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Using Histogram Extracted from Satelite Imagery and Convolutional Network to Predict GRDP in Java Region

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Abstract

Inequality is one of the problems faced by all countries in the world, including Indonesia. The data used to measure development inequality between regions mostly uses GRDP data. However, the GRDP data issued by BPS has a deficiency, it was released after the current year, and this figure is provisional. So, a new data source is needed that can be used to estimate the value of economic activity so that it can be used to measure the level of development inequality in a region. Night-time Light (NTL) satellite imagery data can be an alternative to see socio-economic activity in an area and has been shown to have a strong correlation with socio-economic activity. In this study, we used VIIRS NTL satellite imagery data and Dynamic World land cover data to estimate GRDP. Rather than using statistical features for each area of interest, we use features in the form of histograms extracted from NTL images and land cover images for each area of interest. By using a histogram, we don't lose spatial information from satellite imagery. Then we proposed a deep learning method in the form of a one-dimensional convolutional neural network using the Huber loss function. This model obtained good accuracy with an R square value of 0.8549, beating the baseline method with two-dimensional convolutional networks. The use of Huber loss function can improve the performance of the model, which has a smaller total loss and have smoother gradient.

Keywords: *convolutional; GRDP; NTL; huber*

1. Introduction

Regional inequality is one of the problems faced by all countries in the world, including Indonesia. In Indonesia, the development of the eastern region is lagging behind compared to the western region. This can be seen from the contribution of the gross regional domestic product (GRDP) for the Maluku and Papua regions in 2021, which is only 2.49 percent of the total GDP, while the Java island is still the centre of the Indonesian economy with a contribution of 57.89 percent [1].

GRDP is the main indicator used to measure development disparities between regions [2] [3] [4]. This is because the development policies carried out by the local government aim to gain added value and help economic activities in the region so that the expected output from development is to increase economic activity in the region.

To produce GRDP data, the Statistics of Indonesia (BPS) uses three approaches, the production approach, the expenditure approach, and the income approach. The data used to generate GRDP values are collected from secondary data from data producers and departments and through surveys conducted to determine household expenditure. However, there is a time lag between the current year and the data released by BPS. So we need a new data source to provide an overview of GRDP in the current year.

The use of remote sensing data can be a solution to produce data that can be used to estimate the value of GRDP. When compared to survey-based methods, satellite imagery data has advantages such as objective measurements, complete spatial coverage, and periodic updates. One of the remote sensing data that has a high correlation with economic activity is night-time light (NTL) imagery [5], [6].

NTL imagery data has been widely used to describe socio-economic activities in a coverage area, including estimating electricity consumption [7], extracting built-up areas [8], estimating house rental costs [9], estimating poverty [10], estimating human development index [11], estimating impact of disasters [12], and also to estimate GDP [13]. This is due to the ability of NTL imagery to capture light intensity in an area at night which has a strong correlation with socio-

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economic activity. So NTL image data can be a source of data that can be used to estimate GRDP.

In previous studies, many researchers used hand-crafted features in the form of the total or average light intensity of an area of interest (AOI). [14] Use the sum of NTL value from region to predict cross-sectional dan time series GDP, [15] use the average value of NTL to extract urban area and predict GRDP in Uganda. This is simple to do, but we will lose more detailed information which useful for training deep learning methods [16].

To overcome this problem, we use features in the form of histograms extracted from NTL images and land cover images for each AOI. By using a histogram, we don’t lose spatial information from satellite imagery. So this method has better to use than using statistic features from AOI.

Most of the methods used to estimate GRDP use conventional statistical methods and machine learning methods. [13], [14] used the linear regression method to perform cross-sectional and time series analyses, [15] used the correlation index to create an ELIM model, and [17] used the isolation forest method to estimate GRDP in rural areas. [18] used the SVM, Random Forest, Lasso, and Enet methods to estimate GRDP in Java and create microregional GRDP.

