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ESTIMATE THE FOCAL MECHANISM OF EARTHQUAKE IN INDONESIA BY USING 1-D CONVOLUTIONAL NEURAL NETWORK (CNN)

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ABSTRACT

Indonesia is located between three collision zones of active plate tectonics (Pacific, Eurasia, and Australia), resulting in a high seismicity zone, especially along the subduction zone. Besides that, there are also many faults as a product of these collisions. Both of them could be earthquakes that are controlled by their focal mechanisms. Focal mechanism is the geometry of fault movements, which consists of slip, dip, and rake angles, and the resulting deformation after an earthquake. However, it is important information in depicting earthquake mechanisms, but unfortunately, in Indonesia, the earthquake catalogue data is sometimes not complete. There is some misinformation, especially in focal mechanism data, with more than 6 Magnitudes between January 1st, 1973, and February 1st, 2023, as an example. To fix this problem, a 1-D Convolutional Neural Network (CNN) is applied as a common and powerful method of Machine Learning. Started by classifying the earthquake catalogue data with clear focal mechanism information as the training data with its training label and otherwise as the test data with the unknown label, then applied these training and label data to a convolutional layer with some neurons in hidden layers and an optimization function, CNN can estimate the focal mechanism (label) of the test data. This process is done iteratively, and a good model is observed with little loss value, represented by the L-curve. It means that the result represented by the RMS error becomes smaller due to the iteration, and then the model can be said good enough.

Keywords: focal mechanism; Convolutional Neural Network; CNN; earthquake.

INTRODUCTION

Indonesia is located on the collision between three active plates (Eurasia, Australia, and Pacific), resulting in subduction, faults, and volcanoes as a complex geological form, and it also makes Indonesia a disaster-prone country in Southeast Asia. The subduction zone ranges from the western part of Sumatra to the eastern part of Papua, or in geophysics, it is called a megathrust zone, which can cause earthquakes of various magnitudes and depths, and sometimes tsunamis (shallow depth earthquakes with magnitudes of more than 6.5). For example, the Aceh earthquake resulted in a tsunami in 2004 with 9.2 magnitude and a depth of 26 km. Other examples are earthquakes caused by faults, such as the Yogyakarta earthquake in 2006 and the Cianjur earthquake in 2022. The Opak and Cugenang fault activity caused them. Both of them had 5.9 and 5.6 magnitudes with a depth of 10 km. The high seismicity of Indonesia can be seen in Figure 1. Most of them are concentrated on the boundary plate. Based on [1], the deepest earthquakes are distributed around 600 km depth in the subduction zone and have a magnitude of more than 5. It causes a big impact on the building and society.

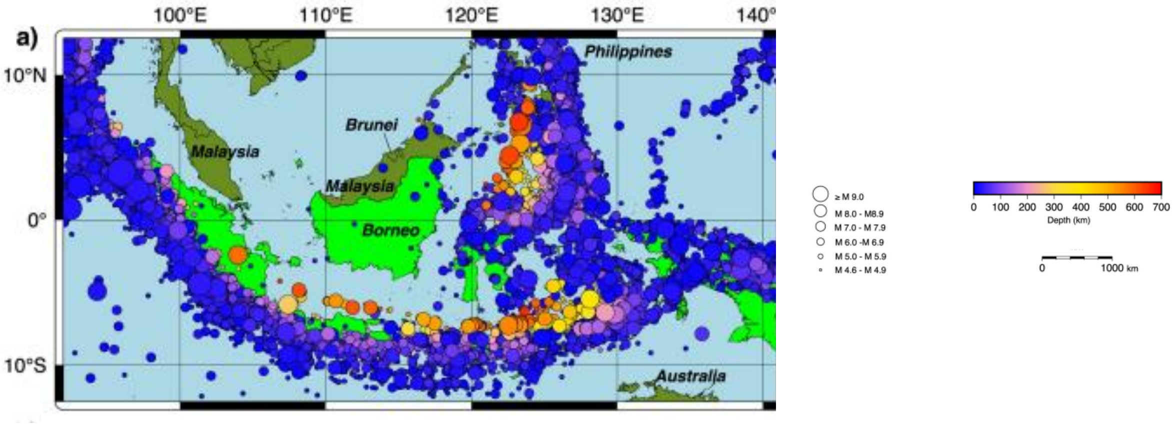


Figure 1. The seismicity of Indonesia from January, 1st 2000 to July, 28th 2020 [1].

