Network Intrusion Detection

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Problem: Detect malicious network actions that are considered as intrusions/attacks to be able to stop them and secure the data under attack. In the past, network engineers used signatures which were basically human made patterns that were designed through knowledge of previous malicious attacks. We aim to use Deep Learning to create a NIDS that detects malicious traffic.

Dataset Description

Dataset: The dataset chosen was the UNSW-NB15 dataset. This dataset was collected by the Australian Center for Cyber Security. It provides about two million records divided into nine classes: Shellcode, Worms, Port Scans, Backdoor, Generic, Reconnaissance, Fuzzers, Exploits, and DoS. it is about 100Mb, and it can be downloaded from here. We chose the UNSW-NB15 as it is more recent and contains more records. Furthermore, it has a more diverse set of attacks such as Worms, Shellcode, and Reconnaissance for example.

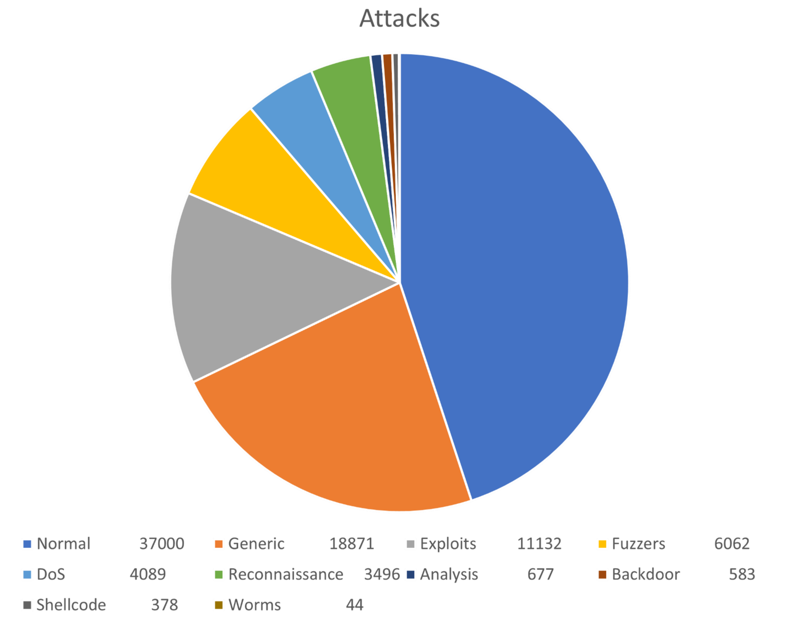
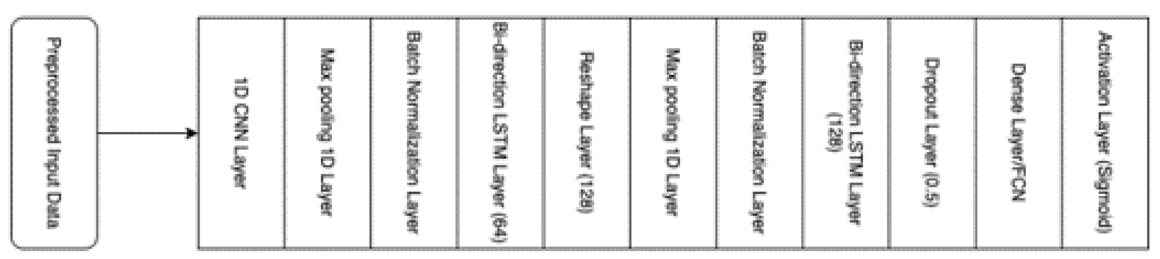


