Classification of Volcano-Seismic Signals with Bayesian Neural Networks

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***Abstract*—Whilst recent advances in the field of artificial neural networks could be applied to monitor volcanoes, its direct application remains a challenge given the complex geodynamics involved and the size of available datasets. However, Bayesian Neural Networks (BNNs) are probabilistic models that could classify and provide uncertainty estimation for transient seismic sources, even under data scarcity conditions. This research focuses on practical applications of BNNs to classify volcano-seismic signals using two variational learning approaches: Bayes by back-prop and Monte-Carlo dropout. We evaluate classification performance on seven classes of isolated events registered at *"Volcán de Fuego"*, Colima. Experimental results show an overall improvement for Monte-Carlo dropout approximation when compared to Bayes by backprop. Being at the intersection of Bayesian learning and geophysics, we demonstrate that BNNs provide uncertainty estimations when internal volcano-seismic sources change, which undoubtedly helps to enhance current early warning systems at volcanic observatories.**

I. Introduction

Magma and gases interact in a very heterogeneous and absorptive media, generating a wide range of seismic events. We can identify the underlying physics of the source process by looking at the registered seismic anomalies [1]. From a machine learning perspective, the study of volcanic eruptions can be highly complex. During eruptions, seismic sources inside volcanoes change, degrading classification performance across different eruptive periods [2] [3]. This leads to constant fine-tuning of volcano monitoring systems, which requires labelled seismic data from new seismic anomalies. The availability of large volcano-seismic datasets is restricted by several factors, including, but not limited to, nature of volcanic eruptions, signal attenuation effects and geophysical interpretations needed to label seismic data. A committee of experts visually examine each seismic waveform and decides the type of event. This leads to *snapshots*: time-framed eruptive periods in which geophysical properties are intensely studied. However, beyond these time-framed *snapshots*, other eruptive periods remain unexplored [4].

In the context of volcanic-seismology, robustness under adverse conditions and data scarcity becomes more imperative than ever. Magma movements modify the energy and waveform of recorded signals: an overconfident or outdated model can underestimate the danger of eruptions, not issuing alerts on time. Uncertainty quantification provides direct knowledge about new seismic anomalies, which extends to scientific understanding of seismic sources variation [4]. Furthermore, crisis eruptions require rapid responses that can affect public safety. In this regard, two are the main contributions of this paper. First, to evaluate classification robustness of Bayesian Neural Networks (BNNs) for transient seismic signals at *"Volcán de Fuego"* (Colima, Mexico). Second, from a signal processing perspective, to empirically show that BNNs can quantify uncertainty across distinct recordings of seismic data from two different volcanoes (*Mount St. Helens* and *Peteroa*), and another period from the same volcano.

The rest of the paper is organized as follows: section 2 discusses the related work in the field. Section 3 introduces BNNs and the variational inference framework. Section 4 describes the datasets. Experimental setup and results are shown in Section 5. Finally, conclusions are described Section 6.

II. Related Work

Machine learning has been extensively applied to classify volcano-seismic signals, including Support Vector Machine (SVM) [5], Hidden Markov Model (HMM) [2] [6], Gaussian Mixture Model (GMM) [7] and Artificial Neural Network (ANN) [8] [9]. Bayesian Trees are the most common Bayesian technique to forecast eruptions from unrest periods [10]. However, these methods rely on pre-processed features and supervised learning to classify seismic attributes from well-studied, short-time *snapshots*. Recent work by [11] introduced Deep Neural Networks (DNNs) as classifiers for volcano seismic signals. Using a combined feature vector of Linear Prediction Coefficients (LPC) and statistical properties, this work proposes unsupervised pre-training to effectively initialize DNNs weights and leverage data scarcity. Whilst deep learning can help to provide accurate monitoring, its application remains a challenge due to the aforementioned problems of data scarcity and volcanic variability. Furthermore, research by [4] emphasizes the necessity to shift from deterministic to probabilistic approaches in order to incorporate fast uncertainty estimation and mitigate data scarcity.