The earthquake that comes from the subduction zone and the fault are included in the tectonic earthquake, while shaking that comes from the volcanic activity is included in the volcanic earthquake. According to the geological condition, tectonic earthquakes are divided into three categories: normal, reverse, and strike-slip faults. They are included in the plate movement description, and in geophysics, they are called a focal mechanism. Furthermore, the focal mechanism is described in the beach ball diagram. In general, the geometry of the fault can be seen in Figure 2.

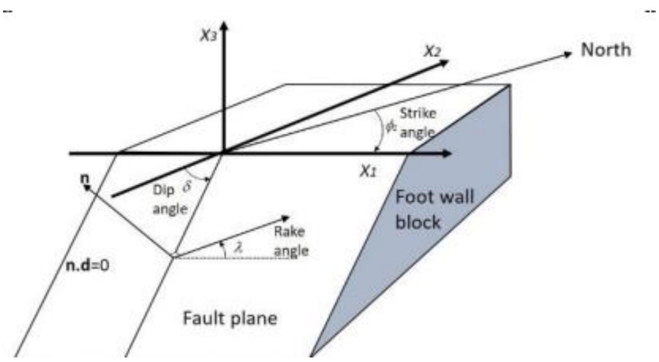


Figure 2. Illustration of the fault [2]

An earthquake is a condition in which the Earth suddenly releases energy to reach a stable condition. When it occurs, some medium slips to the others in the fault plane, with a certain dip and strike angle, giving and accepting the stress from one another and finally causing some deformation [2]. These are depicted in a beach ball as a focal mechanism solution. Practically, the angles are processed in moment tensor inversion to get a focal mechanism geologically [3]. Besides that, there is another way, which is using P-wave polarity (we will discuss this later). However, it is included in the hard process because we need to determine P-wave polarity from the waveform first. The ideal depiction of clear wave polarity is shown in Figure 4 (a), while in the real case, the waveform is influenced by noise (Figure 4 (b)) that needs to be neglected. Furthermore, [4] explains that determining P-wave polarity becomes harder in small earthquakes because of a similar pattern between the wave and the noise, so we need to apply some filters to the waveform to make it free from noise [5].

