Prediction of Earthquakes using Neural Networks

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Introduction to The Topic

- Prediction of the time of occurrence, magnitude of future large earthquakes has been the subject of several scientific efforts with distinctly different conclusions in recent years
- Neural networks are a very powerful tool to approximate complex functions (by the Universal Approximation Theorem)
- We use the Gutenberg Richter Inverse power law as the base of our analysis

Motivation

- Earthquakes are a devastating phenomenon forecasting an earthquake is an extremely difficult task.
- I am very interested in the field of Deep Learning. So can we use this power of neural networks to solve such a difficult problem of earthquake forecasting?

Objective

- The objective of this project is to analyze the performance of the neural network architecture on the time series data of five regions
  - Indian Himalayan Region
  - Sumatra Region(Indonesia)
  - Central Java Region(Indonesia)
  - Sulawesi Region(Indonesia)
  - Asian Region
- Give as inputs 8 seismic indicators to the model and get an output which informs us whether an earthquake of threshold magnitude (4.3 or 5.7) is going to strike soon. (in the next K=30 days)

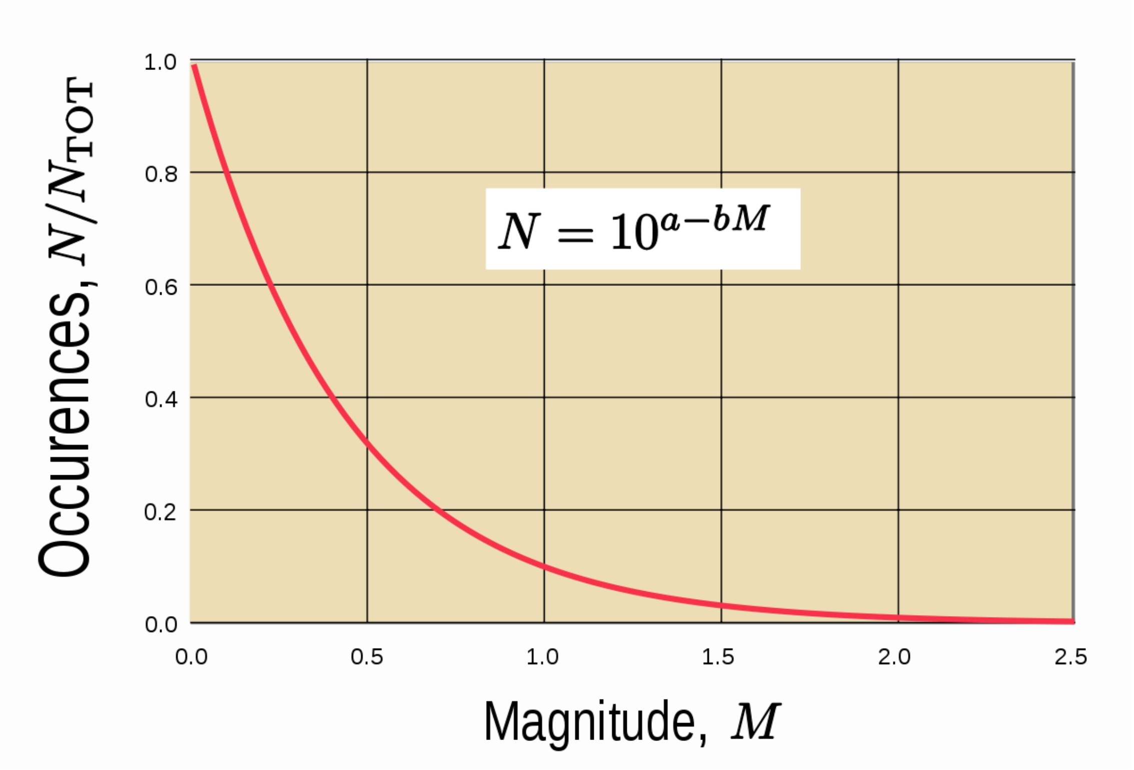
Literature Review

- The seismicity indicators are like a blueprint to the seismicity of an earthquake prone region.
- We have used 8 indicators-
  1. The T value
  2. The Mean Magnitude
  3. Seismic Energy Released
  4. Slope of the Gutenberg Richter Line
  5. Deviation of the data from the Gutenberg Richter Law
  6. Magnitude Deficit
  7. Mean time between characteristic events
  8. Coefficient of Variation of mean Time

The Gutenberg Richter Law

$\log_{10}N = a - bM$
N = number of events with magnitude greater than M
a,b are parameter of the Gutenberg richter law
M = magnitude

- The Gutenberg-Richter inverse power-law establishes an inverse linear relationship between the magnitude of seismic events and the logarithm of frequency of occurrence of events of magnitude equal or greater than that magnitude.



T value

- The time elapsed over the last n events of magnitude greater than a predefined threshold value is defined as

$$T = t_n - t_1$$

- t_n = Time of occurrence of the n^{th} event
- t_1 = Time of occurrence of the 1^{st} event
- A large T value indicates a relative lack of foreshocks which in many seismic regions may indicate a lower probability of occurrence of a forthcoming large seismic event. Inversely a small T value indicates a relatively high foreshock frequency and a higher probability of occurrence of a forthcoming large seismic event.