Our proposed approach explores Bayesian Neural Networks (BNNs) as probabilistic classifiers for volcano-seismic signals. Using the LPC-based feature vector proposed by [11], we evaluate classification performance on seven representative volcano-seismic events from *"Volcán de Fuego"* (Colima, Mexico). Further, we assess generalization capabilities of BNNs when the volcano structure generating the seismic

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signals changes (different eruptive period, but same volcano). Uncertainty in the predictions is estimated with data from other two volcanoes: *Peteroa* and *Mount St. Helens*.

III. Bayesian Neural Networks

Bayesian neural networks (BNNs) are defined as *"artificial neural networks in which a probability distribution is placed over the network weights $w \sim \mathcal{N}(0, I)$"* [12]. BNNs do not compute a single estimate of the network weights, but a probabilistic approximation $p(w)$ over all of them. Given our volcano-seismic dataset $D = \{x_n, y_n\}$, with x_n the feature vector, y_n the associated labels and n the total number of samples, the likelihood is given by $p(y|x, w)$. Class probabilities p_c can be obtained as the output of the softmax probability layer $\tilde{f}$. The posterior distribution over the network weights $p(w|D)$ can be estimated using Bayesian inference:

$$p(w|D) = \frac{p(y|x, w) * p(w)}{p(y|x)} \tag{1}$$

However, to evaluate $p(w|D)$ reveals complicated as the model evidence $p(y|x)$ involves an intractable integral. Variational learning cast the inference approximation as an optimization problem by finding a simpler distribution $q(w|\theta)$, that minimizes the Kullback-Leibler (KL) divergence with respect to the model posterior $p(w|D)$. This can be done by using backpropagation with reparametrization (Bayes by Backprop) [13] or Monte Carlo dropout (MC-dropout) [14].

A. Variational Inference with Bayes by Backprop

The Bayes by Backprop (BBP) algorithm enables learning a variational distribution $q(w|\theta)$ over the network weights by optimizing the variational free-energy [13]:

$$\mathcal{L}(D, \theta) = KL[q(w|\theta)||p(w)] - \mathbf{E}_{q(w|\theta)}[log(p(D|w)] \tag{2}$$

Thus, by minimizing equation 2, we can find a distribution $q(w)$ that minimizes the KL-divergence with respect to $p(w)$. Additionally, we can sample from $q(w)$ to obtain w estimations, later used to make predictions. Intuitively, this equation can be divided into an accuracy term, the log-likelihood $p(D|w)$, and the KL term, or complexity term. This equation reflect how well BNN can classify data (high accuracy) whilst keeping complexity low. KL term will penalize and grow larger for those BNN models whose prior assumptions are not close to the true posterior distribution. Usual backpropagation algorithm can be applied to provide a Bayesian update of the network weights [13].

B. Monte Carlo Dropout

Recent work by [14] demonstrated that traditional neural networks trained with dropout technique can perform variational learning. Dropout is an ANN regularization method based on a random de-activation (with probability p) of network weights [15]. During training stage, dropout leads to a set of thinner architectures with fewer parameters, preventing over-fitting. The optimization is given by the application of dropout regularization technique [14]:

$$\mathcal{L}(D, \theta) = \frac{1-p}{2n}||\theta||^2 - \frac{1}{n}\sum_{i=1}^{n} log[p(D|w)] \tag{3}$$

with p the drop-out probability. Once the network has been trained, uncertainty can be obtained by running T forward passes with dropout activated at test-time:

$$p(y = c|x) \approx \frac{1}{T}\sum_{i=1}^{T} \tilde{f} \tag{4}$$

With $\tilde{f}$ the output from the softmax layer. MC-dropout approximation is mathematically rooted on the stochastic behaviour of dropout regularization technique in which weights are randomly drop with probability p (using a Bernoulli distribution) during test time. As a result, an ensemble of thinner networks produce a probability distribution $q(w|\theta)$ that can be used to approximate the true posterior $p(w|D)$. [14].