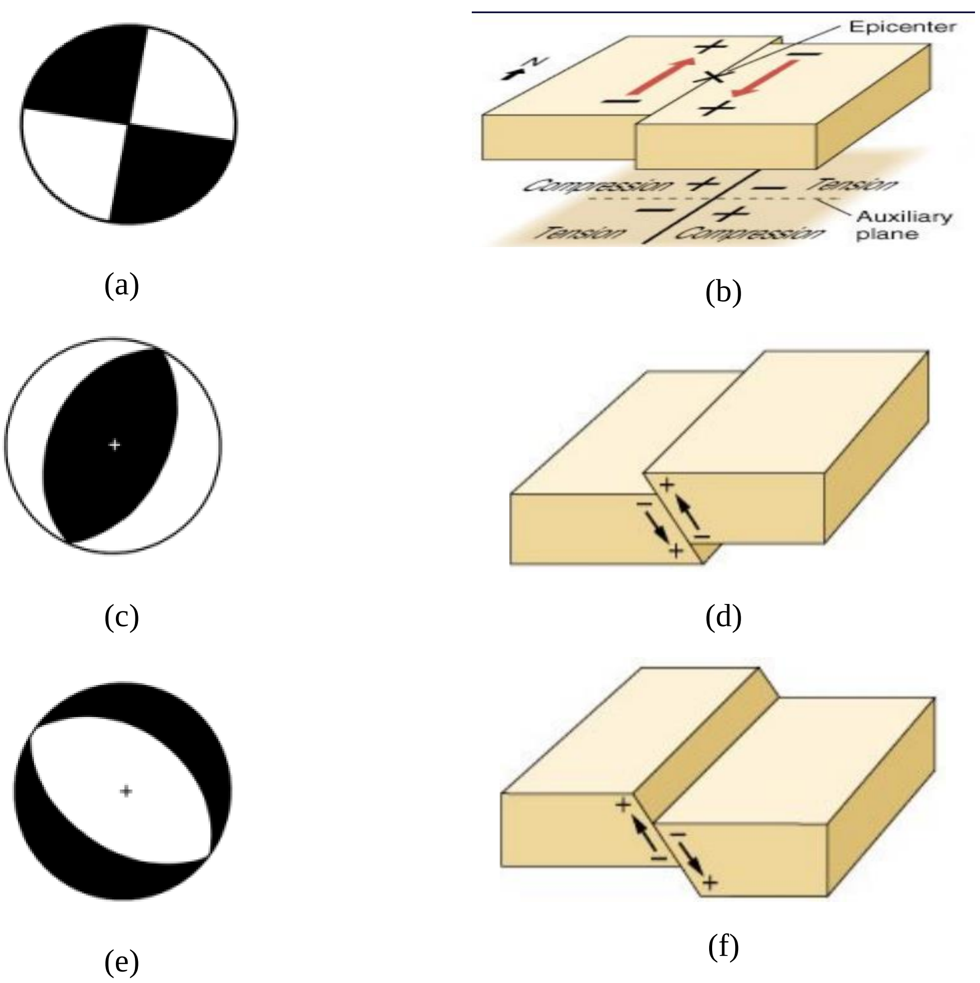


Fig 3. Beach ball diagram [3] and the geometry [6]. (a) and (b) are the strike slip fault; (c) and (d) are reverse fault; (e) and (f) are the normal fault

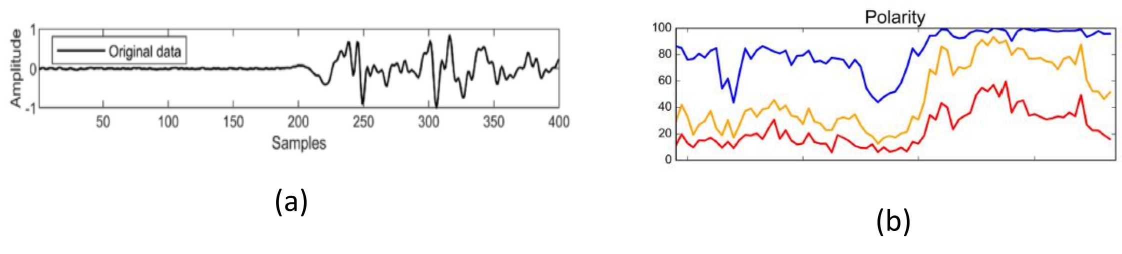


Figure 4. (a) Ideal waveform [4]; (b) Real waveform [5]

The black and white area in Figure 3 represents the tension and dilatation area, while in the geometry illustration, it is signed by positive and negative. Even though, in general, there are three types of fault planes, sometimes earthquakes can be raised by an oblique fault or the combination of two different types of fault plate solutions. Based on this explanation, the focal mechanism is important in the mitigation efforts of earthquakes, especially in providing a description of how an area is influenced by this type of focal mechanism.

Unfortunately, there is some missing data on the focal mechanism of the Indonesian earthquake. Based on the IRIS Website [7], there are 206 data points with no information about the focal mechanism from 1414 data points. Poor information about focal mechanism data can be caused by several factors, such as unclear waveform (very noisy) or a small number of stations recording earthquakes. In seismology, it is important to do waveform signal analysis first from several stations, including making it free from noise. After that, the polarities from several stations are plotted on the stereonet to determine two nodal planes in beach ball form. The area that is dominated by the Up polarity of the P-wave is included in the tension area, and otherwise for the Down polarity.

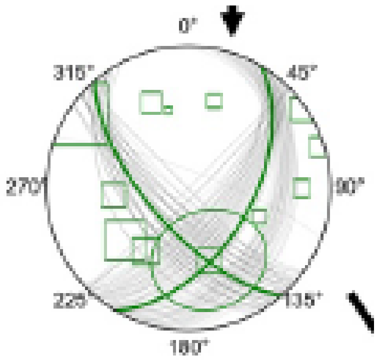


Figure 5. Nodal plane on beach ball are represented by the green line [5]

Today, there are many researchers who use Machine Learning for predicting the focal mechanism by using P-wave polarity from several stations. [8] Try to predict the focal mechanism from 110000 microearthquakes data with a depth of less than 20 km in the Japanese islands. P-wave polarities are classified into Up, Down, and unknown. After that, the data is divided into two types: train and test data. The train data is assumed to be correct. Then, he used a neural network to predict the data test after making sure that the accuracy was good enough, represented by the L-curve. Similar research was done by [9] and [10], who classified P and S phase polarities and then calculated S/P amplitude to predict the focal mechanism. Not only classify P or S phase polarities, but 10 also classifies the waveform to update strike, dip, and rake angles of the ordinary focal mechanism.

