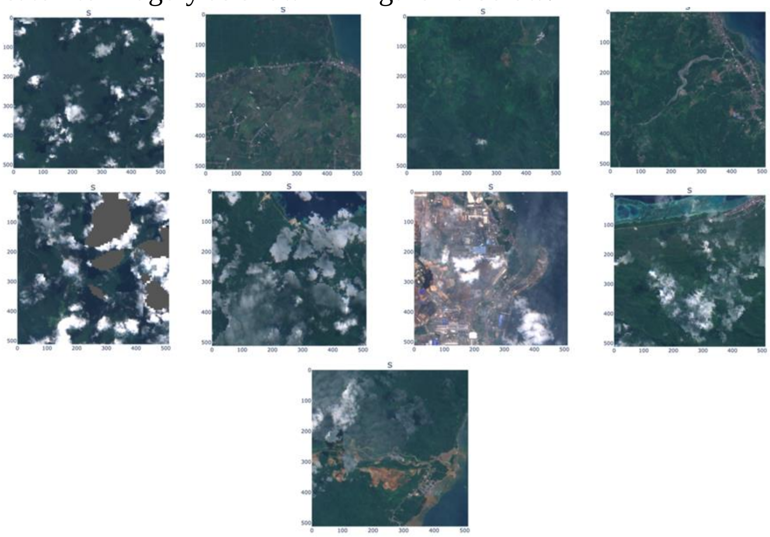

Figure 10. Sentinel-2 imagery from 9 sub-districts in Morowali Regency. Top row from left to right (Witaponda, Bumi Raya, West Bungku, Central Bungku), Middle row (East Bungku, South Bungku, Bahodopi, Menui Kepualaun), and Bottom row Coastal Bungku

The prediction results based on sample data show that 50% of the Morowali district area has the potential to be planted with trees, 20% of the water area (sea, river, lake, swamp), 10% of the land with bushes, 10% is still development land (companies, housing, boarding houses), and 10% is still empty land. From the mapping, it shows that Morowali district has large enough land to be used as land for planting trees (greening). In addition, the Bahodopi sub-district area has the potential to be a mining area and some temporary land for the development process, be it companies, housing, or boarding houses.

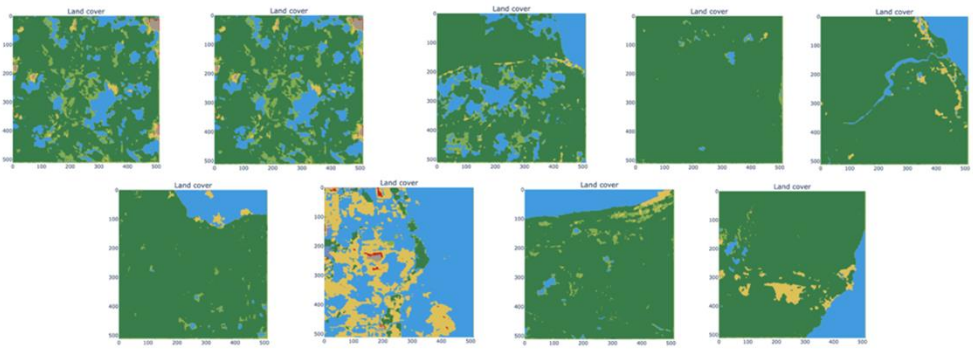

Figure 11. Land Cover of 9 Sub-districts in Morowali Regency. Top row from left to right (Witaponda, Bumi Raya, West Bungku, Central Bungku), Middle Row (East Bungku, South Bungku, Bahodopi, Menui Kepualaun), and Bottom Row Bungku Pesisir

IV. CONCLUSION

Based on this study, it can be concluded that by using the fully convolutional network (FCN) architecture, it can predict land potential in the Morowali district with an error rate of 1.3001 on loss. By using this FCN architecture, it can overcome different image sizes, thus reducing the pre-processing stage. Analysis of land potential in Morowali district shows 50% of the area for tree planting, 20% of water areas, 10% of shrub areas in the highlands, 10% of areas under development, and 10% is still empty land.

REFERENCES

[1] A. Anab, T. Kasnawi, M. A. Ramli, S. Pascasarjana Program Studi Perencanaan dan Pengembangan Wilayah Peminatan Kependudukan Universitas Hasanudin Makassar, F. Ilmu Sosial dan Ilmu Politik, and U. Hasanudin Makassar, "Dampak Kawasan Industri Terhadap Sosial Ekonomi Masyarakat Nelayan Di Kecamatan Bahodop Kabupaten Morowali," vol. 7, no. 2, p. 2023, 2023.

[2] P. C. Latue and H. Rakuasa, "Analisis Spasial Perubahan Tutupan Lahan Di Das Wae Batugantong, Kota Ambon," *Jurnal Tanah dan Sumberdaya Lahan*, vol. 10, no. 1, pp. 149–155, Jan. 2023, doi: 10.21776/ub.jtsl.2023.010.1.17.

[3] D. L. Raja, "Identifikasi Area Pertambangan Menggunakan Citra Satelit Landsat Dengan Machine Learning Pada Google Earth Engine Di Kecamatan Cipatat, Kabupaten Bandung Barat," *GEOMINERBA*, vol. 8, pp. 139–147, Dec. 2023, doi: https://doi.org/10.58522/ppsdm22.v8i2.143.