C. Uncertainty in volcanic seismology

Uncertainty quantification is essential given the chaotic behaviour of volcanoes. Magma migration, reverberations or conduit activation are nonlinear processes operating at different scales. The complexity of these processes are barely captured by traditional monitoring systems, as seismic attributes of recorded signals are constantly changing over time. Uncertainty quantification could be used to detect signal variations and identify potential hazards. Two types of uncertainties can be defined: Epistemic and aleatory. Epistemic uncertainty is associated to the absence of knowledge about the natural process and aleatory uncertainty is associated to the natural variability of eruptions [4]. Quantifying aleatory uncertainty can be very challenging, as it is a direct consequence of the natural randomness of volcanic eruptions, soil composition, thermal conditions and sensor location. However, epistemic uncertainty can be associated to the uncertainty in BNN weights parameters. Following [16], the epistemic uncertainty for C classes can be computed using the entropy $H(p)$ from the per-class probability vector p_c as:

$$H(p) = -\sum_{c=1}^{C} p_c \, log \, p_c. \tag{5}$$

For both models, the probability vector p can be obtained from the softmax probability layer (see 4). In this work, we quantify epistemic uncertainty to explore if BNNs associate its weights uncertainties with seismic changes across different volcano-seismic datasets.

IV. Volcanic Datasets

Three datasets have been used in this study: *"Volcán de Fuego"* (Colima, Mexico), *Mount St.Helens* (Washington, USA), and *Peteroa* (Chile). The geological properties of each volcano have a great impact on the recorded signals, in terms of waveform shape and frequency content. The *"Volcán de Fuego"* dataset contains seven of the most representative

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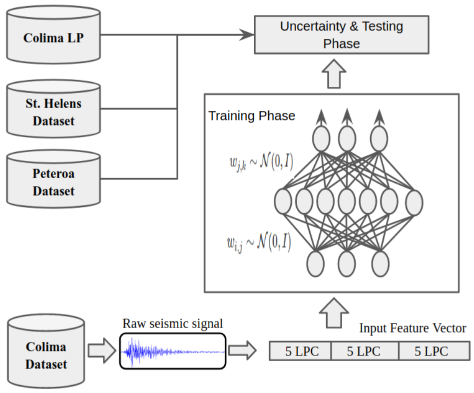

Fig. 1. BNN architecture with one hidden layer and Gaussian priors over all its weights W. For MC-dropout, the neural network is trained with dropout cost function. Five LPC coefficients are computed over three non overlapped segments to capture envelope and spectral information. The input feature vector has 15-dimensions.

volcano-seismic signals that can be registered during an eruption: volcano-tectonic earthquakes (VTE), long-period events (LPE), volcanic tremor (TRE), earthquakes (REG), explosions (EXP), lava flows (COL) and noise (NOISE). Explosions and lava flows contain rocks and fragments that can have devastating effects in nearby populations. In addition, VTE (earthquakes inside volcanic edifices with high frequency content) and LPE are particularly important, as they are often seen as precursory of eruptions [1]. Volcanic tremors have low frequency content and are associated with high activity inside the volcano, but with unclear source mechanisms [2]. The average Power Spectral Density (PSD) for *"Volcán de Fuego"* training dataset is depicted in Figure 2. The rest of datasets can be summarized as:

1) The *"Volcán de Fuego"* is an andesitic stratovolcano [17]. This dataset is composed of 8348 seismic signals, collected from two monitoring stations plus one broadband station, during the eruptive periods of 1998, 2004, 2005 and 2006. It contains 1738 VTE, 1700 LPE, 1170 TRE, 455 REG, 1406 COL, 278 EXP, and 1601 NOISE. An additional subset of 918 LPE events from another eruptive period between 1998 to 2004 were used.
2) *Peteroa* is a basaltic volcano located in the Southern Volcanic Zone, (Chile) with major eruptions in 2010 to 2011. The collected dataset contains 182 VTE from the last 2011 eruption [18].
3) Mount St. Helens is a quaternary dacitic-andesite volcano located in Washington, USA. This dataset was recorded at the eruptive period of September to October 2004. It contains 947 LPE and 553 VTE events. [19].