The machine learning method gets a fairly good accuracy value. However, current research developments have shifted towards the use of deep learning methods. In the machine learning method, we have to do feature engineering before forming a model. Meanwhile, using the deep learning method, we don't need to do this process because the process will be carried out automatically by the deep learning method. One of the studies using deep learning to estimate GRDP is [16]. This research uses convolutional 2D to model GRDP at CONUS and produces an R square of 0.83. Even though it gets good results, the method is not efficient to do because the data dimensions are only two dimensions. To input data into the model, we have to change the data dimensions into four dimensions and in our opinion, this method is not efficient. Based on this research gap, we use convolutional 1D, which can directly carry out the convolution process without changing the dimensions of the data. In addition, this method is more efficient because it only performs a 1-dimensional convolution process. Next, we use the Huber Loss rather than the MSE Loss function to produce smooth loss and better results.

2. Research Methods

2.1. Data

The data used in this study are VIIRS-DNB (Day/Night Band) night satellite imagery (NTL) and Dynamic World LC data for 2017-2022 obtained using the Google Earth engine. Then the GRDP of the Regency/City is used as label data, and the Shapefile of the district boundaries is used as additional data to extract the histogram, which will be used as input.

The night satellite image used in this study is VIIRS-DNB which is available in the Google Earth Engine data catalogue. The VIIRS NTL image is used because it has a higher spatial resolution than the DMSP-OLS NTL image. In addition, according to [19], VIIRS satellite imagery has a higher prediction power for predicting GRDP compared to DMSP-OLS satellite imagery. VIIRS data are available in the Google Earth Engine data catalogue provided by the Earth Observation Group, which has been corrected for stray light and cloud cover. This data consists of 2 bands, namely avg_rad and cf_cvg, with a spatial resolution of 463.83 meters. The band used in this study is avg_rad which is the average value of the light intensity Day/Night Band (DNB). The unit of average radiance is nanoWatts/cm2/sr.

Dynamic World LC (DW) data is a near-real-time (NRT) Land Use/Land Cover (LULC) dataset that includes class probabilities and label information for nine classes. The classes are water, trees, grass, flooded vegetation, crops, shrub and scrub, built, bare, and snow and ice. We drop the last class because the Java region doesn’t have a snow and ice area. Dynamic World predictions are available for the Sentinel-2 L1C collection from 2015-06-27 to the present. The revisit frequency of Sentinel-2 is between 2-5 days, depending on latitude. Dynamic World predictions are generated for Sentinel-2 L1C images with cloudy_pixel_percentage less than equal to 35%. Predictions are masked to remove clouds and cloud shadows using a combination of S2 Cloud Probability, Cloud Displacement Index, and Directional Distance Transform [20].

The GRDP data used in this study is the regency-level GRDP released by the Central Bureau of Statistics (BPS). The data is obtained from publications published on the website bps.go.id. For regency-level data, only annual GRDP data is available in units of billions of rupiah. The data used in this study are GRDP data at constant prices for 2017 – 2021 with a base year of 2010.

Regency/City boundary maps in Java Island were obtained from the Ina-Geoportal website tanahair.indonesia.go.id published by the Geospatial Information Agency (BIG). After the area boundary map is downloaded, the map is uploaded back to the google earth engine. Furthermore, the boundary map of the area will become a feature collection that can be accessed on the Google Earth Engine application project.

2.2. Method

This study consists of several stages, there are:

Thresholding VIIRS image data: The VIIRS image data pre-processing stage is carried out on the Google Earth Engine application. First, thresholding is carried out to eliminate the blooming effect. The lower limit used is one, and the upper limit is 81. These limits are obtained after data exploration of VIIRS data for the Java Island region as shown in Figure 1.

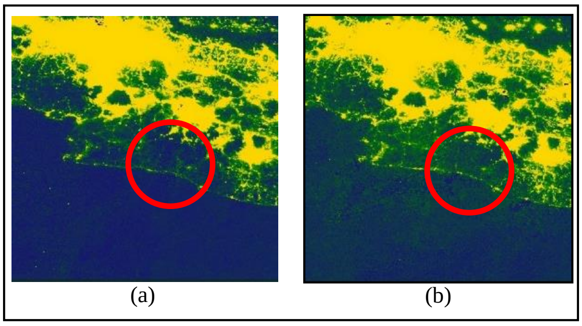

Figure 1. The differences between normal and blooming effect imagery. (a) normal imagery (b) blooming effect imagery

Creating Annual Image VIIRS: The data available in the Google Earth Engine data catalogue is a monthly image. To obtain annual image data, the reduction is carried out using the median value of monthly satellite image data in the year of observation.

