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PREDICTION OF VOLCANOES USING MACHINE LEARNING ALGORITHMS: A SURVEY PAPER

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Abstract : Volcanic eruptions can be extremely dangerous, thus it's critical to be able to predict them as precisely as possible. Despite the fact that data from volcano monitoring has substantially expanded in number and quality over the previous decades, volcano eruption forecasting remains a difficult and contentious topic. Classic Machine Learning technologies, like in many Big Data situations, are now being investigated to automate the analysis of years of recorded data, enabling larger-scale monitoring. This research paper describes methods for automatically classifying seismic occurrences associated with volcanic activity and also includes prediction models developed from a large data set of labelled observations.

***IndexTerms* – Volcanoes, InSAR, Volcanic eruptions, Volcanic hazards, Support Vector Machine.**

I. INTRODUCTION

Volcanoes are natural geological occurrences that have existed for millions of years. Volcanoes are hazardous natural phenomena because they may erupt without warning. Volcanic eruptions, when active, may inflict immense harm and death. In this paper, we discuss prediction algorithms used for volcanic eruption.

Predicting volcanic eruptions is critical because they are dangerous phenomena that can become active without notice. Volcanic eruption prediction is required for public safety in the event of an eruption. Computer scientists and geoscientists have created models that use machine learning to predict eruptions. The models learn from data gathered by volcanologists around the world. Volcanoes emit a wide range of seismic signals related to fluid transport (water, magma, gas) and interaction with solid rock. Geoscientists interpret seismic events to gain useful information about internal volcanic activity. A novel approach based on machine learning is proposed in this paper to automatically classify volcano seismic events.

II. OBJECTIVES

Our goal is to analyse the models used at forecasting volcanic eruptions in order to predict which one provides more accurate results, as that will give us the best perspective on what type of model would be better for determining the prediction of volcanic activity.

III. BACKGROUND

Despite the fact that data from volcano monitoring has increased in quantity and quality in recent decades, forecasting volcano eruptions remains a challenging and disputed topic. A prediction algorithm is beneficial if: (i)the prediction quality is higher than that of a random one; and (ii) the prediction quality is relatively insensitive to changes in the parameters [9]. This data is then utilised to evaluate the volcano and forecast future eruptions. DNNs (Deep Neural Networks) were used. Neural networks are popular way of processing data, but the results can sometimes be disparate. Bayesian Classifiers were also tested; however, the results were mixed. The Support Vector Machines algorithm and Deep Belief Networks has also been used. Some research also attempted to use Principal Component Analysis (PCA) is an example of an unsupervised model. Self-Organizing Maps (SOM) and Principal Component Analysis (PCA) (SOM) Alternatively, Cluster Analysis (CA). However, the results are highly variable [11].

We concentrate on two tasks: (i) detecting significant volcano-seismic occurrences and (ii) classifying them into semantic categories. The STA/LTA approach is by far the most popular of the automatic detection processes. In both operational contexts and published works, STA/LTA is commonly employed.

Once retrieved, volcanic-seismic events must be classified into one of many categories based on the volcano's physical activity: Long-period (LP) events, Tremors, Explosions, Volcano-tectonic events, Hybrid events, Tronillos(screw events). [11].

Model architectures

3.1 DNNS

Deep neural networks (DNNs) solve the limitations of shallow structured topologies by providing a single nonlinearity layer, allowing computational algorithms to learn complex data representations with varying degrees of abstraction. While shallow architectures are adequate, they lack the ability to develop internal data representations since their problems are basic and well-constrained. The DNN is specified as a series of completely linked layers built stacked on top of one other that allow information to flow progressively, with the output of the previous layer acting as the input for the next. However, as the model becomes more advanced, gradient diffusion causes limits to appear. The number of distinct local minima discovered in the severely non convex objective function that defines the model parameter space during the optimization process.