The volcano-seismic events stored in all datasets are the result of a careful labeling process: For each recorded seismic signal, a geophysical interpretation is made by experts, based on their knowledge about the volcano.

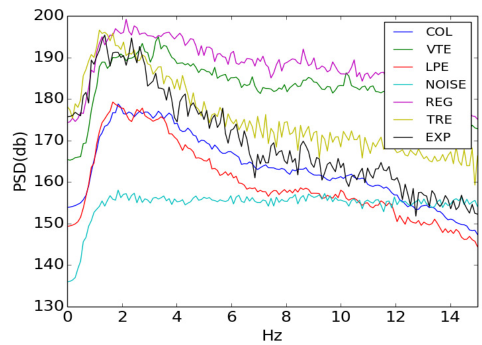

Fig. 2. Average Power Spectral Density (PSD) for each type of event at *"Volcán de Fuego"*.

V. Experiments and Results

A. Experimental Setup

We note MC-dropout the neural network trained with Monte Carlo dropout and BNN the *Bayes by Backprop* approach. The datasets described in Section IV reflect the time variability of volcano-seismic signals: they contain from explosions (with duration of seconds), to long tremors (with duration of hours). Raw seismic signals are very unrefined to be meaningful as input for our neural network. Taking advantage of signal processing algorithms, we can reduce the complexity of raw data to an input feature vector. All signals have been sampled at 50 Hz and band-pass filtered between 1 Hz and 25 Hz. Each signal is segmented into three non-overlapping segments, and 5 LPC coefficients are computed over each segment in order to capture spectral envelop information [11].

We perform data normalization and K-fold validation with four partitions. MC-dropout and BNN are trained with (*"Volcán de Fuego"*) dataset: (75%) training and test (25%) set. Blind tests were performed with Mount *St. Helens* and *Peteroa* volcano. Hyper-parameter optimization was based in grid-search: All models were optimized with stochastic gradient descent (SGD), learning rate of 0.01, *tanh* activation function and mini-batch size set to 10, with best dropout probability at ($p = 0.2$) [20]. Early stopping with patience interval of 3 epochs is used. Dropout and Bayes By Backprop has been implemented as described in Section III. MC-dropout was initialized with Glorot Initialization [20]. Given the size of the dataset and in order to avoid excessive overfitting, we keep only one hidden layer for all the models, as seen in Figure 1. Best results on the test set for best validation scores are reported. We sampled 200 times from the posterior distribution [14]. To evaluate model performance, we compute accuracy (Acc), precision (PR) and recall (RC) metrics:

$$Acc(\%) = \frac{Number\ of\ Correct\ Predictions}{(Total\ Number\ of\ Events)} * 100 \tag{6}$$

$$Precision\,(PR) = \frac{True\ Positives}{(True\ Positives + False\ Positives)} \tag{7}$$

$$Recall\,(RC) = \frac{True\ Positives}{(True\ Positives + False\ Negatives)} \tag{8}$$

TABLE I
BEST ACCURACY (%) RESULTS OBTAINED FOR BNN AND MC-DROPOUT TRAINED ON *"Volcán de Fuego"* DATASET, WITH 5 LPC PARAMETERS, OVER THREE NON-OVERLAPPING SEGMENTS.

# Hidden Units	BNN	MC-Dropout
50	77.28	81.13
250	77.47	**81.78**
500	77.46	81.74
700	77.54	81.58
1250	**77.82**	81.73
1500	77.70	81.67

TABLE II
NORMALIZED PER-CLASS PRECISION (PR) AND RECALL (RC) FOR BEST BNN AND MC-DROPOUT MODELS.

