Incremental versus non-incremental learning in volcano monitoring tasks: A systematic review

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Abstract— Since the beginning of planet Earth, volcanic activity has generated a series of events of great destructive capacity. Many populations located in areas close to volcanoes coexist with a complex combination of benefits and several risks. In order to provide early warning of an eventuality, different approaches have been developed to alert the inhabitants of these areas. Computer scientist have built and tested many automated tools based on Supervised Learning (SL) to solve this problem. However, despite the high potential of SL algorithms, current research does not consider the dynamic nature of volcanoes, which constantly change their baseline over time through interactions in the Earth’s crust. In this study, a documentary review was developed around SL in volcanology. This study shows that Incremental Learning (IL) offers greater advantages than non-incremental learning for this type of application domains. One of them is that incremental learning considers dynamic systems and updates the objective function in real time without retraining the classifiers. Based on the above, this paper presents an updated review of current literature examining different types of learning methods (incremental and non-incremental learning) in the volcano detecting task.

Keywords- Deformation, Dynamic System, Geochemical, Hidden Context, Incremental Learning, Seismology, Supervised Learning, Volcanoes

I. INTRODUCTION

Geological and climatic conditions in Latin America and the Caribbean are conducive to natural disasters. The Andes, Caribbean, and Central American mountains are located over the areas of direct influence and interaction of tectonic plates, a characteristic that determines the high seismicity of this region [1]. Over the years, volcanoes have generated emergency situations causing events with a great destruction capacity. Many populations settled in areas close to volcanoes, coexist daily with a complex combination of benefits and risks. This way, there are several benefits related to agriculture, tourist, therapeutic, among others. However, many other different risks can directly affect the health of the population due to flows, explosions, and gas emissions, causing morbidity from different pathologies and a high level of mortality from exposure to trauma. Indirectly these risks can lead to socio-economic deterioration, damage to vital lines or infrastructure, and the alteration of the living conditions of populations affected by volcanic activity [2].

Computer sciences have addressed many of these problems such as automatic classification and location of volcanic seismic events to determine seismic sources, gas emission forecasts, and deformation of the volcanic cone using supervised learning algorithms as proposed by the authors of [3]–[6]. SL techniques construct different type of classifier from a set of training examples, to detect or predict a value [7]. However, the above-2 mentioned approaches based on SL do not consider the inclusion of new examples once the model is constructed. This generates obsolescence in the classifier since volcanoes are dynamic systems, which implies a constant change in the base line of the earth’s crust, specifically in tectonic plates.

In this sense, the present paper proposes an alternative method to address the detection of volcanic products in dynamic environments through the incremental learning paradigm. This concept allows a model to be updated in real time as new instances are processed [8]. The current literature review does not record the use of IL to detect and classify volcanic products by relating the areas of seismology, geodesy, and geochemistry. To the best of our knowledge, this is the first publication in which the volcano monitoring is considered as a dynamic phenomenon. This is the most important contribution of this paper.

The remainder of this paper is organized as followed: section 2 defines the main topics such as detection of volcanic seismic events by SL and IL. Subsequently, the related works are presented in section 3. Section 4 shows the discussion around the results of the literature review. Finally, section 6 highlights the conclusions of this study.

II. BACKGROUND

This study focuses on the detection of volcanic events, which is a task that needs to be treated as a dynamic phenomenon produced in dynamic environments. A dynamic environment is a system where there is an evolution over time, and failure of some system component causes a variation in its temporal evolution. Usually, the output depends on input variables, parameters, and time; these aspects determine the system status. Thus, the system behavior can be described in terms of evolution from one
state to another. The system evolves over time, and its variables present a variation that can be expressed mathematically by a derivative based on time (dxi/dt), valid for each of the xi variables. The set of n differential equations is called Dynamic System [9].