Mean Magnitude

- The mean of the Richter magnitudes of the last n events is defined as

$$M_{mean} = \Sigma M_i / n$$

- This is due to the fact that the observed magnitudes of foreshocks increase immediately before the occurrence of a major earthquake.

Energy

- The rate of square root of seismic energy released over time T is defined as

$$dE^{1/2} = \Sigma E^{1/2}/T$$

$$E = 10^{(11.8+1.5M)} \text{ ergs}$$

- Sometime the physical system accumulates energy that will be released abruptly in the form of a major seismic event when the stored energy reaches a threshold

Slope of Gutenberg Richter Curve

- This parameter is based on the so-called Gutenberg-Richter inverse power law for earthquake magnitude and frequency which is expressed as

$$\log_{10}N = a - bM,$$

- where N = number of events of magnitude greater than or equal to M
- a and b are constants

Deviation from Gutenberg Richter Law

- This parameter is defined based on the Gutenberg-Richter magnitude-frequency relationship as follows:

$$\eta = \Sigma(\log_{10}N_i - (a - bM_i))^2 / (n - 1)$$

- The lower the η value, the more likely that the observed distribution can be estimated using the inverse power law whereas a high η value indicates higher randomness and the inappropriateness of the power-law for describing the magnitude-frequency distribution.

Magnitude Deficit

$$\Delta M = M_{max,observed} - M_{max,expected}$$

- $M_{max,observed}$ = the maximum observed magnitude in the last n events
- $M_{max,expected}$ = the maximum magnitude in the last n events based on the inverse power-law relationship.
- Since an event of the largest magnitude will likely occur only once among the n events, N = 1, log N = 0 we get

$$M_{max,expected} = a/b$$

Mean time between characteristic events

- This is the average time or gap observed between characteristic or typical events among the last n events. Characteristic events should ideally be separated by approximately equal time periods. The mean time μ is then given by

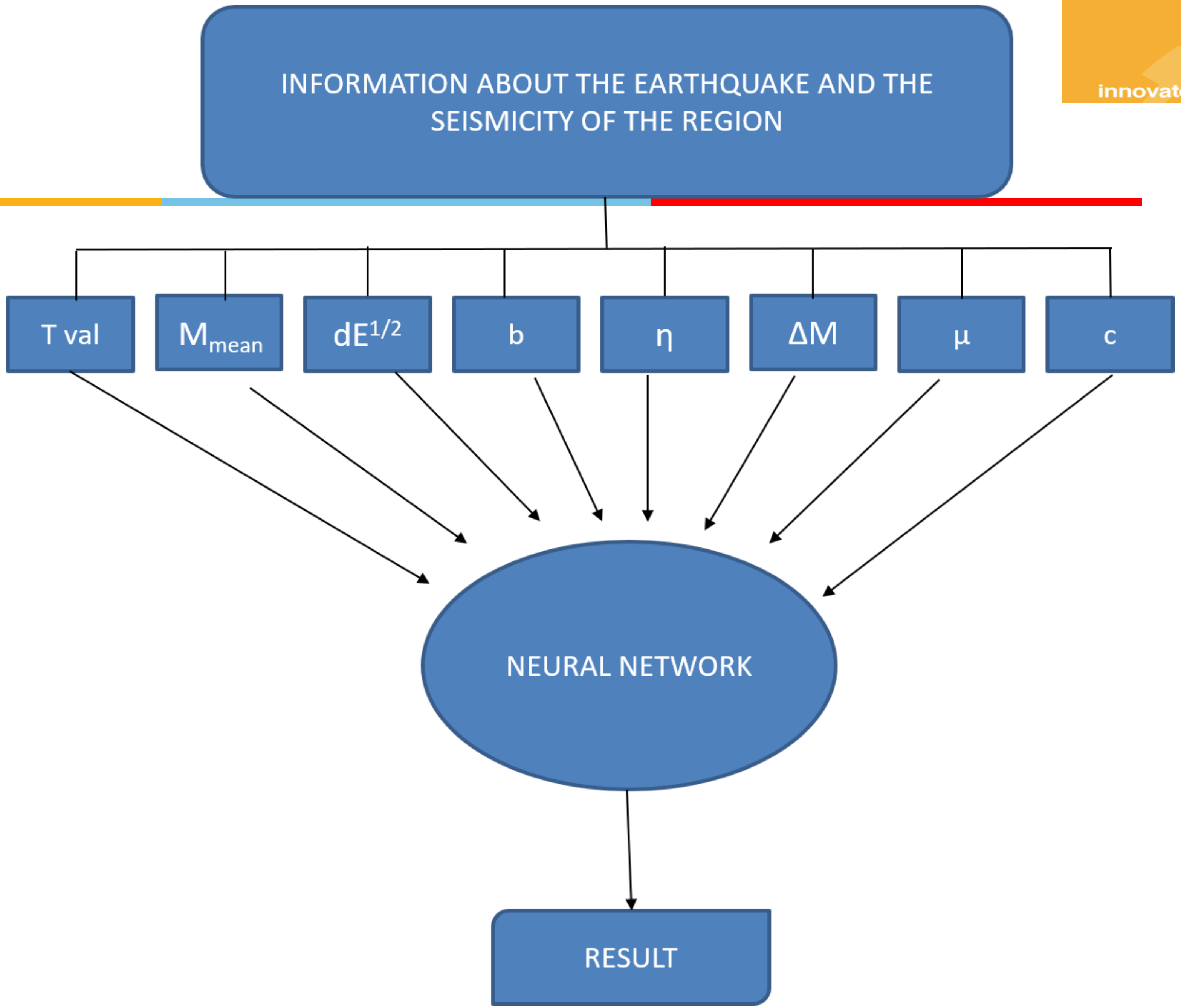
$$\mu = \Sigma(t_{i\ characterisic})/n_{characteristic}$$

