

Group 5 Final Project

AETA Earthquake Prediction

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Background



Part Two

Related
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Discussion

An aerial photograph of a city, likely in Turkey, showing the aftermath of a major earthquake. The foreground and middle ground are filled with the ruins of buildings, with debris scattered across the streets. Several plumes of dark smoke are rising from the wreckage, indicating fires. In the background, a river flows through the city, and mountains are visible in the distance under a hazy sky. The overall scene is one of devastation.

Why earthquake ?

Why earthquake ?

Catastrophic natural disaster

Have claimed millions of lives in the last 100 years

Improvements in technology have only slightly reduced the death toll.

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Discussion

1

Focus on LSTMs
based techniques

Long short -
term memory
(LSTM)



LightGBM



2

Some people see this as a
classification problem

4

For automatic
earthquake
detection using
raw seismic data

Convolutional
Neural Network
(CNN)



LSTM +
CNN



3

Capture both spatial
and temporal
features in the
seismic data

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Data processing

1455

Samples

48

Features

Imbalanced
Class

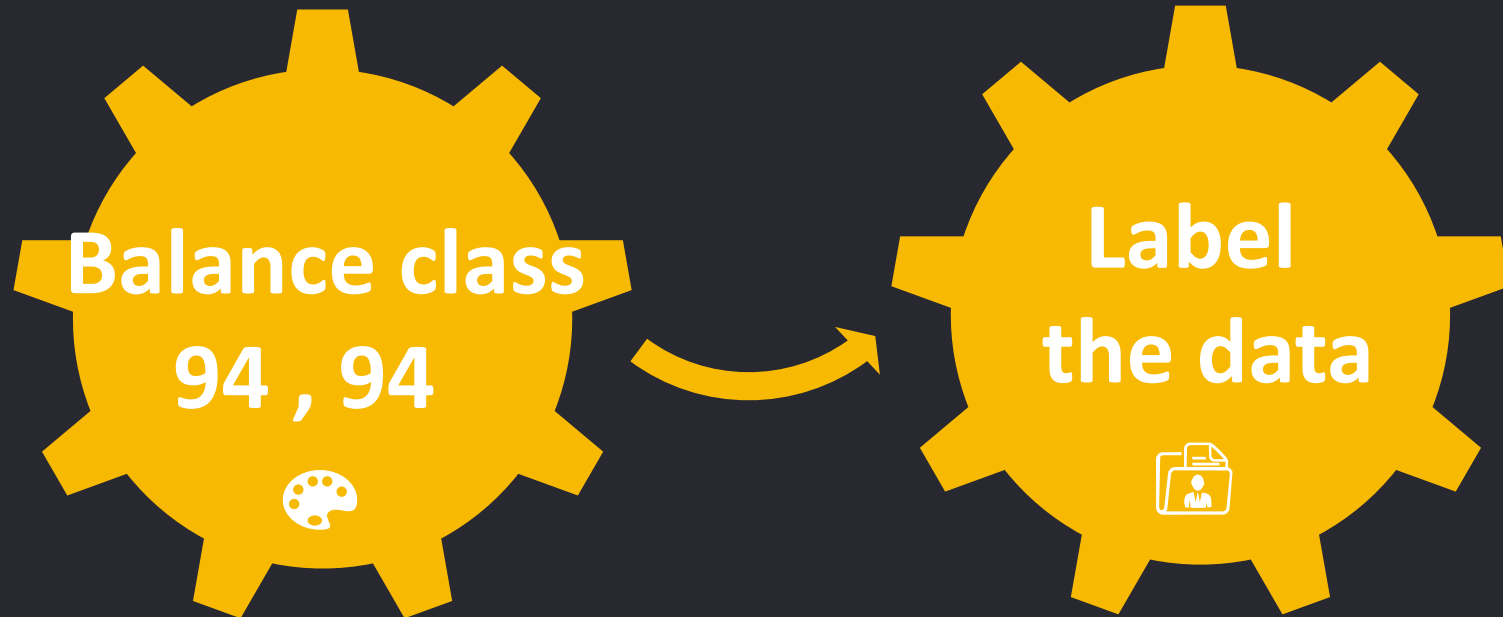
Training data

1113

Negative

94

Positive



0 •----- No earthquake

1 •----- Has earthquake

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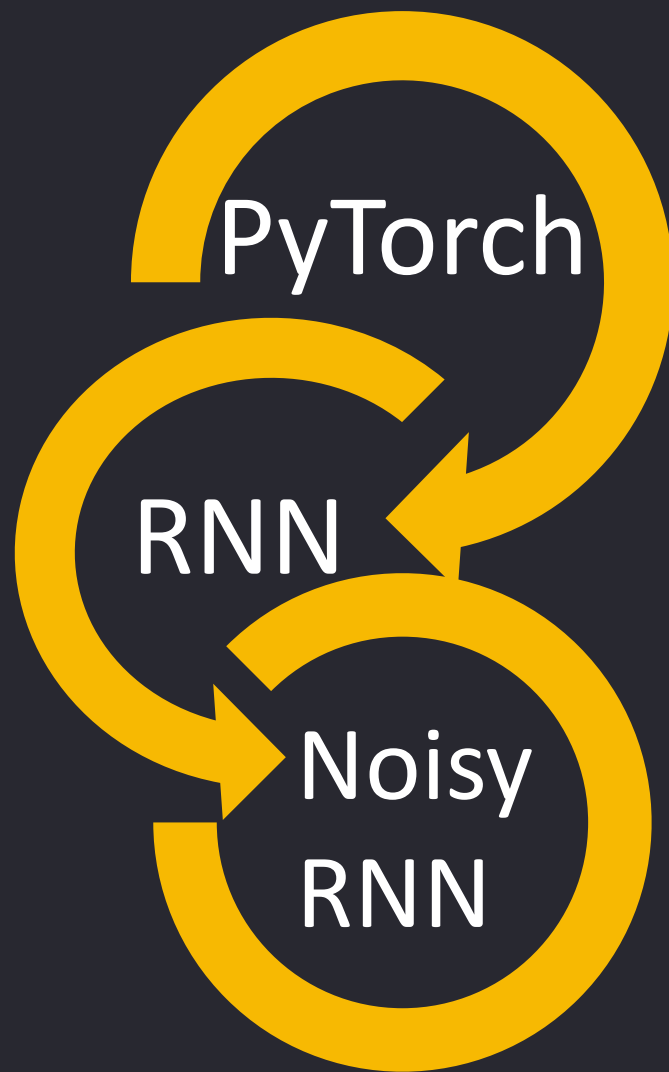
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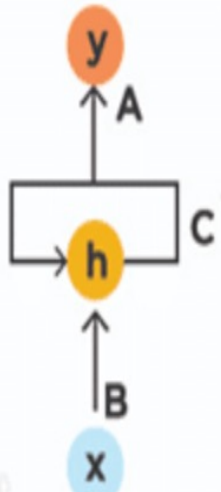
Discussion



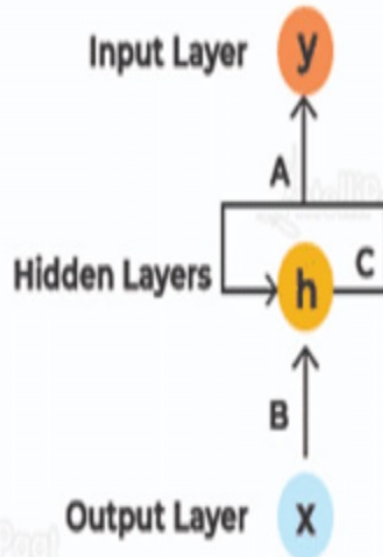
We use PyTorch as our library

Part Four

Model - RNN

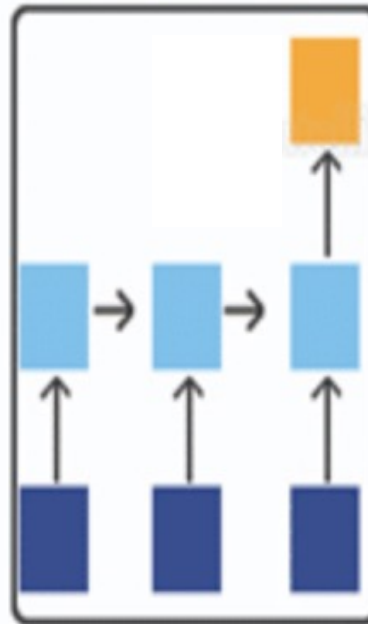


Recurrent Neural Network



A, B, and C are the parameters

Many-to-one



Input layer input size is 48 features
`self.rnn = nn.RNN(48,k,num_layers)`



Linear layer classify class 0 or 1
`self.linear = nn.Linear(k,2)`



Output layer's activation function is leaky ReLU
`outputs = F.leaky_relu(self.linear(output))`

RNN is designed to process sequential data, such as time-series data.