Considering the definition of a dynamic system, it can be clearly established that a volcano belongs to this type of system because it changes its baseline over time and subsequently its internal conditions. In this way, volcanic monitoring refers to the permanent observation of seismic activity to understand the behavior of a specific volcano. This task is crucial for risk assessment and mitigation, as well as eruptions prediction. In order to achieve these objectives, the state of a volcano must be determined by analyzing the seismograms generated, which are records of ground movement in a measurement station as a time function [10]. Volcanoes generate different types of events such as the seismic. The most important seismic events correspond to specific activities and these are divided into four classes: Tremor (TR), Long-Period (LP), Volcano-Tectonics (VT), and Others. TR and LP events are related to the magmatic fluid through ducts; continuous flow corresponds to TR and discrete flow to LP. VT events occur when excess of magnetic pressure provides sufficient energy for rock failure [11].

On the other hand, in volcanic monitoring tasks it is important to consider that an active volcano triggers other phenomenon before an eruption. One of these corresponds to the deformation in the volcanic cone due to inflation or deflation resulting from constant magma injections and the emission of volcanic gases such as SO2, CO2, and Radon, which are generated by magma pressure when trying to escape to the earth's surface.

Considering these aspects, the purpose of this study is to assess the possible benefits of using incremental learning in the detection of volcanic events. Thus, the main characteristics and differences between non-incremental and incremental are presented below.

Supervised learning is a Machine Learning (ML) task where a function is inferred from supervised training data. This data is a set of training examples (each example consists of an input object and the desired output value) which define the behavior of an algorithm [12], [13]. Supervised learning proposes algorithms capable of reasoning from externally supplied instances to produce general hypotheses, which then make predictions about future instances. In other words, the goal of SL is to build a concise model of the class labels distribution in terms of predictive features. The obtained classifier is used to assign class labels to test instances. In this way, the values of the predictor's features are defined, but the value of the class label is unknown [14]. There are several families of algorithms such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), Logistic Regression (LR), Bayesian Networks (BN), Naïve Bayes (NB), Memory-Based Learning (MBL), K-Nearest Neighbors (K-NN), Random Forests (RF), Decision Trees (DT), and Bagged Trees (BT) [15]. Supervised learning can also combine decisions from multiple classifiers; some of the most powerful automatic learning methods available are Boosting, Bagging, and Stacking algorithms, among others [16].

Supervised learning has a great potential in a wide variety of domains. However, its performance can decrease drastically if this learning is used with data that comes from dynamic environments with non-stationary data. In general, a learning task is incremental if the training examples used to solve it are available over time, usually one at a time [17]. In particular, incremental learning or online learning is a SL paradigm where the learning process is carried out and adjusted whenever new examples appear. The main difference between incremental and non-incremental learning is that a sufficient training set is not assumed to be available before the learning process; in contrast, training examples appear over time [18]. An ideal incremental learning algorithm should have the following characteristics: adapt new information when available, ability to work with unlabeled data, ability to process multidimensional data, limited complexity, incrementally learn from empirical data, and manage changes in concepts [19].

There are several types of algorithms which implement incremental learning producing advantages and disadvantages over their corresponding non-incremental algorithm. In this sense, we can mention algorithms such as SVM, ANN, DT, among others [20]. Below are described some of the main incremental algorithms that have been studied in different research works.

- **LEARN++**

  This is an algorithm for incrementally training ANN-type classifier patterns. Allows supervised ANN paradigms, such as multilayer perceptron (MLP), to adapt to new data, including examples that correspond to previously unlabeled classes. LEARN++ does not require access to previously used data during subsequent incremental learning sessions, but at the same time, maintains previously acquired knowledge [21].

- **PECS (Prediction Error Context Switching) and SPLICE (Symbolic Performance & Learning In Continuous-valued Environments)**

  These clustering-based algorithms are designed to adapt to recurrent contexts considering their robustness and noise sensitivity. They store past models in internal memory, allowing them to be consulted at any time and then be updated with the adaptation to change [22], [23].