[4] D. W. Triscowati, W. Pura Buana, and A. H. Marsuhandi, "Pemetaan Potensi Lahan Jagung menggunakan Citra Satelit dan Random Fores Pada GEE …………… (Dwi Wahyu Triscowati, dkk) Pemetaan Potensi Lahan Jagung Menggunakan Citra Satelit Dan Random Forest Pada Cloud computing Google Earth Engine Studi Kasus di 10 Kabupaten Jawa Timur (Mapping Corn Potential Area Using Satellite Imagery And Random Forest On Google Earth Engine Cloud Computing)."

[5] S. E. Manakane, H. Rakuasa, and P. C. Latue, "Pemanfaatan Teknologi Penginderaan Jauh dan Sistem Informasi Geografis untuk Identifikasi Perubahan Tutupan Lahan di DAS Marikurubu, Kota Ternate," *Tabela Jurnal Pertanian Berkelanjutan*, vol. 1, no. 2, pp. 51–60, Jul. 2023, doi: 10.56211/tabela.v1i2.301.

[6] A. Stoian, V. Poulain, J. Inglada, V. Poughon, and D. Derksen, "Land cover maps production with high resolution satellite image time series and convolutional neural networks: Adaptations and limits for operational systems," *Remote Sens (Basel)*, vol. 11, no. 17, 2019, doi: 10.3390/rs11171986.

[7] R. Ade Putri, R. Sibarani, B. Survei dan Pemetaan, K. Atr, and B. Provinsi Bangka Belitung, "Analisis Tutupan Lahan Menggunakan Google Earth … 1031."

[8] E. Miranda and M. Aryuni, "Klasifikasi Tutupan Lahan Menggunakan Convolutional Neural Network pada Citra Satelit Sentinel-2," *SISTEMASI*, vol. 10, no. 2, p. 323, May 2021, doi: 10.32520/stmsi.v10i2.1226.

[9] N. Aendikov and A. Azayeva, "Integration of GIS and machine learning analytics into Streamlit application," in *Procedia Computer Science*, Elsevier B.V., 2024, pp. 691–696. doi: 10.1016/j.procs.2023.12.160.

[10] T. Tian, Z. Chu, Q. Hu, and L. Ma, "Class-wise fully convolutional network for semantic segmentation of remote sensing images," *Remote Sens (Basel)*, vol. 13, no. 16, Aug. 2021, doi: 10.3390/rs13163211.

[11] T. Z. Miranda, D. B. Sardinha, F. Neri, M. P. Basgalupp, and R. Cerri, "A Grammar-based multi-objective neuroevolutionary algorithm to generate fully convolutional networks with novel topologies," *Appl Soft Comput*, vol. 149, Dec. 2023, doi: 10.1016/j.asoc.2023.110967.

[12] S. Wu *et al.*, "Pelvic bone tumor segmentation fusion algorithm based on fully convolutional neural network and conditional random field," *J Bone Oncol*, vol. 45, Apr. 2024, doi: 10.1016/j.jbo.2024.100593.

[13] J. Ji, X. Lu, M. Luo, M. Yin, Q. Miao, and X. Liu, "Parallel Fully Convolutional Network for Semantic Segmentation," *IEEE Access*, vol. 9, pp. 673–682, 2021, doi: 10.1109/ACCESS.2020.3042254.

[14] F. Karim, S. Majumdar, and H. Darabi, "Insights into lstm fully convolutional networks for time series classification," *IEEE Access*, vol. 7, pp. 67718–67725, 2019, doi: 10.1109/ACCESS.2019.2916828.

[15] B. P. Sahoo and S. Tandon, "Face Mask Detection Using TensorFlow, Keras and OpenCV," *Interantional Journal Of Scientific Research In Engineering And Management*, vol. 07, no. 03, Mar. 2023, doi: 10.55041/IJSREM18380.

[16] W. Li, Y. Sun, Y. Zhou, L. Gong, Y. Li, and Q. Xin, "Mapping Irrigated Croplands from Sentinel-2 Images Using Deep Convolutional Neural Networks," *Remote Sens (Basel)*, vol. 15, no. 16, Aug. 2023, doi: 10.3390/rs15164071.

[17] O. Sefrin, F. M. Riese, and S. Keller, "Deep learning for land cover change detection," *Remote Sens (Basel)*, vol. 13, no. 1, pp. 1–27, Jan. 2021, doi: 10.3390/rs13010078.

[18] J. Ren and H. Wang, "Calculus and optimization," *Mathematical Methods in Data Science*, pp. 51–89, Jan. 2023, doi: 10.1016/B978-0-44-318679-0.00009-0.

[19] M. Hamsy Romario, E. Ihsanto, and T. Maya Kadarina, "Sistem Hitung Dan Klasifikasi Objek Dengan Metode Convolutional Neural Network," vol. 11, no. 2, p. 108, 2020.

[20] M. Alom, "Adam Optimization Algorithm." [Online]. Available: https://towardsdatascience.com/adam-latest-trends-in-deep-learningoptimization-

[21] A. Silvanie and R. Subekti, "Aplikasi Chatbot Untuk Faq Akademik Di Ibi-K57 Dengan Lstm Dan Penyematan Kata," *Jurnal Informatika dan Komputer) Akreditasi KEMENRISTEKDIKTI*, vol. 5, no. 1, 2022, doi: 10.33387/jiko.

[22] J. X. Schraut, L. Liu, J. Gong, and Y. Yin, "A multi-output network with U-net enhanced class activation map and robust classification performance for medical imaging analysis," *Discover Artificial Intelligence*, vol. 3, no. 1, Dec. 2023, doi: 10.1007/s44163-022-00045-1.