Variation of the mean time between characteristic events (μ)

- This parameter is a measure of the closeness of the magnitude distribution of the seismic region to the characteristic distribution and is defined mathematically as

$$c = \text{standard deviation of the observed times}/\mu$$

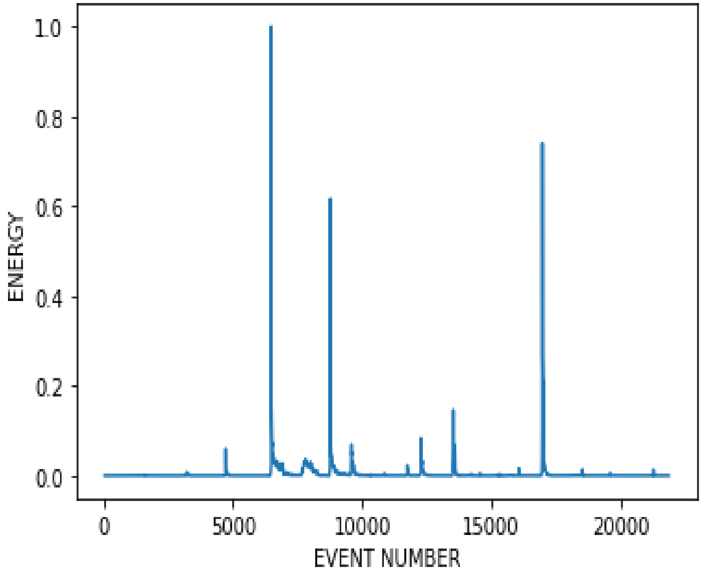
- A high c value indicates a large difference between the calculated mean time and the observed mean time between characteristic events and vice versa

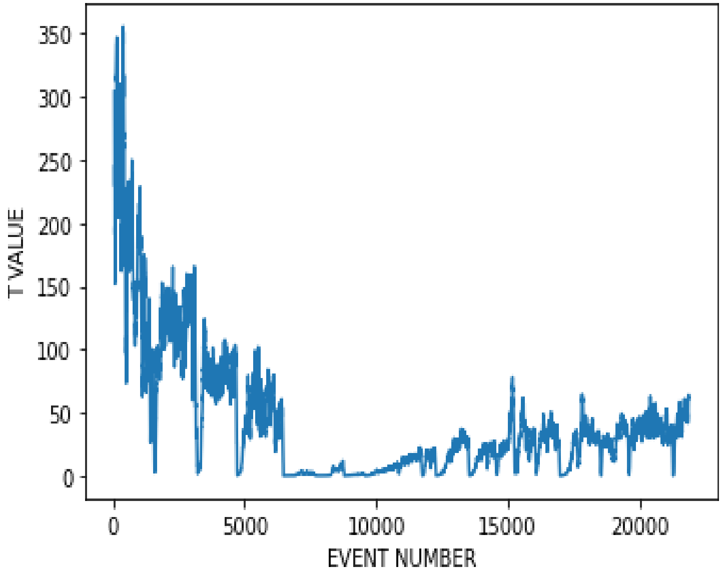

INFORMATION ABOUT THE EARTHQUAKE AND THE SEISMICITY OF THE REGION
T val
M_{mean}
$dE^{1/2}$
b
η
ΔM
μ
c
NEURAL NETWORK
RESULT

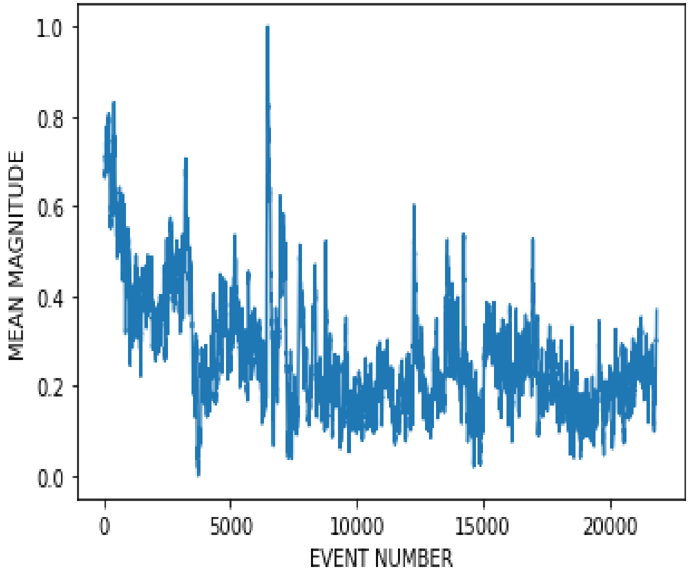
Why will this approach work?

