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Volcanic Seismic Event Classification based on CNN Architectures

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RESUMEN

Este artículo explora el uso de arquitecturas de redes neuronales convolucionales en el contexto de clasificación de eventos sísmicos volcánicos mediante el uso de imágenes de espectrogramas en escala de grises de eventos sísmicos de período largo y volcano-tectónicos. Combinamos las arquitecturas con un conjunto de configuraciones de hiperparámetros que produjeron 720 modelos de clasificación, los cuales fueron capaces de aprender los patrones morfológicos descritos por las imágenes de espectrogramas en escala de grises. Se usó la reducción de escala de todas las imágenes de espectrogramas en escala de grises para reducir el tiempo de computación para cada modelo sin perder rendimiento y evitar cualquier sobreajuste. Las tres arquitecturas exploradas proporcionaron buenos resultados en términos de área bajo la curva receptor-operador. Sin embargo, al considerar el puntaje de exactitud (*accuracy*) en el proceso de selección, el mejor modelo que clasificó imágenes de spectrogramas en escala de grises de ambos tipos de eventos sísmicos fue la arquitectura CNN3 con filtro de convolución y *pool* de tamaño (3×3), tipo de padding *same*, 150 iteraciones (*epochs*) y 1×10^{-4} como tasa de aprendizaje, el cual alcanzó los valores de área bajo la curva receptor-operador y valor de exactitud de 0.94 y 94.13%, respectivamente.

Palabras clave: clasificación de eventos sísmicos volcánicos, clasificadores de aprendizaje automático, clasificadores basados en CNN, imágenes de espectrogramas.

ABSTRACT

This paper explores the use of convolutional neural network architectures in the context of volcanic seismic event classification through the use of gray-level spectrogram images of long-period and volcano-tectonic seismic events. We combined the architectures with a set of hyper-parameter configurations that produced 720 classification models, which were able to learn the morphological pattern described by the gray-level spectrogram images of seismic events. Downscaling of all gray-level spectrogram images was used to reduce the computation time for each model without losing performance and avoiding any overfitting. The three explored architectures provided good results in terms of the area under the receiver operating characteristic curve scores. However, when considering the accuracy scores in the selection process, the best model to classify gray-level spectrogram images of both types of seismic events is the CNN3 architecture with a (3×3) convolutional and pool kernel size, *same* padding type, 150 epochs and 1×10^{-4} as the learning rate, which achieved an area under the receiver operating characteristic curve and accuracy values of 0.94 and 94.13%, respectively.

Key words: volcanic seismic event classification, machine learning classifier, CNN based classifiers, spectrogram images.

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I. INTRODUCTION

Monitoring volcanic activity is an indispensable factor in reducing the associated effects that could be produced by volcanic eruptions, especially in highly populated cities located near active volcanoes, such as Mexico City (Mexico) close to the Popocatépetl Volcano, Tokyo (Japan) near Mt. Fuji, Naples (Italy) close to Mt. Vesuvius or Seattle (USA) close to Mt. Rainier, among others (Schmincke, 2004). In fact, this type of natural phenomena has been responsible directly and indirectly for thousands of deaths since the year 1500 (Tilling, 1996). Usually, volcanoes are monitored by analysing their seismic signatures (Malfante et al., 2018) (Schmincke, 2004).

A wide range of approaches using machine learning have been developed in recent years to address the problem of volcanic seismic event classification, such as: random forest (RF) (Rodgers et al., 2018) (Pérez, Venegas, et al., 2020), decision trees (DT) (Lara-Cueva., 2016a), hidden Markov models (HMM) (Benítez et al., 2006), Gaussian mixture models (GMM) (Venegas et al., 2019a), support vector machine (SVM) methods (Lara-Cueva et al., 2016b) (Apolloni, 2009) (Curilem et al., 2014) (Pérez, Venegas, et al., 2020), boosting strategies (Venegas et al., 2019b) and artificial neural networks (ANN), especially multi-layer perceptrons models (Curilem et al., 2009) (Scarpetta et al., 2005) (Langer et al., 2006) (Pérez, Venegas, et al., 2020). However, the majority of these methods require feature calculation and selection stages to minimize the volume of information used to feed the models, which helps them avoid overfitting during model training. This extra workload makes some models non-practical to be used for the classification of spectrogram images of seismic events. Convolutional neural networks (CNN) are special ANN architectures that are gaining more attention in image analysis contexts (Shin et al., 2016) (Chauhan et al., 2018). They avoid using intermediate fully connected layers to employ pooling ones and thus to optimize the information pass-through from layer to layer. Lately, there is evidence of deep CNN models used to classify spectrogram images of seismic events with successful performance (Curilem et al., 2018). However, the classification of volcanic seismic events remains as a challenging and useful problem to solve along the time.