Generally, Machine Learning is capable of predicting the target or label based on the input data, whatever it is. In seismology, there are already many researchers who use Machine Learning for seismic data processing [11]. For example, [12] tries to develop the earthquake catalog by using Machine Learning for seismic analysis, predicting ground motion and deformation. Some of the Machine Learning utilities are shown in Figure 6.

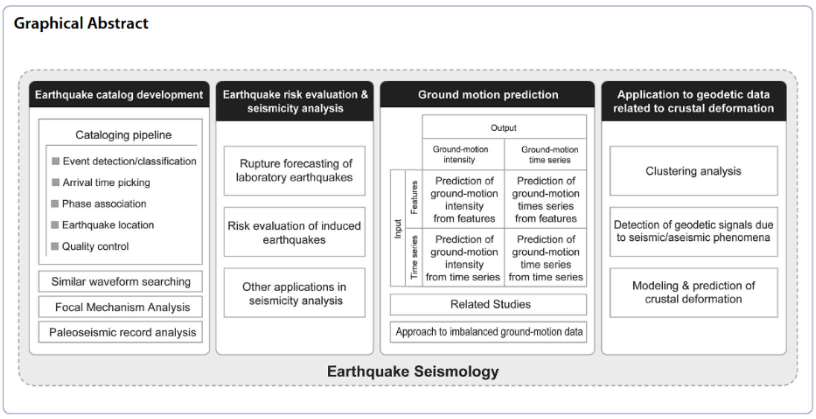


Figure 6. Some utilities of Machine Learning in Earthquake Seismology [12].

Based on some references, in this paper, we try to predict the focal mechanism based on the earthquake catalogue from the IRIS Website by using a 1-D Convolutional Neural Network (CNN). We use hypocenter locations as the input data, while the focal mechanism is the target/label. Some of the IRIS catalogue data are missing the focal mechanism, and we set it as our test data to estimate the focal mechanism.

We chose CNN because it is a very flexible method. The User can use any number of parameters, and it is not important if there are physical relations between the parameters or not. The train data is then multiplied by the activation function in some neurons, which is called the hidden layers. Finally, the result is validated by the loss function to make sure that the CNN works well (suitable for geological/geophysical conditions).

METHOD

CNN is a method that is widely used in geophysics. [13] used it to classify the local earthquake and tremor around Sanriku Oki, Japan. They classified these categories based on waveform signal data in the spectrum form and then used it as an input in the 2D CNN method. With some training data, the computer would separate the test data automatically.

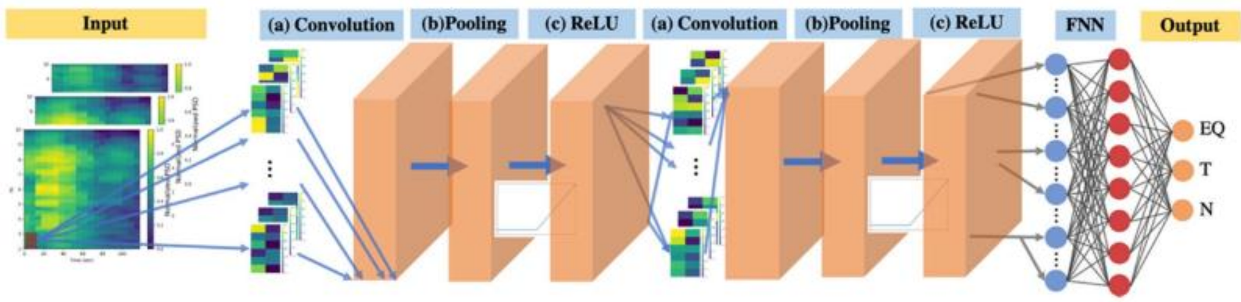
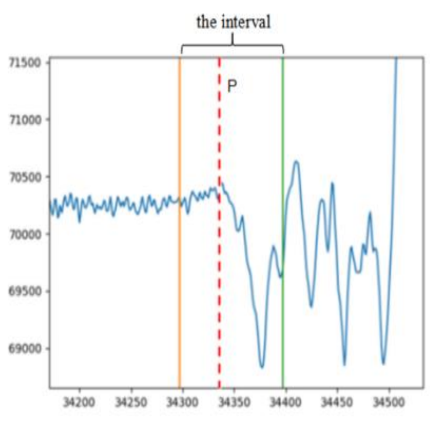
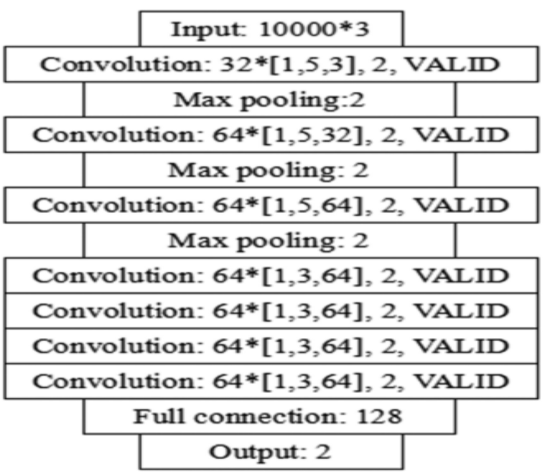