An example-

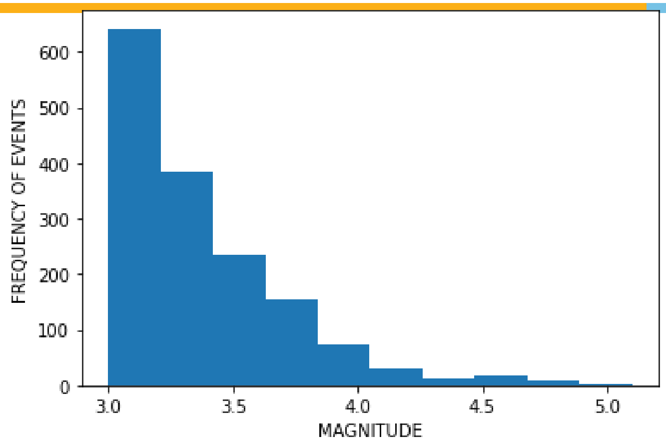
Dataset of SUMATRA REGION (Indonesia)



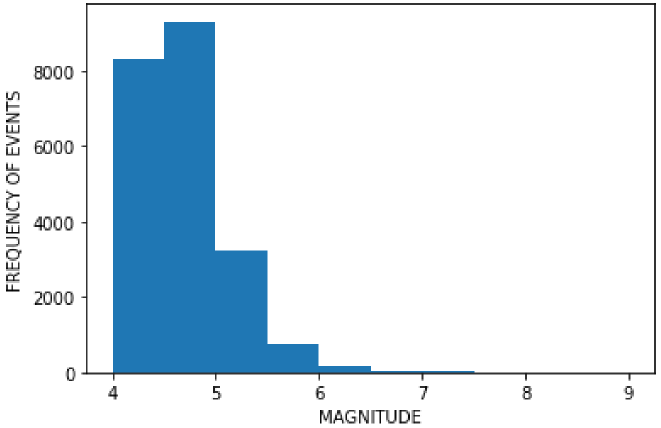




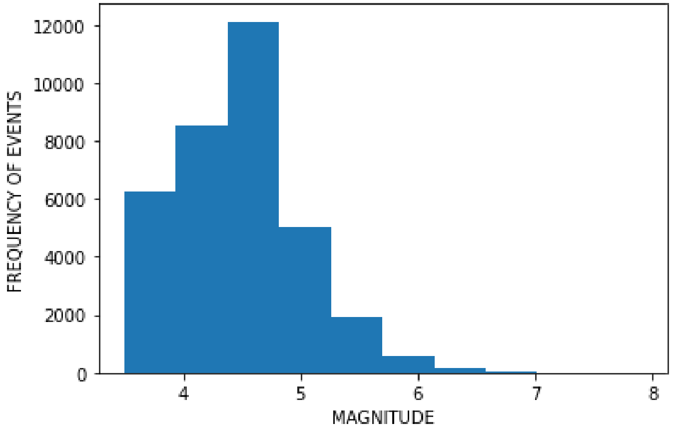
VISUALIZATION- FREQUENCY VS MAGNITUDE



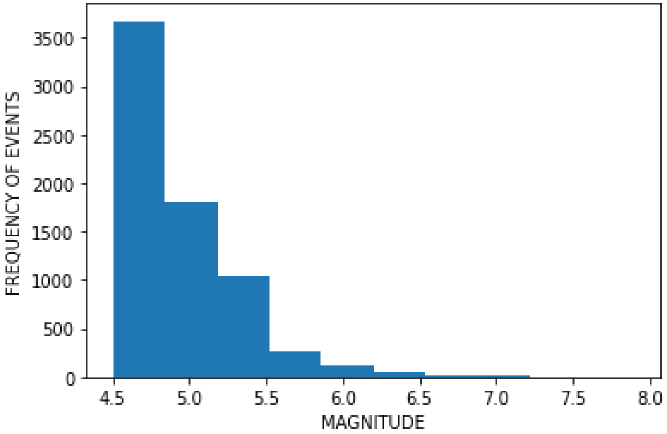
INDIAN REGION



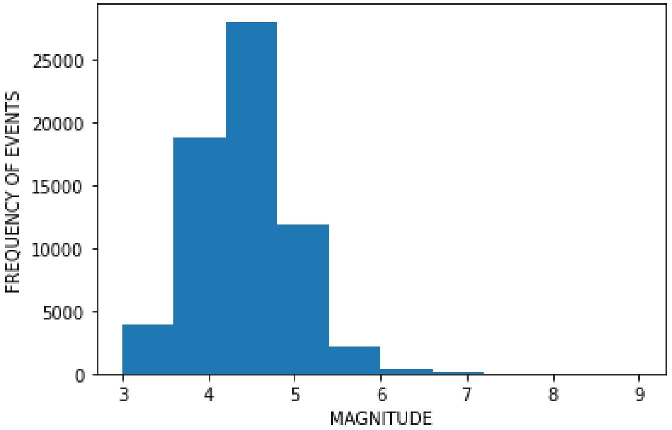
SUMATRA REGION(INDONESIA)



SULAWESI REGION (INDONESIA)