- **STAGGER**

  Robust, noise tolerant algorithm capable of modeling concepts in non-stationary environments. In addition, you
modify the rules only when they are highly inconsistent. It does not use, or store misclassified past examples, calculated statistics are used to represent the training set and guide the review process [24].

- **FLORA (Floating Rough Approximation)**
  This algorithm automatically adapts to changes in the environment as well as frequent and recurrent variations in the target function. A set of rules are obtained from a time window schema based on the time of arrival. Training examples are processed sequentially by filling consecutive positions in the window. These are discarded after a threshold time [25].

- **WINNOW**
  It is an algorithm based on Bayesian networks, uses a fixed size window and models recurrent environments [26].

- **CVFDT (Concept-adapting Very Fast Decision Tree)**
  It is an extension of VFDT based on decision trees using Hoeffding’s inequation as an error coordinate to determine the number of new examples needed for tree expansion. Through a forest, it models non-stationary domains, eliminating obsolete trees [27].

- **FACIL (Fast and Adaptive Classifier by Incremental Learning)**
  Used for the classification of high-speed sequences with numerical attributes. It induces the model with an incremental scheme of progressive coverage and classifies non-covered examples from unknown regions. It has a high sensitivity to noise and the order in which examples arrive [28].

- **OISVM (Online Incremental SVM) and Growing Neural Gas SVM**
  Despite being SVM induction algorithms, the main deficiency is its high computational cost. This strategy uses several data blocks and part of the past data. It is updated during learning and perceives context change [12], [29].

- **IADEM (Incremental Algorithm Driven by Error Margins)**
  It is prepared to extract knowledge in the form of a decision tree for sets of very large experiences without being affected by size and performance [30].

- **MultiCIDIM-DS (System multi classify for Data Stream based in CIDIM)**
  This multi-classifier uses CIDIM as a learning algorithm and has the ability to work with data streams. Bagging method is used to generate this multi-classifier. It stores the most accurate basic classifiers for later use [27].

- **SEA (Streaming Ensemble Algorithm)**
  Classifiers are combined into a fixed size set using a heuristic substitution strategy. The result is a large-scale fast algorithm or streaming data classified as a single decision tree based on the entire dataset. It requires constant memory and quickly adjusts to changing contexts [31].

### III. STUDY AND RESULTS

In this study, a systematic review approach [32] was conducted around the non-incremental and incremental learning techniques applied in volcanology. The following two research questions were proposed to develop this review and establish the current research trend.

- **RQ1.** Which computer science approaches are used to detect volcanic events?
- **RQ2.** What are the most commonly used supervised learning algorithms in volcanology?

#### A. Supervised Learning in Volcanology

Supervised learning has been widely applied in volcanology and its different sub-areas. In this sense, it is important to analyze not only the goal of the different studies but also the different algorithms used.

1. **Main topics applied in volcano monitoring**

   First, this study proposes the analysis of the five main topics were identified in which Supervised Learning has been the research focus:

   - **CSE** (Classification of volcanic or tectonic Seismic Events),
   - **CSS** (Selection most relevant characteristics of Seismic Signals),
   - **LSE** (Location of Seismic Events where its hypocenter and epicenter is located),
   - **Geochemistry** (emission of volcanic gases), and
   - **Geodesy** (subsurface and volcanic cone deformation).

   Figure 1 shows the studies selected and classified in these categories between 2001 and 2017.
The previous figure shows that the seismic signal classification (CSS) presents the greatest number of research papers (32 studies). This classification is one of the most relevant and intensive tasks in volcanic monitoring considering that in critical periods, real-time classification of the different types of volcanic seismic events is an important factor in emergency decision-making. These quick decisions play an important role in improving the capability to respond volcano disasters. In addition, there are also several studies related to Geochemistry (14 studies) since this area in volcanology is used as a reference framework to monitor changes in the emission of volcanic gases CO2, SO2, as well as temperature in fumaroles and thermal sources. Additionally, it is important to point out that the low number of studies about CES, LES and Geodesy is due to the fact that these areas do not provide an accurate view of the current state of a particular volcano, since these are complementary to seismology in the context of volcanic monitoring. Generally, geochemistry and geodesy can determine seismic events such as rock fracture due to magma pressure and fluid movement. Finally, Location of Seismic Events (LSE) has not been extensively addressed in research considering that it only provides information about the location of a seismic event, whether volcanic or tectonic, at the time of detecting and classifying this event, which is important only to inform the population about the epicenter of the seismic event.