Clipping District Boundaries: To obtain data for each regency area, the monthly VIIRS image data that has been obtained is clipped to the Regency/City area boundary data.

Extracting the Image into a Histogram: The process of extracting images into histograms is carried out for each district. With the district boundaries as the area of interest. VIIRS and DW have two different types of data, so fixed bin histogram transformation was performed separately. VIIRS data type is float, and more bins can represent the distribution more accurately in a limited range. The number of bins was set to 240 at intervals of 0,33 with an avg_rad value range from 1 to 81. DW data label has a value range from 0 to 8, representing nine different land covers. We drop the label number 8, which represents snow and ice. So, the DW data has a number of bins 8 with a value range from 0 to 7.

Export data: Data export is carried out because the training and testing stages are carried out outside the Google Earth Engine platform. We then used a Python environment to build the model.

Perform Pre-Processing Data: The data pre-processing process carried out at this stage includes the process of concatenating data, normalising, and converting data into a PyTorch data loader object.

Build a Deep Learning Model**:** The deep learning model built in this study uses three convolutional layers and a fully connected layer. The model architecture will be explained further in the model architecture section**.**

Conduct training: The parameters used in the training process are the loss function used, Huber Loss, using the Adam optimiser, and a learning rate of 0.01. The training process is carried out for 100 epochs with a batch size of 32.t

The GRDP prediction modelling process stages can be seen in Figure 2.

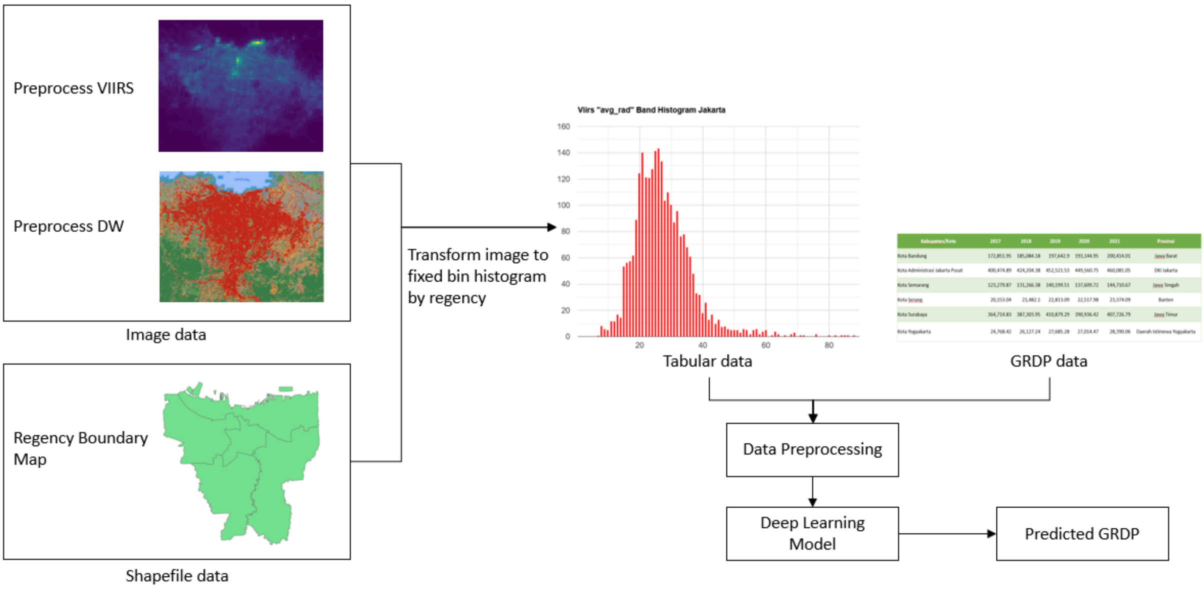

Figure 2. GRDP prediction modelling process

2.3. Model Architecture

The architecture of the model built is a combination of 3 convolutional layers and fully connected layers. The model is built using the Pytorch library in the Python programming language. Fig. 3 shows the architecture of the model. The model built is a Convolutional 1D (Conv1D) model.