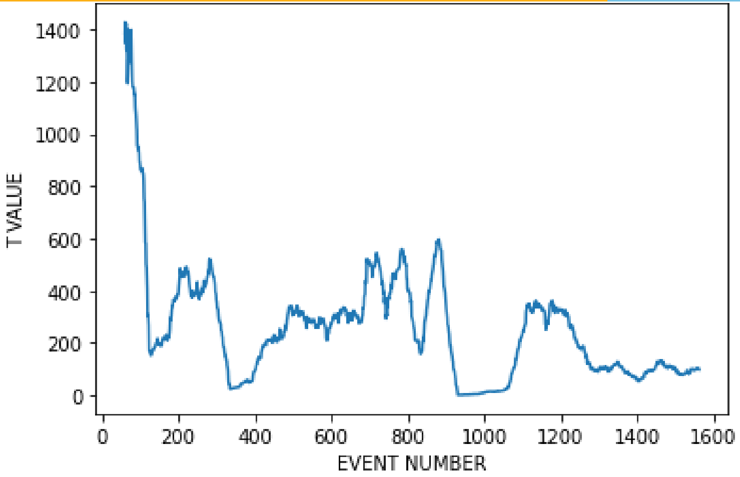


CENTRAL REGION(INDONESIA)

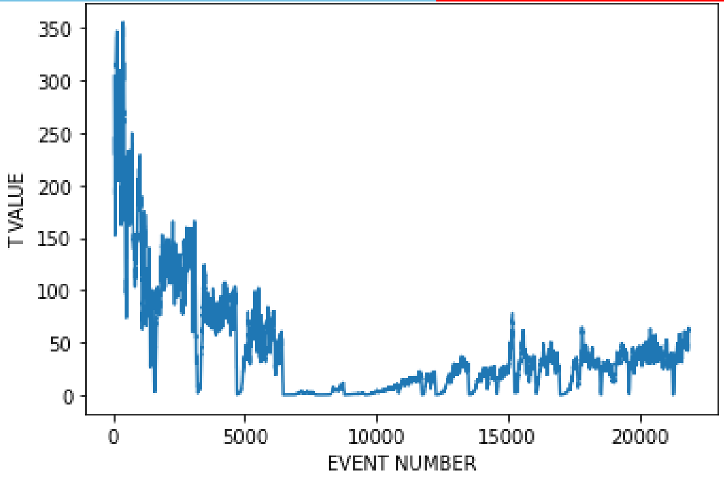


ASIAN REGION

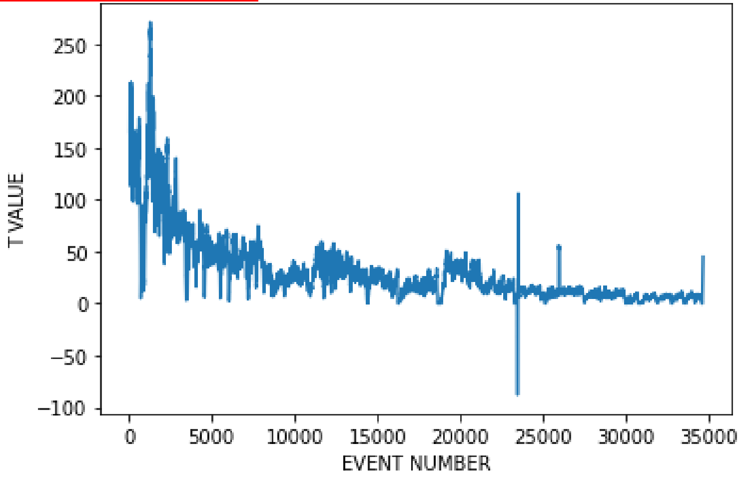
VISUALIZATION- T VALUES



INDIAN REGION



SUMATRA REGION(INDONESIA)



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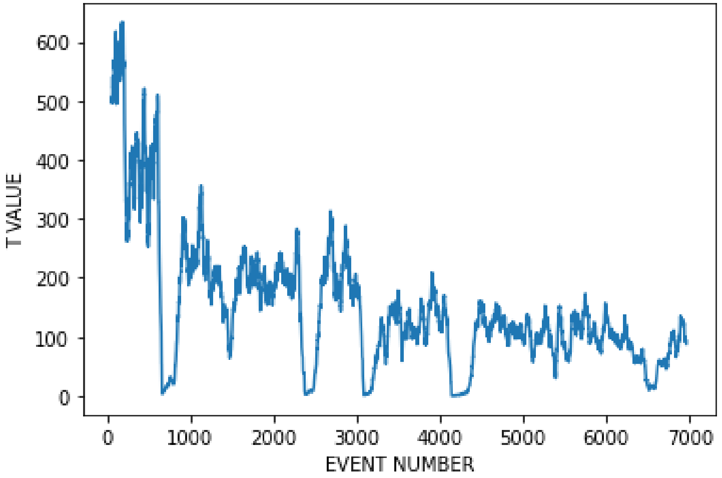