This work proposes a CNN classifier-based exploration to tackle the problem of seismic event classification, especially regarding long-period (LP) and volcano-tectonic (VT) seismic events recorded from the Cotopaxi Volcano in Ecuador. It is based on a combination of three different CNN classifiers that learn the morphological pattern described in the gray-level spectrogram images of both types of events. Then, the most accurate model per architecture is selected, and a final decision rule determines which model could be considered as the best solution. We selected CNN-based classifiers instead of other MLCs mainly because they do not involve any feature calculation/selection stages and have demonstrated a high capability to handle image analysis problems (Shin et al., 2016) (Chauhan et al., 2018).

The remainder of this paper is organized as follows: the Materials and Methods section presents the experimental spectrogram images dataset used for our experimentation, the considered CNN architecture-based classifiers and the experimental setup design used in this work. The Results and Discussion section presents an exploratory comparison based on the obtained area under the receiver operating characteristic curve (AUC) scores for each CNN-based model and the accuracy (ACC) scores against the state of art-based methods. Finally, Conclusions and Future Work are drawn in the last section.

II. MATERIALS AND METHODS

A. Experimental dataset

The (*MicSigV1*) dataset from the ESeismic repository, which is the first annotated Ecuadorian volcanic seismic public repository containing several samples recorded at the Cotopaxi Volcano (Pérez, Benítez, et al., 2020), was used in this study. The *MicSigV1* dataset was provided by courtesy of the Institute of Geosciences and collaborators, and it is available at http://www.igepn.edu.ec/eseismic_web_site/index.php.

The *MicSigV1* dataset is composed of a total of 1187 seismic records from two different seismic stations (VC1 and BREF) installed at the Cotopaxi Volcano. The dataset contains samples distributed in five classes corresponding to: LP, VT, regional (REG), hybrid (HB), and icequakes (ICE). Some examples of seismic events inside this dataset are shown in Fig. 1. Due to the small number of samples from REG, HB, and ICE events available within the *MicSigV1* dataset, we only considered the use of LP and VT events classes for this study. The selected samples belong to the same seismic station (BREF) to guarantee the same acquisition protocol and to avoid mixed signals. Therefore, the formed experimental dataset contains a total of 668 spectrogram images distributed in 587 cases of LP and 81 cases of VT seismic event classes.