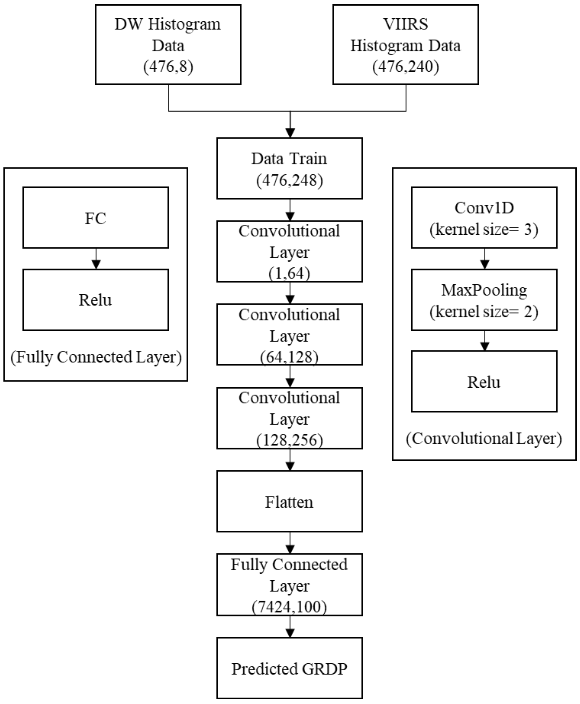

Figure 3. Deep learning model architecture

Conv1D is used because it is more advantageous for a certain application and preferable compared to Conv2D in dealing with one-dimensional data [21]. We concat NTL and LC data before they were fetched into the model. Conv1D layers process the raw 1D data and learn to extract such features, which are used in the classification task performed by the Fully Connected (FC) layer. Then Max Pooling layer could condense the feature map and preserves the most important features, which could greatly reduce the dimension of the feature maps and avoid overfitting.

The parameters of the model are as follows: The number of filters from 3 Conv1D layers is 64, 128, and 256, with a Kernel size of 3 for Conv1D and 2 for MaxPooling Layer. Furthermore, the number of units from the FC layer is 100. The activation function used in Conv1D and the fully connected layer is the rectified linear unit (ReLu): $\mathrm{ReLU(x) = max(0, x)}$. ReLu activation function has a major advantage that reduces the likelihood of the gradient vanishing. Then Relu is more computationally efficient and tends to show better convergence performance than sigmoid and tanh [22].

We use the Huber loss function to train the model. This loss combines the advantages of both L1 loss and MSE loss [23]. The parameter delta-scaled L1 region makes the loss less sensitive to outliers than MSELoss, while the L2 region provides smoothness over L1 Loss near zero. The equation can be seen in Formula 1.

$$\mathrm{l}_n = \begin{cases} 0.5 * (y - \hat{y})^2, & if|y - \hat{y}| < delta \\ delta * (|y - \hat{y}| - 0.5 * delta), otherwise \end{cases} \quad (1)$$

We set the value of the delta parameter to 10.000 because the average absolute error from MSE loss predicted output is around 10.000. If the delta approach infinity, the loss will approach the MSELoss.

2.4. Evaluation Metric

There are two evaluation metrics used in this study, namely Root Mean Square Error (RMSE) and R Square. The formula for RMSE is shown in Formula 2.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}} \sum_{\mathrm{i=1}}^{\mathrm{n}} (\mathrm{Y_i} - \hat{\mathrm{Y}}_\mathrm{i})^2} \quad (2)$$

Where n is the number of data, Y_i is the i-th reference data and $\hat{Y}_i$is the i-th estimation result. The smaller the RMSE value, the smaller the error and the better the performance of the model built. While the R Square formula is shown in Formula 3.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2} \quad (3)$$

Where n is the amount of data, Y_i is the i-th reference data, $\hat{Y}_i$ is the i-th estimated data, and $\bar{Y}$ is the average value. R squared is used to evaluate how well the predicted values can reconstruct the variations of real GRDP. In addition to calculating the error for each regency, percentage error (PE) metrics are used in Formula 4.