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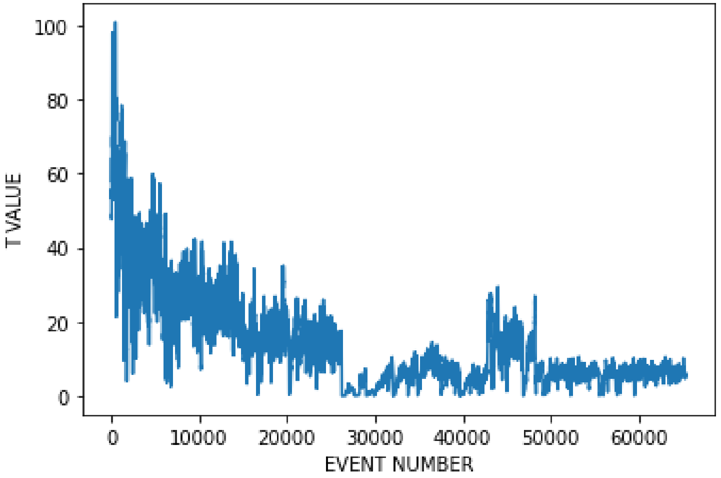
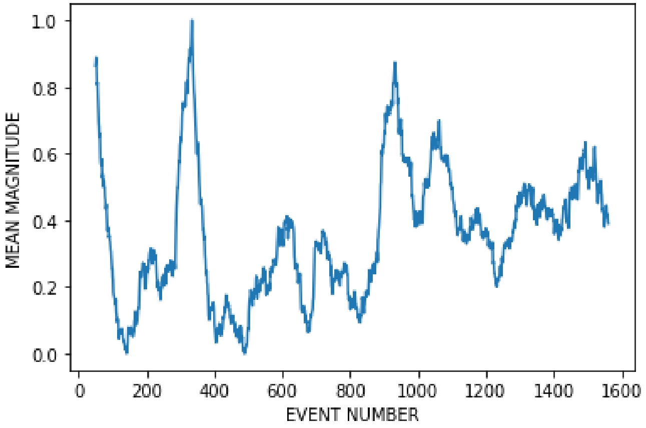
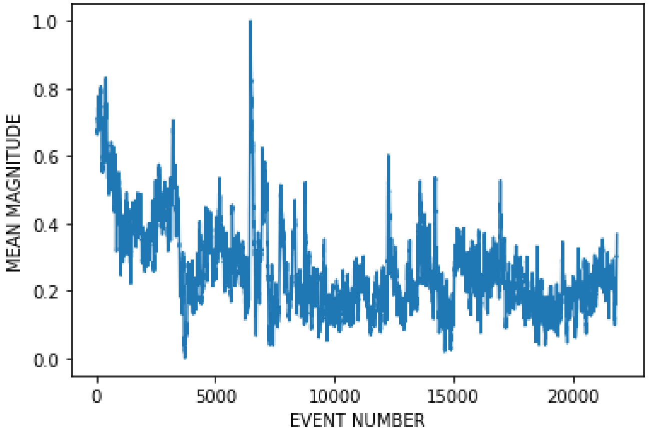


ASIAN REGION

VISUALIZATION- MEAN MAGNITUDES



INDIAN REGION



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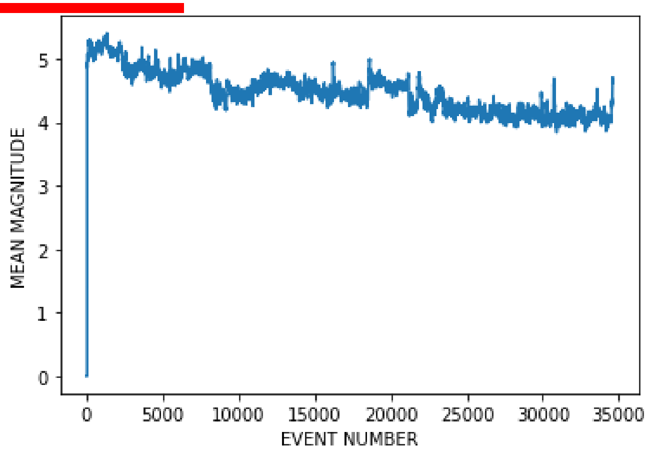

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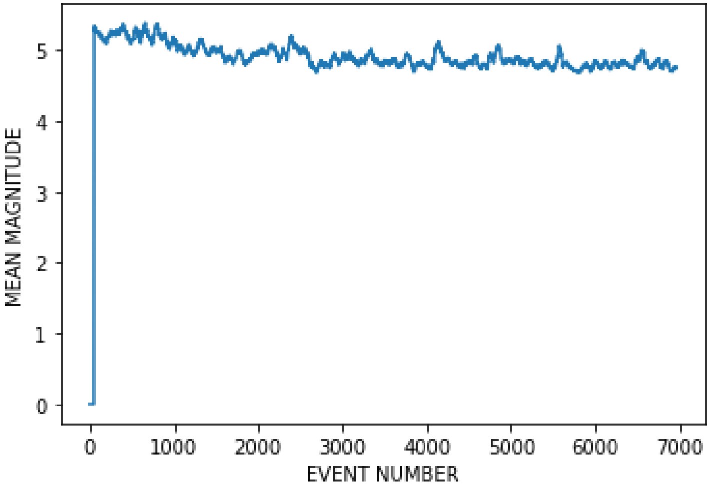