Figure 7. Some steps of 2D CNN to classify the event of earthquake in Sanriku-Oki [13]

Besides that, [14] also used CNN to separate between tectonic and non-tectonic seismicity around East Asia based on the differences between P and S phases arrival time. They identified the earthquake phases in the waveform signal phase. Because it is a time series, a 1D CNN is a suitable method to get the description of signal characterization. Tectonic earthquakes have different characteristics compared to the others, where the difference between the P and S phases' travel time in tectonic earthquakes reaches minutes, longer than the volcanic or microseismic earthquakes.



(a)



(b)

Figure 8. (a) Waveform signal example with three lines, the orange is the origin time, red dash line is P phase and green line represents the S phase. (b) Schematic steps of 1D CNN to classify the event [14]

Figures 7 and 8 represent 2D CNN and 1D CNN applications in seismology. Both of them use waveform data, especially P phase polarity, as input because it is an important thing in seismology. It is used not only to determine the focal mechanism but also to calculate hypocenter relocation. Even [15], [16], and [17] do CNN for detecting P phase arrival time as an input for these two cases. The other application of CNN is the research done by [18] band [19], who used CNN to predict the magnitude and intensity of the earthquake based on a database of some stations.

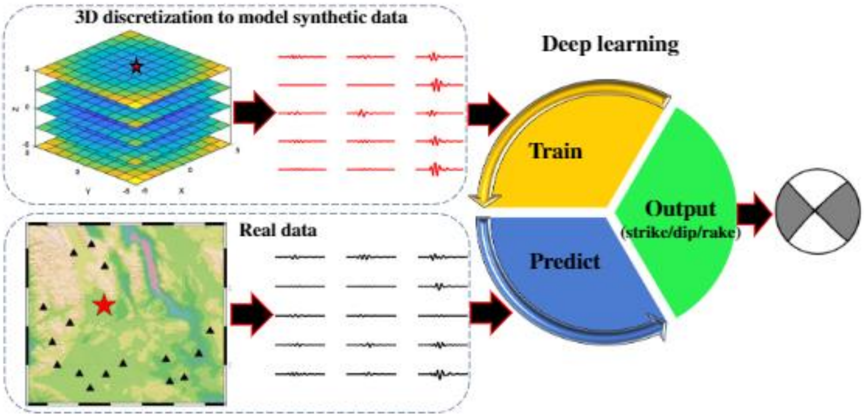


Fig 9. CNN application in identifying P phase from the waveform to observe focal mechanism [17]

Both 2D CNN and 1D CNN have similar processes; the differences between them are just in the Kernel matrix in the hidden layers. The kernel matrix consists of some activation functions that are located in the neuron. In CNN, it is free to use any number of hidden layers and neurons. The process started with the multiplication process between the input data and the activation function in each hidden layer. For example, in Figure 8 (b), there are seven hidden layers, each of which has its own number array (32 and 64) as an activation function. The simple formula of the activation function is linear regression, defined as in Eq. 1

$$y = ax + b \quad (1)$$

a and b variables in Equation (1) are the weight factor and the input data. In CNN, there are also ReLU and MaxPooling functions. They are used to diminish some data from the convolutional process between the data and hidden layers, and make sure that the product has the same size as the input data. They are included in the final step to get the CNN result. Besides linear regression, another activation function is the sigmoid formula (Eq 2)

