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# Precision Monitoring: A Scalable CNN-Based signal Classification Framework

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## INTRODUCTION AND MAIN RESULTS

This study introduces a CNN-based method for volcanic seismic signal classification, relevant to CTBT monitoring. An enhanced MobileNet with Ghost modules autonomously extracts features, eliminating expert intervention.

The model achieves over 98,71% accuracy while significantly reducing computational cost, offering an efficient and scalable solution for seismic monitoring.

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## Introduction

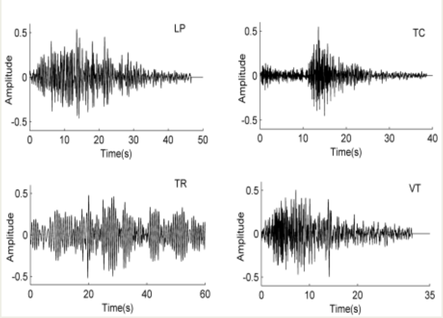
Seismic activity monitoring is a fundamental tool that supports a wide range of scientific and practical applications, including investigations of the Earth’s interior, assessments of volcanic activity, and the detection of underground explosions. With the expansion of global seismic networks, the massive volume of data necessitates automatic classification to reduce analysis time and workload. Nuclear explosion detection remains a key application, particularly in the context of test ban treaty verification. While traditional classification approaches such as multilayer perceptrons (MLPs) have shown good performance, their effectiveness depends heavily on feature selection. To address this limitation, this study explores the use of convolutional neural networks (CNNs), which can automatically learn complex patterns from data, offering a more objective and efficient approach to seismic signal classification. However, CNNs are often criticized for their high computational cost, a drawback that is addressed in this work through the adoption of the Ghost technique. The latter significantly reduces computation while preserving accuracy.

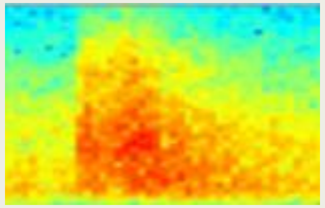
## Methods/Data

| Type / Stride | Filter Shape | Input Size |
|---|---|---|
| Conv / s2 | 3×3×3×32 | 224×224×3 |
| Conv dw / s1 | 3×3×32 dw | 112×112×32 |
| Ghost Module with a ratio equal 2 | 1×1×32×64 | 112×112×32 |
| Conv dw / s2 | 3×3×64 dw | 112×112×64 |
| Ghost Module with a ratio equal 2 | 1×1×64×128 | 56×56×64 |
| Conv dw / s1 | 3×3×128 dw | 56×56×128 |
| Ghost Module with a ratio equal 2 | 1×1×128*128 | 56×56×128 |
| Conv dw / s2 | 3×3×128 dw | 56×56×128 |
| Ghost Module with a ratio equal 2 | 1×1×128×256 | 28×28×128 |
| Conv dw / s1 | 3×3×128 dw | 28×28×256 |
| Ghost Module with a ratio equal 2 | 1×1×256×256 | 28×28×256 |
| Conv dw / s2 | 3×3×256 dw | 28×28×256 |
| Ghost Module with a ratio equal 2 | 1×1×256×512 | 14×14×256 |
| 5× Conv dw /s1 | 3×3×dw | 14×14×512 |
| Ghost Module with a ratio equal 2 | 1×1×512×512 | 14×14×512 |
| Conv dw / s2 | 3×3×512 dw | 14×14×512 |
| Ghost Module with a ratio equal 2 | 1×1×512×1024 | 7×7×512 |
| Conv dw / s2 | 3×3×1024 dw | 7×7×1024 |
| Ghost Module with a ratio equal 2 | 1×1×1024×1024 | 7×7×1024 |
| Avg Pool / s1 | Pool 7×7 | 7×7×1024 |
| FC / s1 | 1024×4 | 1×1×1024 |
| Softmax / s1 | Classifier | 1×1×4 |

The proposed classifier consists of three main steps:

1. Compute the spectrogram of the seismic signal.
2. Convert the spectrogram into an RGB image.
3. Input the RGB image into the proposed CNN for classification.



typical signals belonging to the four classes:
LP: Long Period TC: Tectonic
VT: Volcano-Tectonic TR: Tremor

MobileNet is a well-known CNN model that balances accuracy and computational efficiency. The CNN architecture adopted in this study is based on an enhanced version of MobileNet, whose detailed structure is presented in the accompanying table. To further optimize the model, the Ghost module replaces costly pointwise (1×1) convolutions by first generating a small set of intrinsic feature maps and then producing additional 'ghost' feature maps through inexpensive linear operations. This approach reduces the number of parameters from 3.2M to 1.6M, lowers computational cost, and improves efficiency without compromising accuracy. The proposed classifier was evaluated on seismic data from Llaima volcano in Chile, consisting of four classes with a total of 3592 signals. Using the hold-out method, the data were split into 70% training, 15% validation, and 15% test sets. Data augmentation increased the training diversity, resulting in a final dataset of 38960 signals.

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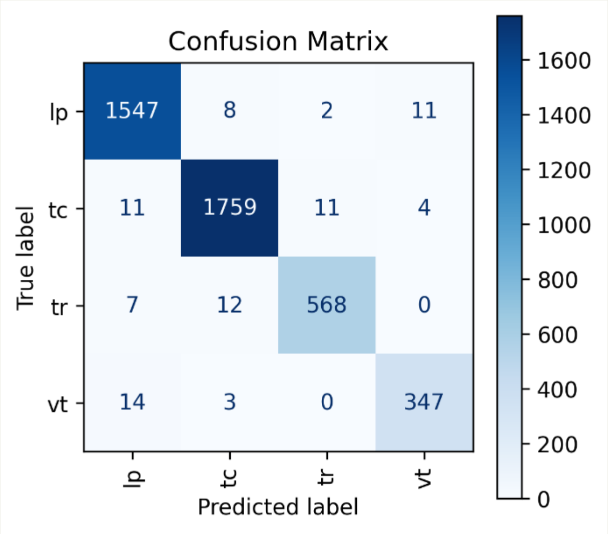
## Results

The proposed CNN model was trained on the training dataset, with early stopping applied to prevent overfitting and reduce training time. Its performance was evaluated on the test dataset, and the results are summarized in the confusion matrix.




From the confusion matrix, it is evident that the classifier achieves strong performance on the volcanic data, with an overall accuracy of 98,71%. Further evaluation was carried out by computing Precision, Sensibility, Specificity, accuracy, and Error. The obtained results are presented in the table below.

| Class | Precision (%) | Sensibility (%) | Specificity (%) | Accuracy (%) | Error (%) |
|---|---|---|---|---|---|
| LP | 97,97 | 98,66 | 98,83 | 98,77 | 2,03 |
| TC | 98,71 | 98,54 | 99,09 | 98,86 | 1,29 |
| TR | 97,76 | 96,76 | 99,65 | 99,26 | 2,23 |
| VT | 95, 86 | 95,33 | 99,62 | 99,26 | 4,14 |

## Conclusions

In this study, a CNN-based classifier was applied to classify volcanic seismic signals into four main classes: LP, TR, VT, and TC. The results demonstrated high accuracy, highlighting the efficiency and objectivity of the proposed method. Beyond volcanology, this approach has strong potential for extension to other domains, such as nuclear explosion recognition via transfer learning, thereby opening promising perspectives for automatic seismic activity monitoring and detection.