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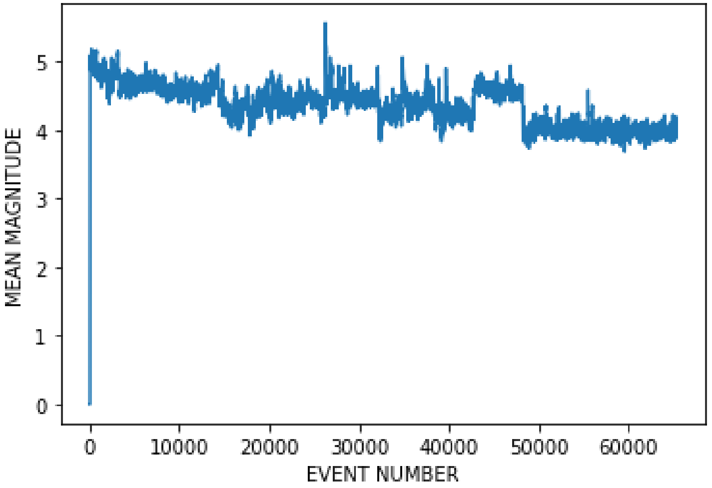
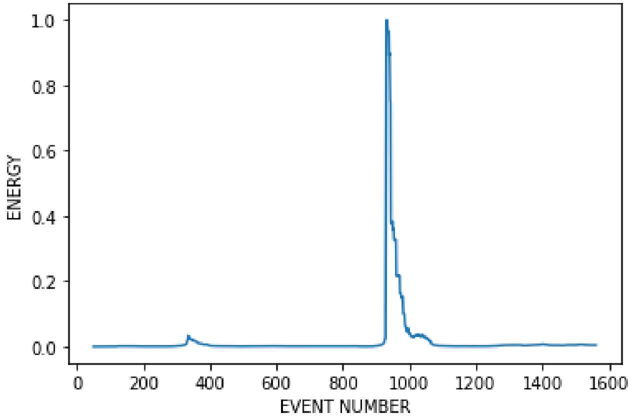
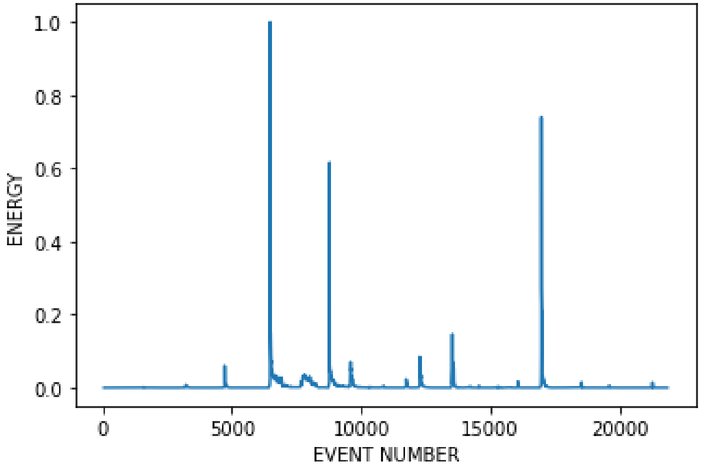


ASIAN REGION

VISUALIZATION - ENERGY



INDIAN REGION



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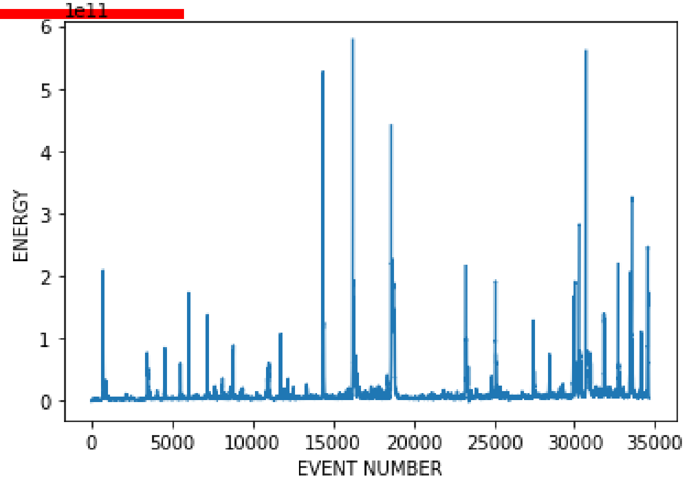

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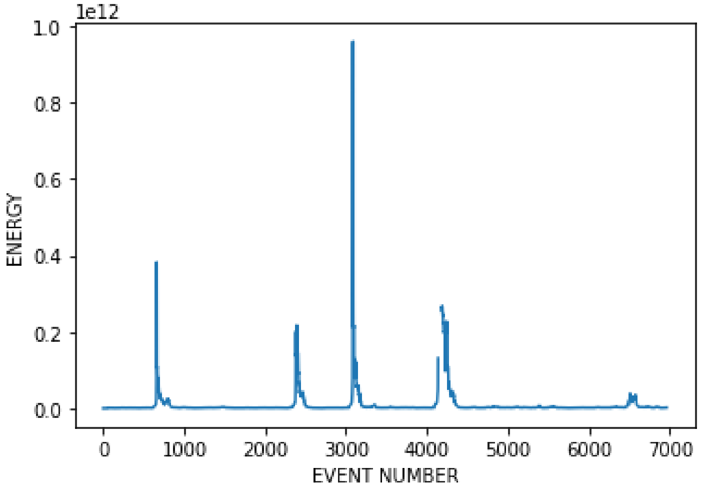