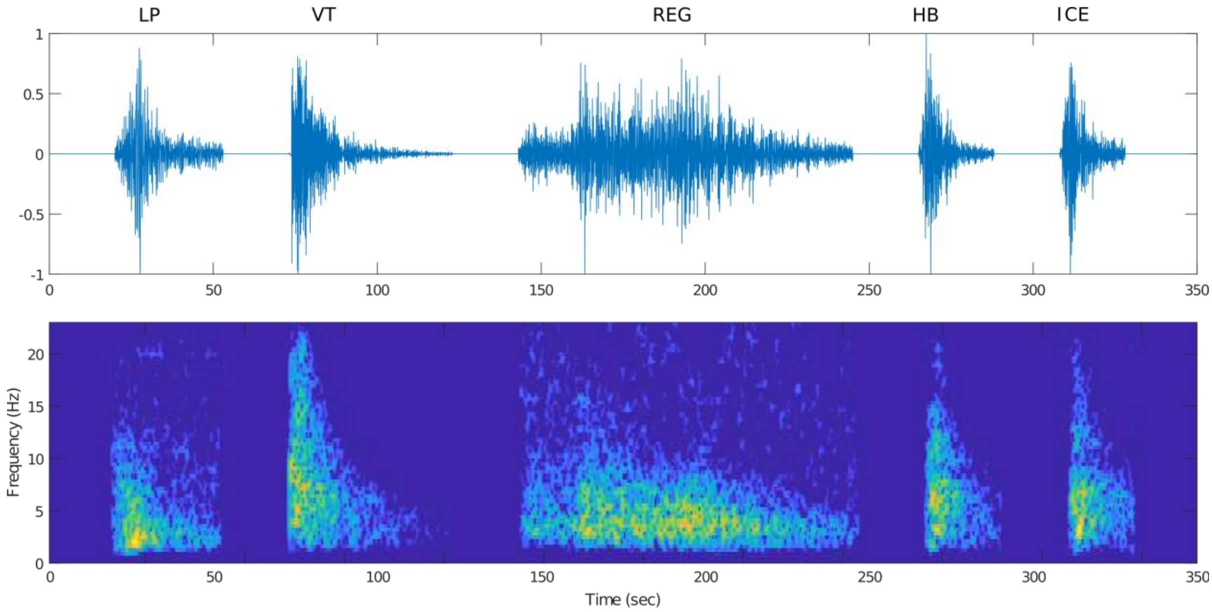

Figure 1. Wrapped examples from the *MicSigV1* dataset: time-domain signals (top) and their respective spectrogram (bottom). The time signals were normalized by their maximum absolute value. Figure taken from Pérez, Benítez, et al. (2020).

B. CNN classifiers

CNN classifiers have been widely adopted as a reliable MLC for developing computer vision and image recognition systems (Albawi et al., 2017) (Zeiler & Fergus, 2014). The traditional structure consists of a sequential workflow starting at the convolutional layer, which generates the set of feature maps extracted from the inputs by convolving the original image (input) with a set of learned filters. The features are represented as matrices that are then passed to an activation layer, usually with the sigmoid function. Afterward, a pooling layer is used for the purpose of sampling and performing feature reduction through the use of max pooling, min pooling, or average pooling methods. In the last step, a fully connected or dense layer and an output activation layer are included to provide the classification capabilities of the model (Albawi et al., 2017).

We adopted the general structure of the CNN architecture to build three different classifiers, as it is shown in Fig. 2. The classifier design was mainly focused on the variation of the number of filters in the convolutional layer. Therefore, CNN1, CNN2, and CNN3 classifiers were formed with a total of 8, 16, and 32 filters, respectively. Exploring the classification space under this variation will allow us to better understand the relationship between the model performance and its complexity.