	BBP		MC-dropout	
Seismic event	**PR**	**RC**	**PR**	**RC**
NOISE	0.97	0.96	0.96	0.97
VTE	0.73	0.86	0.83	0.90
LPE	0.75	0.79	0.76	0.82
TRE	0.70	0.63	0.70	0.66
REG	0.65	0.16	0.70	0.41
COL	0.77	0.92	0.85	0.95
EXP	0.52	0.10	0.52	0.14
Average	**0.72**	**0.63**	**0.76**	**0.69**

TABLE III
EPISTEMIC UNCERTAINTY FOR BEST MC-DROPOUT AND BNN MODELS (250 AND 1250 HIDDEN UNITS) TESTED AGAINST OTHER VOLCANOES

	BNN	MC-dropout
Colima vs. Colima (LPE)	0.79	0.83
Colima vs. Peteroa	0.60	0.55
Colima vs. St.Helens	0.62	0.61

For a given model, these metrics can diagnose how many events are correctly detected and classified. Concretely, recall evaluates how good the model can detect events from a given class, whereas precision measures how good models classify specific instances [21].

B. Recognition of the "Volcán de Fuego" dataset

Table 1 depicts the accuracy for best BNN and MC-dropout models. In the context of volcano-recognition systems, all models attain good results. We think that the reason of BNN worse performance is related to a very strong regularization effect by the priors over the BNN weights, and higher variances by the gradient during the learning process. In this case, and from equation 2, the balance between generalization and prior complexity penalizes the log-likelihood $p(D|w)$ by pushing up the KL divergence and decreasing performance. Therefore, as the KL divergence measures divergence between probability distributions, our network weight estimates are far from the posterior. For a dataset the size of *"Volcán de Fuego"*, prior assumption may locate weights into a poor local minima, making the optimization problem harder. MC-dropout shows an improvement over the BNN approach. This behavior is expectable, as MC-dropout is using a family of *dropout* distributions to approximate a posterior Gaussian distribution. This translates into more refined weight distributions, with smaller variance, that can approximate better the posterior distribution. In addition, the multiple stochastic forward passes with dropout activated enhances classification performance, as remaining activated weights provides more information to the model.

From Table 2, notice that BNN and MC-dropout have low recall (RC) but high precision (PR) on average. Recognition results are affected by the variability in the signals, frequency attenuation and sensor location. However, MC-dropout improved the performance in terms of precision and recall, being more robust to signal variations. In the case of explosions (fast, energetic, short events), both models have very low recall, but same precision. This suggest that only very characteristic events are detected and recognized. Additionally, BNNs detect less REG events than MC-dropout. From a geophysics perspective, REG events are regional earthquakes outside the volcanic cone. As compared to VTE events, which are earthquakes inside the volcano, this confusion is not critical, as both events share similar geophysical properties but differ only in arrival times [2]. The high recall but low precision in lava flows (COL) and tremor (TRE) classes suggest both models are sensitive to seismic events that occur simultaneously in time, such as lava flows and tremors. An interesting result is obtained for TRE class with low recall but good precision for both models: volcanic tremor is one of the most difficult signals to classify, and even experts can be confuse them with background noise. The multiple forward passes from MC-dropout increase the robustness of classification, as the ensemble of drop-out networks capture more information from the non-dropped weights: more hidden units are randomly activated for the input data. Finally, notice that magma flows (LPE) and volcanic earthquakes (VTE), are consistently detected and recognized, attaining good precision and recall values.