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Model – Noisy Recurrent Neural Networks (NRNNs)

```
if self.add_noise > 0:
    add_noise = self.add_noise * torch.randn(h.shape[0],
h.shape[1]).float().to(self.device)

if self.mult_noise > 0:
    mult_noise = self.mult_noise * torch.rand(h.shape[0],
h.shape[1]).float().to(self.device) + (1-self.mult_noise)
```

1

Earthquake data is often noisy

2

The noise acts as a form of regularization, which helps to prevent overfitting

3

Better capture the underlying dynamics of the data

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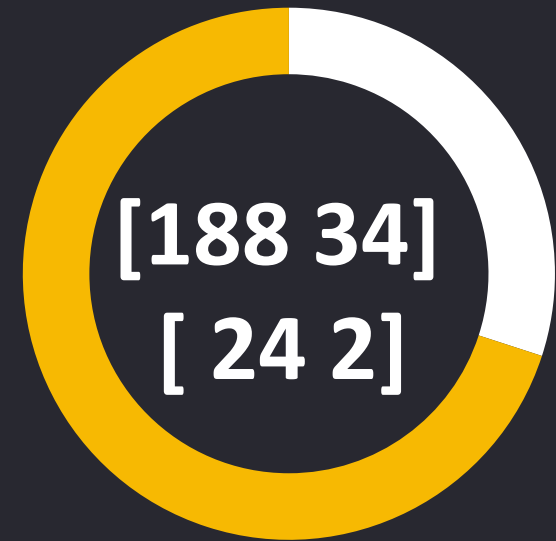
Model Evaluation – training data



F1 Score



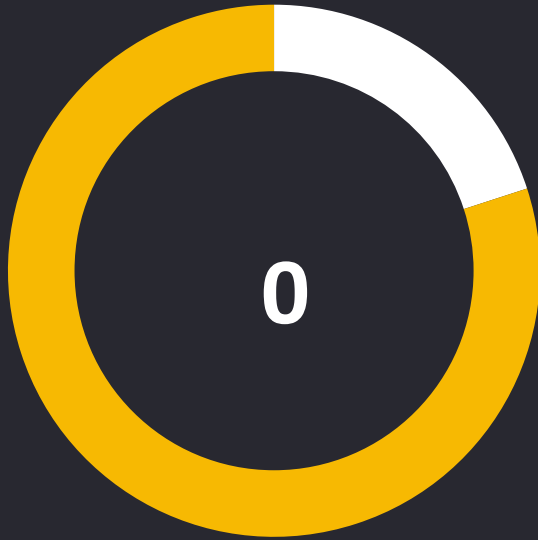
Accuracy



Confusion Matrix

Part Five

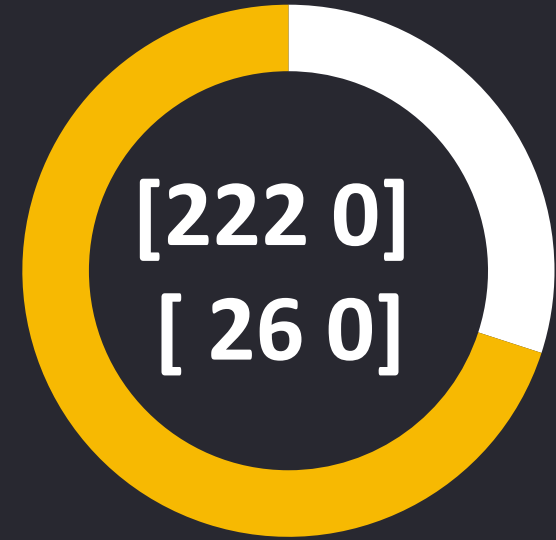
Model Evaluation – test data



F1 Score



Accuracy



Confusion Matrix

Technically, Noisy RNN should have better result
F1 score 0 it failed in predicting has earthquake

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Real-world data quality

Seismic data is often noisy and can be difficult to interpret



Traditional modeling techniques may not be well-suited

New approaches may need to be developed in order to improve accuracy.



Limited understanding

Seismic activity is influenced by a wide range of factors

Thank you for watching |

References

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