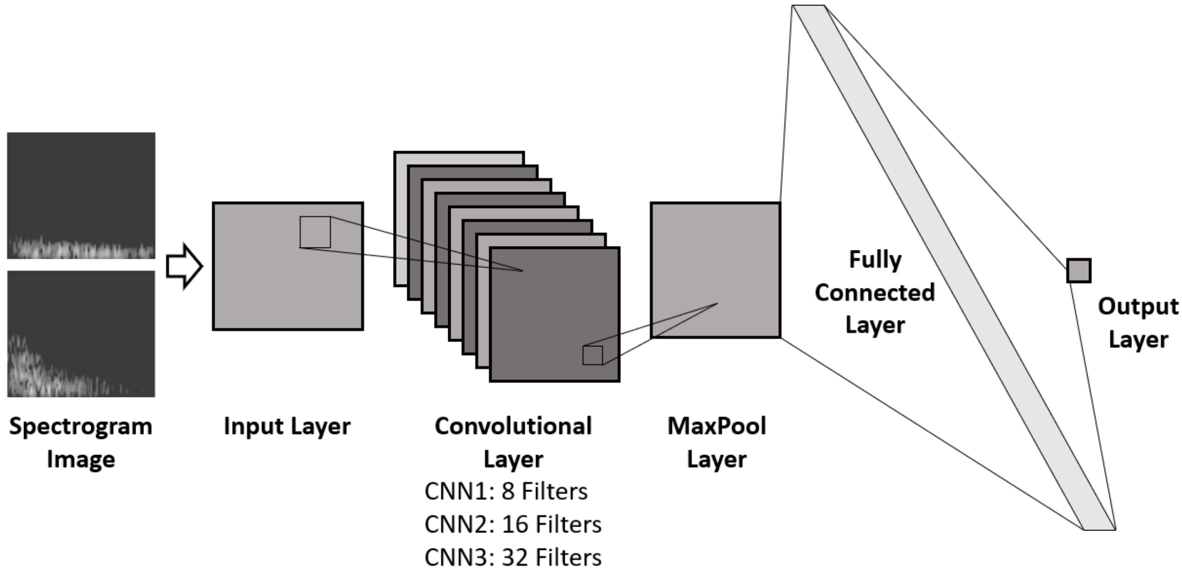

Figure 2. CNN structure used in this work, from left to right: input layer, convolutional layer with its filters (one set of filters per architecture), activation layer with a sigmoid activation function, max-pooling layer, fully connected layer (flattened) and a binary activation layer (output) with a sigmoid function.

C. Experimental setup

The designed setup involved the spectrogram images preprocessing, training and test partitions, CNN configurations, assessment metrics, and selection criteria, which are essential aspects to be described next.

1) Spectrogram images preprocessing

Since the spectrogram images in the *MicSigV1* dataset are in RGB (red, green, blue) format and the color information is irrelevant in the context of volcanic event pattern analysis, we first transformed them into a gray-scale space to reduce the information channel of each pixel in the image. Also, the spectrogram image dimensions were downscaled to 25% of the original image sizes to reduce the number of pixels per image and to decrease the computational requirements of the learning models. The *MicSigV1* dataset provides spectrogram images free of noise, thus, the downscaling operation does not affect the seismic event pattern presented on each image. This operation has been well developed and employed in other research works (Kesim, Dokur & Olmez, 2019) (Quan, 2018). Moreover, the pixel values of each spectrogram image were normalized using the min-max method (Jain & Bhandare, 2011) to bring them into the range between -0.5 to 0.5, thus avoiding data dispersion.

2) Training and test partitions

We applied five-times the 10-fold cross-validation method (López et al., 2006) before the classification stage to form disjoint training and test partitions. In this way, individual CNN models will be trained on different training sets and, thus, will learn from different input space representations. Testing on these different sets leads to variability in the resulting classification for individual samples. However, it is essential to note the imbalance representation between the number of LP and VT sample cases. Therefore, we tuned the *k*-fold cross-validation to be stratified during the partition stages, ensuring the observation ratio between both types of events along all folds. This adjustment allows us to obtain reliable results.

3) CNN configurations

Since the employed models belong to the same classifier, for all models, the convolutional kernel size was optimized using (3×3), (7×7) and (15×15) dimensions; the padding types were tuned to *no_padding* and *same*, which means whether or not to add padding such that the resulting filter retains the same dimensions of the input image; the learning rate was optimized in the range from 1×10^{-4} to 5×10^{-4} with increment steps of 2×10^{-4}; the max-pooling kernel size used a (3×3) and (2×2) dimensions with a stride of 3 and 2, respectively; the number of iterations (epochs) varied from 50 to 500 with increment steps of 50 units. Finally, the models used the *Adam* optimizer, which is based on adaptive estimation of lower-order moments and was designed to combine the advantages of the well-known optimizers AdaGrad and RMSProp (Kingma & Ba, 2014).

4) Assessment metrics

The classification performance of all employed CNN models was based on the AUC of the receiving operating characteristic curve and ACC metrics; the statistical comparison was carried out using the Wilcoxon signed-rank statistical test, a non-parametric alternative test to the paired *t*-test. This test ranks the differences in performances of two MLCs (Demšar, 2006), providing a fair comparison among them, and therefore a reasonable selection of the best classification models. We used a significance decision level value of 5% $(\alpha = 0.05)$ for a two-tailed test (Hollander, Wolfe & Chicken, 2013) on all comparisons.