$$Percentage\ Error\ i = \frac{|Y_i - \hat{Y}_i|}{\hat{Y}_i} \mathrm{x}\ 100\% \quad (4)$$

3. Results and Discussions

3.1. Performance of Proposed Method

Data training was carried out five times to see the consistency of the output. The output shows good results with average, highest, and lowest R squared consecutively 0.8549, 0.8918, and 0.8278. It shows that the model can explain around 85,49 percent variance of Regency GRDP value and indicates that there is a strong correlation between the reference data and the estimation result. Furthermore, the RMSE value obtained by the proposed model is around 44783.5 billion rupiahs, and the highest and lowest RMSE was 46452.8 and 41854.1 billion rupiahs consecutively. The performance comparison of the model can be seen in Table 1.

Fig. 4 plots the observed vs predicted GRDP best output from our proposed method. The RMSE is 44057 billion rupiahs and can explain 89,18 percent of the variance in

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the observed GRDP, which indicates a strong correlation between actual and predicted GRDP.

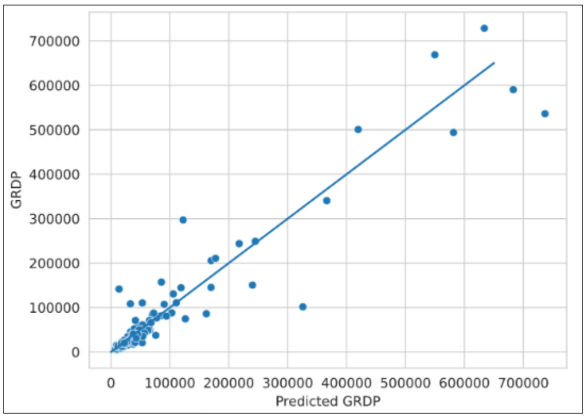

Figure 4. Observed vs Predicted GRDP by the proposed method

The data from Fig. 5 and 6 is visualised using the jenks natural break algorithm to get a group range of data. The jenks method can be advantageous because it identifies real classes within the data. The group is created by minimising differences between data values in the same group and maximising the differences between groups [24].

From Fig. 5, we can see the choropleth map of predicted and observed Regency GRDP for 2021. The darker green colour means the higher value and vice versa. From the results of visualisation of the data using jaccard jack with a total of 6 classes, the data range for each group is obtained consecutively, 4679-42690, 42690-87864, 87864-157151, 157151-340431, 340431-590228, and 590228-728386. From the results of this grouping, there are eight predicted GRDPs that are underestimated and 13 predicted GRDPs that are overestimated compared to the group in the observed GRDP.

(a)

(b)

Figure 5. Observed (a) and Predicted (b) Regency GRDP in Java 2021

From Fig. 6, we can see the percentage error of the predicted GRDP value compared to the observed data. The percentage error value varies randomly. Most of the predicted GRDP have a percentage error below 30 percent compared to observed data, which is 81,51 percent. The percentage of predicted Regency GRDP with PE above 50 is 13,44 percent. This indicates that the model has good accuracy in estimating GRDP in the region using existing models and data.

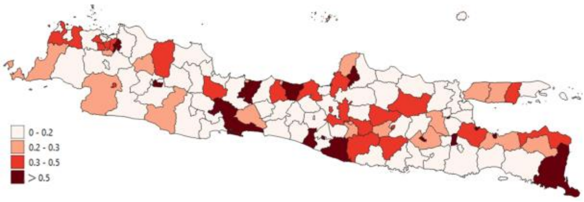

Figure 6. Percentage Error (percent) of Predicted Regency GRDP in Java

The regency which has PE greater than 50 percent is mostly an urban area with a total of 9 regencies. The largest contribution to GRDP from urban areas is the secondary and tertiary sectors which should have a strong correlation with viirs data. This error is caused by the coverage of the area. Kota Bandung, Kota Kediri, and Kota Yogyakarta get underestimated values because the area of the regency is smaller than the other city with the same characteristic of data. Then Kota Banjar, Kota Batu, Kota Bekasi, Kota Mojokerto, Kota Pasuruan, and Kota Probolinggo get value over coverage. On the other hand, it indicates that our model performs well in predicting GRDP in Regency with have bigger contribution in the primary sector.