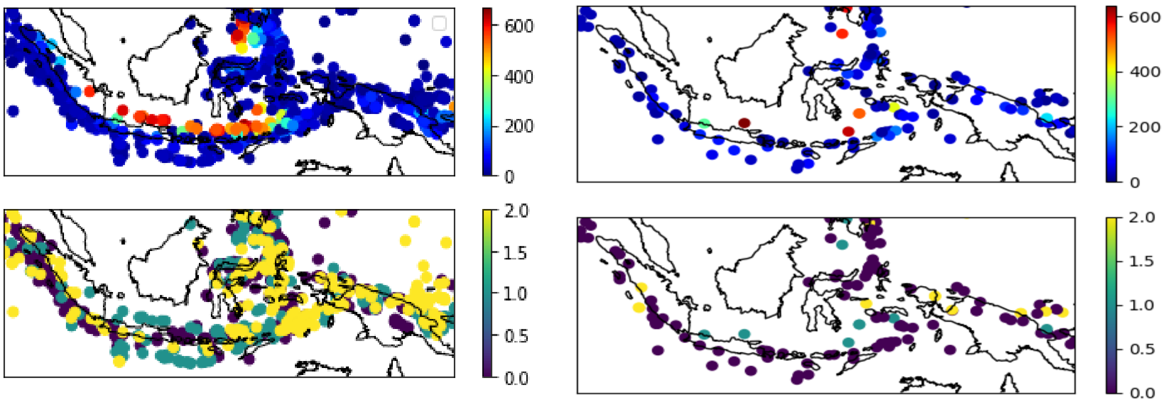
$$\sigma(x) = \frac{1}{1+\exp(-x)} \quad (2)$$

Finally, the validation result of the CNN is clarified by the loss function using the L curve. It represents the error function of calculation [20]. Generally, the utilization of CNN in geophysical applications is proof that machine learning or deep learning is very flexible in adapting to various needs. Deep learning itself is the standard method in the computational process of Machine Learning [21].

RESULT AND DISCUSSION

This research was started by collecting hypocentre earthquake catalogue data of more than 6 Magnitude (damaging earthquakes) in Indonesia between January 1st, 1973, and February 1st, 2023, from the IRIS website [7] and its focal mechanism. Anyway, there are 206 hypocentres data points with unknown focal mechanism information (test data). For clear focal mechanism data, we set it as the training data and labelled the earthquake catalogue data into three general types of fault plane solution (0, 1, and 2 for normal, thrust, and strike-slip fault).

In this research, we used four hidden layers consisting of 64 and 32 neurons to get the best result (after several trial-and-error processes). The process uses 100 iterations with 200 batch size. The initial and output model can be seen in Figure 10, while the validation in the L curve is in Figure 11.



Initial model (training data and labels)

CNN result (test data)

Figure 10. Initial and CNN result of focal mechanism. The top maps in both initial model and CNN result show the earthquake distribution based on the depth (km) represented by the scale bar, meanwhile the bottom maps represent the focal mechanism with 0, 1 and 2 in the scalebar are code for Normal Fault, Reverse Fault and Strike Slip Fault

According to the initial model in Figure 10, the earthquake's depth is more than 600 km. Normal Fault dominates around the subduction zones (near the Australian plate) with shallow depth earthquake distribution. This is included in the fore arc basin area. Reverse Fault dominates at the back arc basin, while strike-slip Fault dominates the eastern area of Indonesia. This data is then assumed as the training data and label of the CNN for reference when the CNN tries to classify the test data after we are sure that our CNN architecture is good enough by looking at the L-curve.

The L-curve consists of the RMS between the predicted and original data from the data train. This means that before CNN is applied to the real test data, we should first check whether the predicted data and original data from the training data have a low RMS value during the iteration. After we are sure that the CNN's architecture has a good L-curve pattern, we apply it to the real data. In this case, regarding the L-curve in Figure 11, the loss function decreases until less than 1 with each iteration. Although there are other validation terms for Machine Learning, like the confusion matrix, we only use the L-curve because we only use the hypocentre location, which includes longitude, latitude, and depth, and there is no need to search for any of the relations between them. A confusion matrix is used when we use several parameters, for example, Gamma Ray, Velocity, and Density in mining cases, to predict the lithology. We also need to know the relations between these parameters.