5) Selection criteria

Since the CNN1, CNN2, and CNN3 classifiers explored several model configurations, it was necessary to select the best MLC according to a decision rule. Due to the lack of a universal rule to select the best classifier that considers both the AUC and ACC assessment metrics, we established a “rule of gold” for the selection process based on the following criteria: (1) the highest AUC score statistically per classifier and, (2) if there was a tie rating performance in AUC scores, the classifier that reached the highest ACC value was preferred. It should be noted that it is possible to select more than one model depending on whether or not there is an AUC-based significant difference between the classification models. Thus, the ACC scores will determine the final selection.

The implementation of all classifiers was done in *Python* language version 3.6.9 (Python Core Team, 2019) with the *scikit-learn* (*SKlearn*) library (Pedregosa et al., 2011) and *Keras* (Chollet, 2018) with *MXNet* backend (Chen et al., 2015) CNN classifiers.

III. RESULTS AND DISCUSSION

A total of 720 CNN-based models were evaluated on the experimental dataset containing 668 gray-level spectrogram images. The direct statistical comparison based on the mean of AUC performance over 50 runs revealed interesting results for the classification of LP and VT seismic events, as described next:

A. Performance evaluation

Agreeable to the first selection criterion, a total of 3 out of 720 classification models were obtained after exploring the whole space of classifiers. According to the Wilcoxon statistical test at $\alpha = 0.05$, the best model using the CNN1 classifier was formed by the (3×3) convolutional and pool kernel size, *no_padding* type, 50 epochs and 3×10^{-4} as the learning rate, reaching AUC and ACC values of 0.95 and 91.89%, respectively. The best model provided by the CNN2 classifier was composed by a (3×3) convolutional kernel size, (2×2) pool kernel size, *same* padding type, 100 epochs and 1×10^{-4} as the learning rate, reaching AUC and ACC values of 0.94 and 93.20%, respectively. For the CNN3 classifier, the best model was formed by a (3×3) convolutional and pool kernel size, *same* padding type, 150 epochs and 1×10^{-4} as the learning rate, reaching AUC and ACC values of 0.94 and 94.13%, respectively.

The three selected models reached similar AUC scores $(p > 0.05)$ performance without incurring any overfitting during the training step, as it could be seen in Fig. 3. Thus, it is possible to state that any of them could be used to handle the problem of LP and VT seismic events classification based on their gray-level spectrogram images. However, in terms of ACC values, the CNN3 classifier-based models provided the best results. This situation could be related to the fact of having 32 filters in the configuration of this classifier, and, as long as more neurons are learning about the pattern in the gray-level spectrogram images, the classification will be more accurate. As a drawback, the CNN3 classifier-based models demand more interactions (epochs) to converge to the minimum error during the training and validation process (see Fig. 3, bottom row). Despite the good performance of the three considered models and according to the second selection criterion, the best classifier for the problem at hand was the model based on the CNN3 architecture.