2. Algorithms used in volcano monitoring.

Similarly, researches addressing volcanology problems were classified by types of algorithm such as SVM, ANN, BN, DT, KNN, and multi-classifiers, as shown in Figure 2.

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B. Incremental Learning in Different Domain Applications

According to the systematic review developed in this study, no research papers that apply incremental learning algorithms to volcanology problems were found. However, several incremental algorithms have been used in many other different domains as is described below.

1. Domains of the incremental algorithms

First, it was explored the incremental algorithms in other application domains between 2000 and 2017 as shown in Figure 3.

Among the most popular application domains using incremental learning algorithms are the artificial vision area (18 studies), which generally is used in face recognition where facial aspects change over time. In health area, incremental learning uses these techniques to detect and classify new viruses generated in living organisms for a certain period (11 studies). These strategies can be adapted to the characteristics of new viruses. In robotics, incremental learning is used for the progressive training of robots to overcome obstacles that can be added or subtracted from the training field (15 studies). Finally, incremental learning has also been used for predicting and detecting vehicle traffic in urban areas (9 studies), applications for speech detection (voice may deteriorate over time due to hormonal changes or diseases), and text prediction by updating models when informal words are added to the jargon of a culture (21 studies). Speech and text domains are the most explored by IL algorithms, given their popularity due to the rise of smartphones, where many applications are based on text prediction and speech recognition.
2. **Type of Incremental algorithms**

The algorithms used by the related studies are presented in Figure 4.

![Fig. 4. Incremental learning-based algorithms applied.](image)

From the previous figure, it can be seen that the ISVM algorithm [11] (based on vector support machines) is the most used in the application domains consulted (27 studies from 2006 to present) considering the high classifications accuracy obtained by this algorithm. In contrast, the incremental algorithm CVFDT [14] has been the least used (9 items), considering a lower accuracy when using decision trees as base classifiers.

**IV. DISCUSSION**

In dynamic environments such as volcanoes, data are acquired over time (nonstationary data) and dynamic behavior is also observed in these systems. This implies that classifiers generated by non-incremental learning algorithms decrease their accuracy over time (non-adaptive models). In this sense, non-incremental learning algorithms are not suitable for application in these domains. Table I summarizes the studies referring to non-incremental learning in volcanology.

<table>
<thead>
<tr>
<th>Volcanology Area</th>
<th>Approach</th>
<th>Research Studies</th>
<th>AS Algorithms</th>
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<tbody>
<tr>
<td>Geophysics</td>
<td>Classification of Volcanic Seismic Events</td>
<td>[4], [6], [34]–[50]</td>
<td>ANN, SVM, DT, BN</td>
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<tr>
<td></td>
<td>Features Selection</td>
<td>[10], [51]–[55]</td>
<td>ANN, HMM</td>
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<tr>
<td></td>
<td>Classification of Tectonic Seismic Events</td>
<td>[52], [56]–[58]</td>
<td>SVM, ANN</td>
</tr>
<tr>
<td>Geochmstry and Geodesy</td>
<td>Gas emission detection and deformation changes</td>
<td>[59]–[71]</td>
<td>ANN, SVM</td>
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</table>