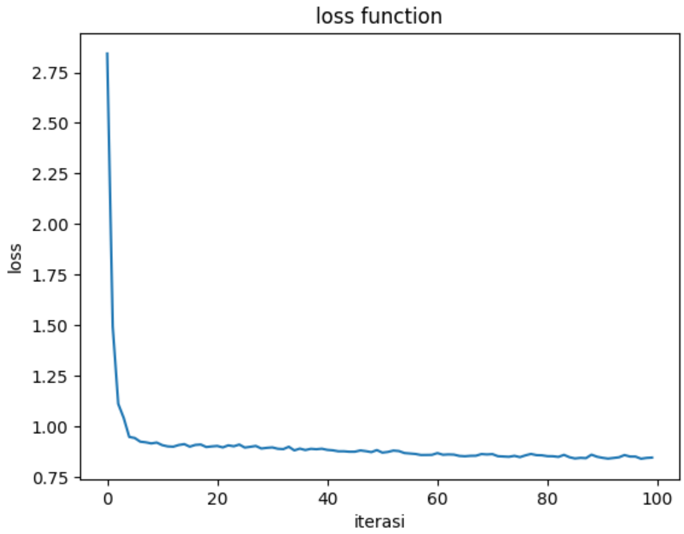


Figure 11. Loss function of training data as the validation way

Besides the L-curve, another insight to check our result is that it is good enough. We need to look at the focal mechanism pattern to determine whether it is suitable for the geological condition or not. Subduction zones should be dominated by Normal or Reverse fault, while when we look at the CNN result in Figure 10, it gives almost a Normal Fault, and it makes sense.

The test data is dominated by shallow earthquakes located at the fore arc basin for Sumatra and Java Island, while the eastern part of Indonesia is located at the collision boundary between the three plates. We try to combine the initial model and the CNN result to get the complete description of the focal mechanism of Indonesia, like in Figure 12.

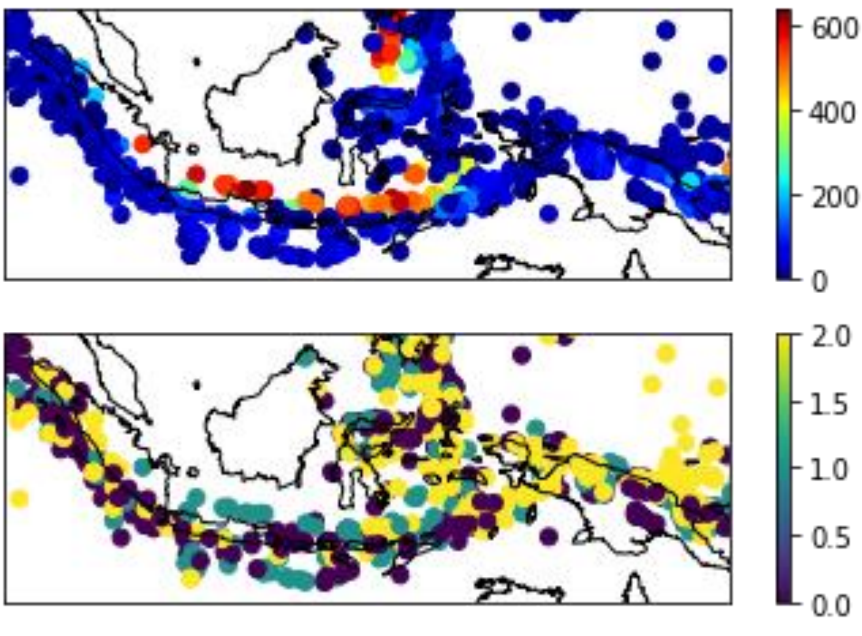


Figure 12. Complete description of earthquake distribution in Indonesia and its focal mechanism by CNN. The scalebars represent the depth for the top map and focal mechanism's type for the bottom map

CONCLUSION

CNN is a powerful way of machine learning or deep learning to classify the data. It can combine any parameters as input data without worrying about the parameters that we choose. CNN consists of hidden layers and their neurons, including the activation function. We arrange our CNN's architecture code to predict the unknown focal mechanism of the Indonesian earthquake by using the hypocenter location (longitude, latitude, and depth) as the input data. CNN can clarify the focal mechanism into the fault plane solution types, referring to the data train. The result is validated by using the L-curve. We also need to make sure whether it is suitable for the geological conditions of Indonesia or not by looking at the focal mechanism's type for each earthquake source (subduction zone or fault). However, because CNN is very flexible, many possible models can result from CNN. The control from the user to check the CNN result is very important.

DATA AVAILABILITY

All seismic data were downloaded through the EarthScope Consortium Wilber 3 system (*https://ds.iris.edu/wilber3/*)

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