C. Blind test across volcanoes

Given the low number of volcano-seismic events at *Peteroa* and *St. Helens* datasets, we are more interested in showing how *BNN* and *MC-dropout* trained on *"Volcán de Fuego"* can capture epistemic uncertainties for similar seismic events at other volcanoes. This will help geophysicists to understand if seismic signals behave differently. Our base system is selected from the best models obtained at Table I. The epistemic uncertainty is computed as described in Section III-C. Table III shows the obtained results for *Peteroa* and *St. Helens* volcanoes, and additional LPEs events from another eruptive period recorded at *"Volcán de Fuego"*. First, notice that volcanoes do not follow similar data distributions, and uncertainty remains high for all cases. MC-dropout and BNN are able to equally quantify uncertainty for unknown seismic sources and similar seismic waveforms from other volcanoes. Interestingly, when seismic waves change within the same volcano, both models increase epistemic uncertainty, as seen from *"Volcán de Fuego"*, and the LPE period. This can be explained by the eruptive dynamics, generating more energetic LPEs events in the new period, confusing both models with more energetic signals. Surprisingly, for both andesitic volcanoes (*St.Helens* and *"Volcán de Fuego"*), epistemic uncertainty remains roughly the same. This can be an indicative that similar volcanoes share similar seismic attributes. Epistemic uncertainty with the dataset of Peteroa volcano remains low, which suggest that VTE events share common generation mechanisms across distant volcanoes.

VI. Conclusions

When traditional machine learning models are trained with volcano-seismic data, the uniqueness of each volcano emerges. This work explores the practical implementation of Bayesian neural networks as probabilistic classifiers of volcano-seismic signals. Three datasets, *"Volcán de Fuego"*, Peteroa and *St. Helens* are used. Variational learning methods, such as MC-dropout and Bayes by Backprop, prove essential to fine-tune Bayesian neural networks in the detection of magma fluctuations (LPE) and volcanic earthquakes (VTE). However, in the case of explosions, both models attain poor performance. Explosions are energetic events, often accompanied by rockfalls and earthquakes. Seismographs measure these events together, and only very characteristic explosions are consistently recognized by these models.

MC-dropout networks provide an overall improved accuracy, whereas Bayes by Backprop has stronger regularization effect over network weights. As seen in Table II, both models are very sensitive to signal variation. However MC-dropout shows more robustness, with increased precision and recall performance. Furthermore, in the case of volcano-seismic signals, the strong prior assumption could penalize classification performance. Epistemic uncertainty can be quantified from the weights of the Bayesian neural network to measure the variability of seismic signals, and provide geophysical knowledge about the eruptions. For the studied datasets, we empirically show that BNNs can be used as volcano-seismic monitoring systems as they are able to extract signal information to perform classification whilst quantifying uncertainty. The epistemic uncertainty of both models enlighten interesting signal properties, as volcano-seismic signals from distinct sources could share similar attributes.

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References

[1] B. Chouet, "Volcano seismology," *Pure and Applied Geophysics*, vol. 160, pp. 739–788, June 2003.

[2] J. Ibáñez, C. Benítez, L. Gutiérrez, G. Cortés, A. García-Yeguas, and G. Alguacil, "The classification of seismo-volcanic signals using hidden markov models as applied to the stromboli and etna volcanoes," *Journal of Volcanology and Geothermal Research*, vol. 187, pp. 218–226, November 2009.

[3] C. Hibert, F. Provost, JF. Malet, A. Maggi, A.Stumpf, and V. Ferrazzini, "Automatic identification of rockfalls and volcano-tectonic earthquakes at the piton de la fournaise volcano using a random forest algorithm," *Journal of Volcanology and Geothermal Research*, vol. 340, pp. 130–142, June 2017.

[4] RSJ. Sparks and WP. Aspinall, "Volcanic activity: frontiers and challenges in forecasting, prediction and risk assessment," *The State of the Planet: Frontiers and Challenges in Geophysics*, vol. abs/1703.04977, 2004.

[5] M. Masotti, S. Falsaperla, H. Langer, S. Spampinato, and R. Campanini., "Application of support vector machine to the classification of volcanic tremor at etna, italy," *Geophysical research letters*, vol. 33, pp. 130–142, October 2006.

[6] G. Cortés, R. Arámbula, L. Gutiérrez, C. Benítez, J. Ibánez, P. Lesage, I. Alvarez, and L. Garcia., "Evaluating robustness of a hmm-based classification system of volcano-seismic events at colima and popocatepetl volcanoes," in *Geoscience and Remote Sensing Symposium,2009 IEEE International,IGARSS 2009*. IEEE, 2009, vol. 2, pp. II–1012.