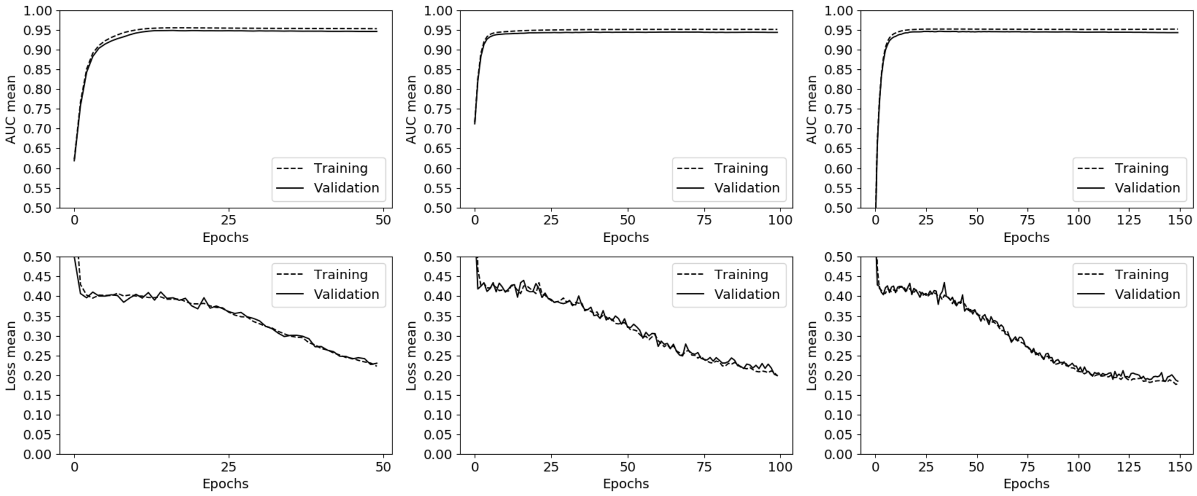

Figure 3. Performance results of the best-selected model from CNN1 (left), CNN2 (center) and CNN3 (right) classifiers based on the AUC (top row) and binary cross-entropy loss function (bottom row) metrics in the training and validation sets.

B. State of the art-based comparison

Regarding the classification performance, it was not possible to make a statistically direct comparison against previous methods found in the literature, since most of them involve a feature calculation and a feature selection stage instead of working directly on the spectrogram images, like in our work. Therefore, we focused to conduct the comparison based on the ACC scores reported by the state-of-the-art methods.

From Table 1, it is possible to notice that the selected CNN3-based model was able to reach a competitive ACC score when compared to previously developed methods. Except for the RF and feed-forward back-propagation based ANN developed in Pérez, Venegas, et al. (2020), which also worked on a dataset containing overlapped signals, the remaining related works performed the classification on a controlled dataset environment (balanced dataset, signals without overlapping, etc.). Also, it should be noted that all the state of the art-based methods computed and reduced the feature space in some way to decrease the heavy load of information before feeding the MLCs. Therefore, the proposed CNN3-based model could be considered faster in terms of computation time and lesser algorithmic complexity, since it avoids any feature calculation/selection stages.

Table 1. *Comparison based on the ACC between related previous works available in the literature and the best selected model produced in this work.*

Method	**Number of samples**	**Computed features**	**Spectrogram images**	**ACC* (%)**
ANN (Lara-Cueva et al., 2016a)	914	6	No	97
DT (Lara-Cueva et al., 2016a)	914	3	No	96
ANN (Pérez, Venegas, et al., 2020)	637	17	No	95
RF (Pérez, Venegas, et al., 2020)	637	17	No	93
linear SVM (Lara-Cueva et al., 2016b)	914	5	No	97
ANN (Curilem et al., 2009)	1033	8	No	94
HMM (Benítez et al., 2016)	-	5	No	90
GMM (Venegas et al., 2019a)	667	2	No	94
CNN3 model	**668**	**-**	**Yes**	**94**

Note. ACC – accuracy; *values rounded to the closest integer

IV. CONCLUSIONS AND FUTURE WORK

This work proposed a CNN classifier-based exploration to tackle the problem of seismic event classification, especially on gray-level spectrogram images related to LP and VT events from the Cotopaxi Volcano. We used a combination of three different CNN architectures with a set of hyper-parameter configurations that produced 720 classification models, which were able to learn the morphological pattern described by the gray-level spectrogram images of both types of events. Downscaling of all gray-level spectrogram images was used to reduce the computation time required by each model without losing AUC and ACC performances, avoiding any overfitting. The three explored CNN architectures provided good results in terms of AUC scores. However, the CNN3-based models were much better when considering the ACC scores in the selection process. Therefore, the best model to classify gray-level spectrogram images of LP and VT seismic events was the CNN3 model with a (3×3) convolutional and pool kernel size, *same* padding type, 150 epochs and 1×10^{-4} as the learning rate, which reached AUC and ACC values of 0.94 and 94.13%, respectively.

As future work, we plan (1) to incorporate new classification models by including other MLCs such as radial basis function networks, (2) to explore other preprocessing techniques of the original *MigSigV1* dataset, as well as (3) to expand the hyper-parameter configurations to understand the performance limits of the developed models.

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