Table I shows that most studies correspond to seismology, one of the most important areas in monitoring active volcanoes in real time. Research focuses on the discovery of seismic activity patterns and identifying seismic sources according to the location to establish the eruption probability [33]. On the other hand, surveillance networks are also made up of several instruments that measure physical parameters in other areas such as geodesy and geochemistry. Geodesy allows the quantification and qualification of volcanic deformations through processing, systematization, analysis, and interpretation of data. Through this process, it is possible to develop a comparative control in order to determine the degree and amount of deformation suffered by the volcanic system in a specific period of time. Finally, volcanic monitoring in geochemistry involves periodic sampling for diffuse gases in soil (Radon and CO₂), thermal sources and fumarolic field (sampling of gases and temperature measurement).

On the other hand, incremental learning algorithms can be adapted to volcanology, specifically in detecting volcanic products. In this way, it is important to analyze the most relevant aspects of these algorithms such as the type of context change and noise sensitivity. Similarly, the relationship between the types of context changes and the volcanic monitoring areas most currently applied should be highlighted, according to the feedback provided by experts from the Vulcanological and Seismological Observatory of Popayán - Colombia (OVSP). On this basis, incremental learning techniques have been categorized by algorithm families, types of context changes (gradual or abrupt), and the noise contained in data streams.

Some incremental learning algorithms implement decision trees such as PECS and SPLICE (adapt to recurrent changes and noise), CVFDT (adapt to gradual changes), and IADEM (adapt to abrupt changes) as shown in Figure 5 (a). Although these algorithms are based on decision trees, PECS and PSLICE retain past models in memory. These models can be used at any time and updated by adapting to change. In addition, these algorithms are robust in handling noise, CVFDT uses probabilistic representation, however accuracy tends to decrease with a very large data volume. While IADEM stores data from previous instances in main memory to predict new values. This feature could generate physical storage problems, to the point of collapsing depending on the business model.
The family of algorithms based on decision rules includes techniques such as FACIL and FLORA (adaptation to abrupt changes and noise), FLORA2 (management of abrupt and recurrent changes, and adaptation to noise), and STAGGER (management of abrupt changes and noise), as shown in Figure 5 (b). The advantages of these approaches over decision trees are the great adaptability to change in high-speed data streams and their low computational cost as the FACIL algorithm, however a relevant problem is that these approaches only work with numerical attributes.

Techniques based on black box algorithms (K-NN, ANN, and SVM) are presented in Figure 5 (c). This family of algorithms groups together techniques such as IBLDS (KNN-based algorithm that handles recurrent changes), WINNOW (Bayesian network-based algorithm that handles recurrent changes), and OISVM (SVM-based algorithm that handles incremental changes). These algorithms are generally more accurate; however, they have some notable deficiencies such as the WINNOW algorithm, which adapts very slowly to context changes. In the same sense, OISVM has a main deficiency the high computational cost. In this strategy, several data blocks use much of the information from the previous data.

Figure 5 (d) shows the incremental algorithms based on multi-classifiers such as OzaBagADWIN (manages gradual and abrupt changes), MULTICIDIMDS (manages gradual changes and noise), SEA (manages gradual changes), and ACE (manages recurrent and gradual changes). OzaBagADWIN is the incremental version of the bagging algorithm, which uses a change detector called ADWIN. The adaptation mechanism is based on the replacement of the worst classifier (in an instant of time) with a new basic classifier created more recently. SEA, like MULTICIDIMDS, is based on windows of fixed and independent size, where all examples are consecutive and replaced in block according to the instances window.

ACE is the most complete of the four previous algorithms, since it has the particularity of detecting recurrent changes better than a conventional algorithm for four reasons. First, this technique consists of a simple classifier that works with the input data one by one incrementally. It replaces the multi-classifier in prediction tasks, when abrupt changes of concept occur. However, the multi-classifier takes a long time to update when waiting for the next block. Second, it uses another multi-sorter as a concept change detector. Third, a sliding window used to store the accuracy results and confidence intervals for each classifier on the most recent data. Finally, a buffer used to store recent training examples and build new classifiers.