[7] C. Benítez, L. García, A. Alos, J. Prudencio, I. Alvarez, and A. de la Torre., "A comparative study of classifiers based on hmm, gmm and svm for the vt, lp and noises discrimination task.," in *EGU General Assembly Conference Abstracts*. EGU, 2014, vol. 16, p. 11783.

[8] S. Diersen, E. Lee, D. Spears, P. Chen, and L. Wang., "Clasification of seismic windows using artificial neural networks.," *Procedia Computer Science*, vol. 4, pp. 1572 – 1581, June 2011.

[9] M. Kuroda, A. Vidal, A. Maria, and A. De Carvalho., "Interpretation of seismic multiattributes using a neural network.," *Journal of Applied Geophysics*, vol. 85, pp. 15–24, October 2012.

[10] R. Sobradelo and M. Joan, "Understanding causality and uncertainty in volcanic observations: An example of forecasting eruptive activity on soufriére hills volcano, montserrat," *Journal of Volcanology and Geothermal Research*, vol. 341, 2017.

[11] M. Titos, A. Bueno, L. García, and C. Benítez, "A deep neural networks approach to automatic recognition systems for volcano-seismic events," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 11, no. 5, pp. 1533–1544, May 2018.

[12] R. Neal, *Bayesian learning for neural networks*, vol. 118, Springer Science & Business Media, 2012.

[13] C. Blundell, J. Cornebise, K. Kavukcuoglu, and D.Wierstra, "Weight uncertainty in neural network," in *International Conference on Machine Learning*, 2015, pp. 1613–1622.

[14] Y. Gal and Z. Ghahramani, "Dropout as a bayesian approximation: Representing model uncertainty in deep learning," in *Proceedings of The 33rd International Conference on Machine Learning*. PMLR, 2016, vol. 48, pp. 1050–1059.

[15] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov, "Dropout: A simple way to prevent neural networks from overfitting," *The Journal of Machine Learning Research*, vol. 15, no. 1, pp. 1929–1958, 2014.

[16] A. Kendall and Y. Gal, "What uncertainties do we need in bayesian deep learning for computer vision?," *NIPS 31th conference*, vol. abs/1703.04977, 2017.

[17] M. Palo, J. Ibáñez, M. Cisneros, M. Bretón, E. Del Pezzo, E. Ocaña, J. Orozco-Rojas, and A.M Posadas, "Analysis of the seismic wavefield properties of volcanic explosions at volcan de colima, mexico: insights into the source mechanism," *Geophysical Journal International*, vol. 177, pp. 1383–1398, June 2009.

[18] Felipe Aguilera, Óscar Benavente, Francisco Gutiérrez, Jorge Romero, Ornella Saltori, Rodrigo González, Mariano Agusto, Alberto Caselli, and Marcela Pizarro, "Eruptive activity of planchón-peteroa volcano for period 2010-2011, southern andean volcanic zone, chile," *Andean Geology*, vol. 43, no. 1, 2016.

[19] SC. Moran, S. Malone, D. Stephen, A. Qamar, W. Thelne, A. Wright, and J.Caplan-Auerbach, "Seismicity associated with renewed dome building at mount st. helens, 2004-2005," *US Geological Survey professional paper*, vol. 1750, pp. 27–60, November 2008.

[20] H. Larochelle, D. Erhan, A. Courville, J. Bergstra, and Y. Bengio, "An empirical evaluation of deep architectures on problems with many factors of variation," in *Proceedings of the 24th International Conference on Machine Learning*. ICML 07, 2007, pp. 473–480.

[21] Marina Sokolova and Guy Lapalme, "A systematic analysis of performance measures for classification tasks," *Information Processing & Management*, vol. 45, no. 4, pp. 427–437, 2009.