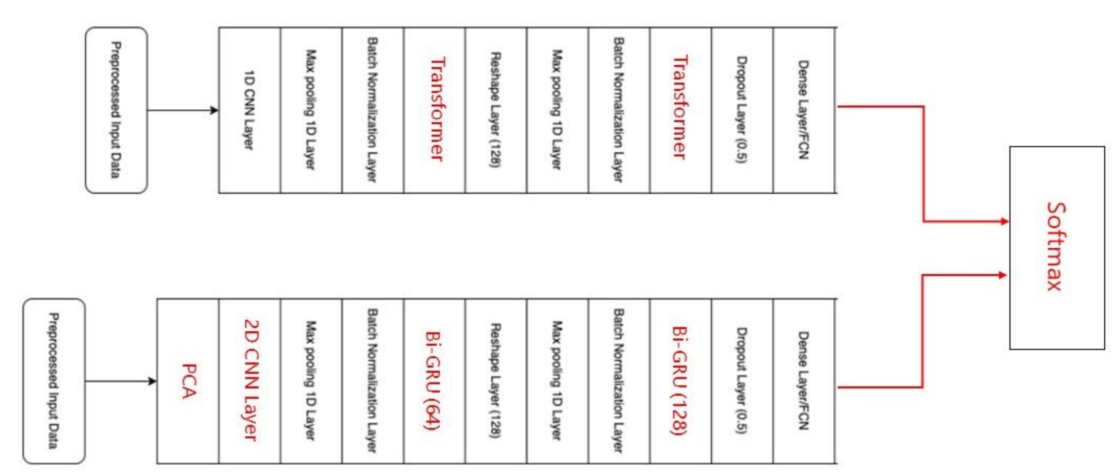
Fig. 1. Class Distribution of UNSW-NB15 Dataset

Different Models

Original Model by Sinha et al.



Final Proposed Model



Final Model Description

- An Ensemble Model consists of two models
  - CNN-Transformer
  - 2D CNN with PCA
- Loss Function used was Categorical Cross entropy
- Output is Softmax with 10 nodes.

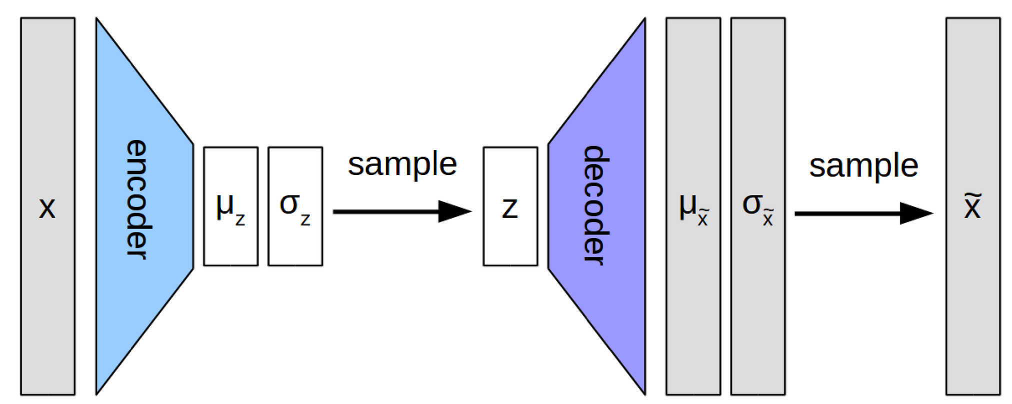
Discussion and Data Preprocessing

We encountered a limit for the training accuracy in our experiments at 86%.

We suspected this had to do with the uneven distribution of the dataset.

To solve this problem, we used:

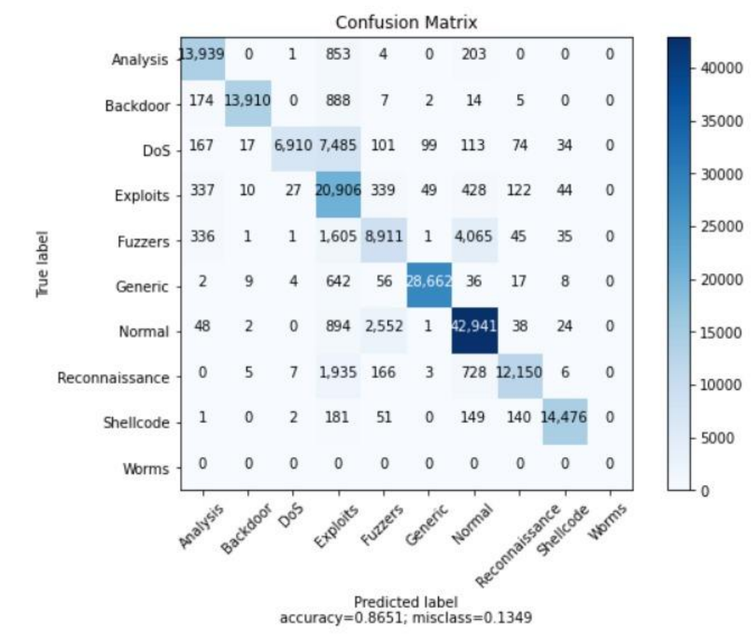
- Oversampling
- Variational AutoEncoders (VAE)



Results

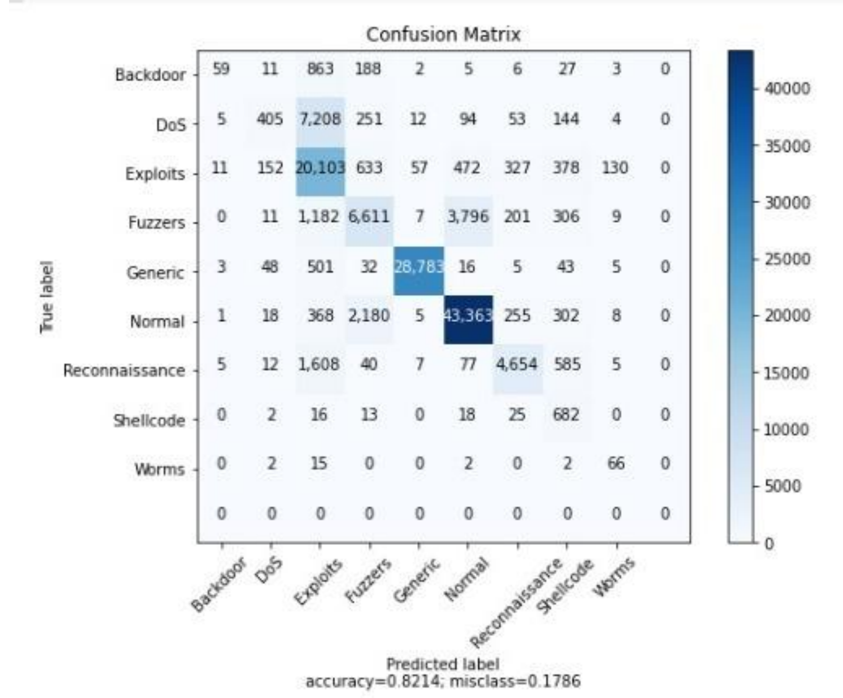
The Original Results with only the basic modification of GRU units:

- Loss: 0.3459
- Training Accuracy: 87.31%
- Validation Accuracy: 86.51%
- Confusion Matrix:



Results with Oversampling method

- Loss: 0.2486
- Training Accuracy: 89.83%
- Validation Accuracy: 82.16%
- Confusion Matrix:



The Results with VAEs

- Loss: Same as Proposed
- Training Accuracy: Same as Proposed
- Validation Accuracy: Same as Proposed

Conclusions

- 2D CNNs seemed to lose the temporal features
- PCA led to overfitting in training
- The data distribution was a real issue that needed a lot more investigation than what we did.
- Oversampling turned out to be an effective solution to classes with low frequency in the dataset (i.e. worms)
- With the skewness of the dataset, measures like recall and precision might be better indicators than accuracy.
- However, accuracy still remains to be the main issue with the UNSW-NB15 dataset, and any improvement will be based on it.

References

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