3.2 DBNs

Deep Belief Networks a type of neural network, were introduced after much research. Using a technique known as greedy layer-wise pretraining, these networks may be efficiently taught. constructed comparable structures but employed a different pretraining technique in both situations, these pretraining stages demonstrated an efficient strategy for subsequently training deep structures. Parameter initialization is helpful to improve convergence in the optimization process, and unsupervised pretraining has been observed to achieve faster convergence by initializing network parameters near a convergence zone. Glorot recommends that network weights be initialized with a Gaussian (or uniform) distribution. Random initial values for weights have resulted in poor results in the field. The training of a fully connected DNN using unsupervised pretraining is divided into two stages: greedy layer-wise unsupervised pretraining and fine tuning [1].

3.3 sDA

Stacked Denoising Autoencoders is a multilayer generative model that was trained with an autoencoder on noisy data. Successful training of this layer has explicitly corrupted the input feature vector for denoising purposes. As a result, the learned layers' recovery of noise corruption improves generalisation for a supervised learning task. We can train an autoencoder to reconstruct what it thinks machine learning is all about. We do this by minimizing its reconstruction error. The hidden representation of the first autoencoder is used as the input for the upper layer. This pretraining technique is applied layer by layer until the kth layer is reached, resulting in a set of hidden layers that we can stack in a multilayer generative model. To compute per-class probabilities, a softmax layer much like DBNs (deep belief networks) can be added on top of it [1].

Based on pretraining initialization, we understood DNNs for automatic classification of volcano-seismic events in this study. Using seismic data collected from Colima's "Volcán de Fuego," (Mexico) two alternative DNNs, DBN and sDA, are tested. We find that sDA and DBN can classify seismic events more precisely and reliably than older systems. Furthermore, deep architectures are more sensitive to recognising concurrent events, such as EXPs and TREs. Finally, because of the nature and volume of volcanic snapshots (dataset), using raw volcanic events as training data results in unsuitable representations, making direct application of cutting-edge deep learning architectures challenging [1].

3.4 SVM

Support Vector Machine is an algorithm that can separate instances in a two-dimensional space by class, that is either class 0 or 1. Instead of a linear line like in a normal simple regression, SVMs use hyperplanes which are nonlinear, they are usually asymptotes to what we call the separating hyperplane.

Defining the margin of a classifier is an important concept in machine learning where it pertains to the data points that aid in producing a classifier. Supported by these points, or support vectors, the margin is their distance away from the hyperplane and only these points are considered central to any type of classification. These data points alone define the hyperplane so they're essentially called the support vectors. Further information on them can be found here. The scientists have analysed existing methods and suggested an efficient procedure for automatically classifying volcano-seismic occurrences in this research. Cross validation is used to evaluate the SVM model using 70856 data, and it achieves a 92.2 % accuracy [11].

Detecting Volcanic Deflections Employing Sentinel-1 InSAR Time Series Demonstrated by the 2017–2018 Agung Unrest in Indonesia.

The researchers evaluated two techniques for automatically detecting brief uproar: (1) basic series data thresholding and (2) sequential anomaly methods. In 2017, a swarm of earthquakes hit the island of Bali in Indonesia, prompting volcanologists to study the situation in order to see if there was going to be an eruption from Mount Agung. Due to the natural setting of Agung (areas located within tropical volcanoes experience atmospheric delays), InSAR satellites need to be compensated for in order to get accurate results. This method was able to detect activity at Mount Agung with 95% confidence within 2 days of acquisition, clearly showing that it has great potential as a monitoring system method that could be used by volcanic observatories around the world [5].

IV. CONCLUSION

The success of artificial intelligence in predicting magma movement could revolutionize volcano prediction as we know it. This paper analyses the results produced by different machine learning techniques. Artificial intelligence is helping turn volcanology on its head, which means that now instead of waiting to intervene until a volcano explodes, scientists might be able to predict right before an eruption is likely to occur and plan preventive action, saving lives and property. With 92.2 percent accuracy, we conclude that using cross validation SVM produces the best results in volcanic eruption prediction.

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