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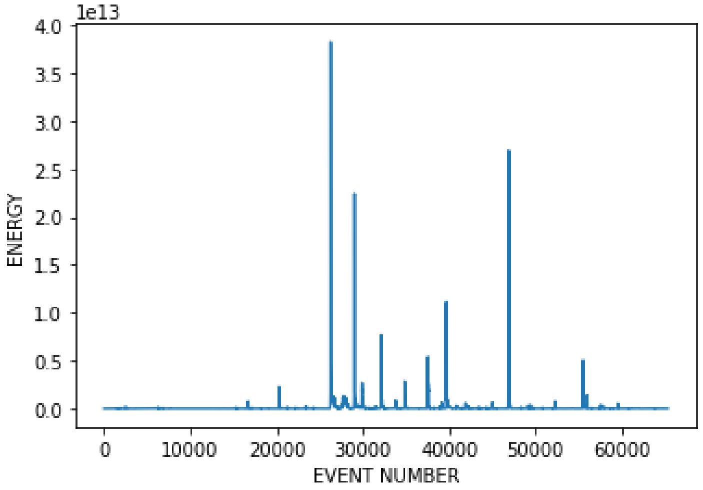


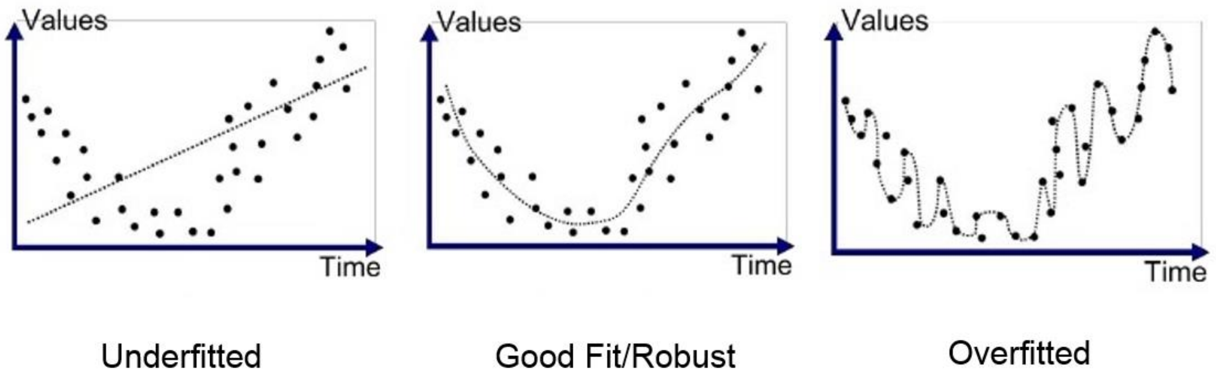
ASIAN REGION

NETWORKS USED

	HIMALAYAN	SUMATRA	CENTRAL	SULAWESI	ASIAN
Input Layer	8	8	8	8	8
Activation Function	ReLU	ReLU	ReLU	ReLU	ReLU
Hidden Layer	24	4	24	14	12
Activation Function	ReLU	ReLU	ReLU	ReLU	ReLU
Hidden Layer	24	4	24	12	12
Activation Function	ReLU	Sigmoid	ReLU	Sigmoid	ReLU
Hidden Layer	12	1	12	1	12
Activation Function	Sigmoid		Sigmoid		Sigmoid
Output Layer	1		1		1

Why use these networks?

- If the training accuracy is high but the validation accuracy is low then it means that the model is overfitting. Decreasing the number of layers(complexity) or applying regularization is the right approach here
- If the training accuracy as well as the validation accuracy is low, then it means that the model is underfitting. Increasing the number of layers(complexity) is the right approach here



Results

F1 accuracy is one of the best metrics to evaluate the model performance. It is calculated by taking the harmonic mean between precision and recall.

$$F_1 = \frac{2}{\mathrm{recall}^{-1} + \mathrm{precision}^{-1}} = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}} = \frac{\mathrm{tp}}{\mathrm{tp} + \frac{1}{2}(\mathrm{fp} + \mathrm{fn})}.$$

After training the models has their f1 accuracies as follows-

REGION	F1 ACCURACY
Indian Himalayan Region	0.8928571428
Sumatra Region	0.81291895185
Central Java	0.9011832427
Sulawesi Region	0.8692946058
Asian Region	0.8557046979

Conclusion

- Neural networks can be a very powerful tool to help forecast upcoming earthquakes. We just need to find the right input as well as the right architecture

- A high accuracy means that the earthquakes that happen depend heavily on the seismicity indicators. This is supported by the results obtained as the models with higher accuracies have their datasets following the Gutenberg Richter Law

- A major problem that hinders earthquake forecasting is the lack of data, as we do not have data of earthquakes of high magnitudes.

References

- Ashif Panakkat and Hojjat Adeli, “Neural Network Models For Earthquake Magnitude Prediction Using Multiple Seismicity Indicators”, International Journal of Neural Systems, Vol. 17, No. 1 (2007) 13–33.
- Asencio-Corte, G.; Martı´nez- A´lvarez, F., Troncoso, A., Morales-Esteban, A.(2015), “Medium–large earthquake magnitude prediction in Tokyo with artificial neural networks”.Springer Neural computing and Applications, 28(5), pp.1043-1055.

THANK YOU