Finally, Table II shows the relationship between the types of context changes in incremental learning and the most relevant volcanic monitoring areas (used in the different volcanoes monitored by the Colombian Geological Survey - SGC). This table has been constructed considering the opinion of experts in volcanology of the Vulcanological and Seismological Observatory of Popayán - Colombia and the knowledge acquired in the development of this research around incremental learning algorithms.

<table>
<thead>
<tr>
<th>Change of context in IL</th>
<th>Seismic evaluation</th>
<th>Geochemistry</th>
<th>Geodesy</th>
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<td><strong>Gradual</strong></td>
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<tr>
<td>MultiCIDIM-DS</td>
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<td>CVFDT</td>
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<td>MultiCIDIM-DS</td>
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V. CONCLUSIONS

The active volcanoes are monitored 24/7 by stations of different areas in volcanology such as: Seismology, Deformation, Geochemistry, Magnetometry, Climatology, among others; the first three are the most important. In volcanology, most research focuses on the detection and automatic location of Tectonic (VT), Tremor (TR) and Long Term (LP) earthquakes. Other works focus their efforts on the automatic detection of tectonic earthquakes (produced by the impact of tectonic plates) of local (TL), regional (RE) and distant (DS) tectonic type. In contrast, a low percentage of these works are related to geochemistry and deformation
in domains other than volcanology. These researches refer to complementary methodologies to seismology, making it possible to predict seismological events in some occasions during a later time, for example, an inflation of the volcanic cone can be a precursor of a seismic swarm. These techniques are related to each other, but there is currently no work that integrates the three pillars of volcanic surveillance to correlate the variables of each area. Despite the efforts of different researchers to detect volcanic events through nonincremental supervised learning, these studies do not include new examples that allow to keep updated the classifier. This causes obsolescence in the objective function considering that volcanoes are dynamic systems since they constantly suffer interactions in the Earth’s crust, specifically in the tectonic plates; additionally, when volcanoes experience transitions in their phases of eruptive activity, their baseline changes completely. Currently, there are multiple algorithms for incremental learning, which are used in application domains such as robotics, artificial vision, health, and speech and text recognition; however, these research papers do not evaluate whether the incremental learning algorithm they use fits correctly to the selected application domain.

There are different incremental learning algorithms which can be adapted to the volcanology domain, some specifically to abrupt, gradual recurrent changes, or even be noise tolerant. These characteristics were cross-checked with the different volcanic monitoring areas, obtaining a list of incremental learning algorithms that could be implemented in volcanic monitoring systems. From the systematic review of incremental learning algorithms, it was established that the most commonly used is ISVM (26 studies between 2000 and 2017), however most work is done after 2006 when its application was intensified mainly in the field of robotics. On the other hand, the least used technique is CVFDT (7 studies between 2000 and 2017).

Classification of both tectonic and volcanic seismic events has been a focus of research around automatic learning systems from 2008 to the present, maintaining a tendency to increase the number of investigations. From the studies corresponding to the volcanic application domain, it has been shown that neural networks and support vector machines are the two most commonly used algorithms for this type of research.

On the other hand, studies that apply incremental learning techniques in traffic networks (vehicle or computer package) had a high growth from 2006 to 2013, however, this trend has now decreased and domains such as machine vision and robotics are at the top of the current research trends. Although the Incremental Support Vector Machine (ISVM) algorithms were widely used from 2006 to 2014, subsequently the incremental algorithms that have played a major role in future research are AQ11 and LEARN+++.

VI. FUTURE WORKS

In order to extend the current systematic review of incremental and non-incremental learning techniques in volcanic environments and other application domains, it is important to conduct further research on other methods and techniques that are being massively used to solve similar problems, such as evolving systems and time series. In addition, it is necessary to generate a functional prototype to compare an incremental learning algorithm with a non-incremental one using a data set belonging to a volcanic monitoring season.

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