3.2. Comparison of Model Performance

In this study, we also compared our proposed method to the baseline method proposed by [24], which uses the Conv2D model. Then we also include a model with two different losses to verify the effect of huber loss function in the model. We train the model five times consecutively to get the statistics performance of the model.

The average R square score of the baseline model is 0.8034, with an average RMSE 49973 billion rupiah. Compared to our proposed model, we have better performance with an average R Square value of 0.8549 with an average RMSE 44783 billion rupiah. The proposed model also gets the highest R square value, 0.8918. and more stable performance with the lowest R square above 0.8. With our proposed method, we don't need to reshape input for Conv2D and train the model faster because of its simplicity. Then, by using huber loss function, we get a smaller loss than the MSE loss.

Table 1. The Performance Comparison of Baseline Models with the Proposed Method

Model		R Square ↑	RMSE ↓
Conv2D Baseline	Highest	0.8568	54898
	Lowest	0.7694	44221
	Average	0.8034	49973
	Highest	0.8493	51277

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Conv2D HuberLoss	Lowest	0.7984	46452
	Average	0.8210	49504
Conv1D HuberLoss	Highest	0.8918	47715
	Lowest	0.8278	41854
	Average	0.8549	44783

3.3. Discussion

This study proposed a Conv1D-based model for GDRP Estimation using VIIRS NTL and DW LC data at the Regency level in Java. We use early data fusion by concatenating VIIRS NTl and DW LC before fetching to the model. To obtain information regarding the data fusion method, we conducted an experiment by comparing early data fusion with late fusion, which concatenates the results of data extraction from the convolutional layer. We also use different loss functions to see the impact of using different losses.

Table 2 shows the performance comparison of the data fusion model with a different loss function. From the table, we can see the best performer is the Conv1D model early fusion MSE Loss with an average R square value of 0.8708 and RMSE value of 41054. Then the model with early data fusion gets better performance compared to late fusion with an average R square above 0.85. By using Huber loss Function, model with late data fusion get better performance but not at early data fusion model. The performance of early data fusion with MSE loss gets better results than Huber loss. But if we look at the predicted GRDP from the MSE loss function, we often get a minus value. It is because the total cost of MSE loss is bigger and trying to minimise square error. The solution to this problem we can use the log value of the label, but if we want to use the real GRDP value back, we can get exponential variance because of using the log.

Table 2. The Performance Comparison of Data Fusion Method

Model		R Square ↑	RMSE ↓
Conv1D Late Fusion MSELoss	Highest	0.7906	52859
	Lowest	0.7318	49310
	Average	0.7693	51194
Conv1D Late Fusion HuberLoss	Highest	0.8621	50221
	Lowest	0.7958	47045
	Average	0.8385	48381
Conv1D Early Fusion MSELoss	Highest	0.8947	43149
	Lowest	0.8479	38342
	Average	0.8708	41054
Conv1D Early Fusion HuberLoss	Highest	0.8918	47715
	Lowest	0.8278	41854
	Average	0.8549	44783

4. Conclusion

Based on the experiment result from previous chapters, it can be concluded that The built deep learning model is able to estimate GRDP. The performance of the built model, when compared to the baseline method, gets better accuracy with the R square 0,8549 and RMSE 44.783 billion rupiahs. Most of the predicted GRDP have a percentage error below 30 percent compared to observed data, which is 81,51 percent. The percentage of predicted Regency GRDP with PE above 50 is 13,44 percent which is dominated by urban areas with a total of 9 cities. The use of Huber loss function in Conv1D late data fusion can improve the performance of the model, which has smaller total loss and have smoother gradient. But it gets almost the same result in Conv1D early data fusion.

There is a place to make improvements to the model using other additional data. The performance of the built model can be further improved. We can also take advantage of geospatial big data in the form of infrastructure location data that has a strong correlation with economic activity, such as office locations, school locations, supermarket locations, factory locations, and so on. In the future, we will try to carry out this experiment using additional data that has a strong correlation with socio-economic activity so that the accuracy obtained by the model can be further improved.

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