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Dimensionality Reduction and Classification of Sismic Events at Cotopaxi Volcano

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Dimensionality Reduction and Classification of Sismic Events at Cotopaxi Volcano

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DEDICATORIA

Dedicado a mi familia, quienes me enseñaron el valor de la persistencia y el esfuerzo constante. A mis sobrinas y sobrino, en quienes veo un gran potencial y espero ser un ejemplo a seguir. Y, finalmente, a la mujer que me ha acompañado durante todo este proceso, por su amor y apoyo inquebrantable.

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RESUMEN

En este estudio se compararon los métodos para la reducción de dimensionalidad para mejorar la precisión de la evaluación sísmica, para lo cual se introdujeron los principios básicos de los algoritmos PCA, LLA, SVM, KNN posteriormente se estableció un modelado para analizar las características de respuesta de fallas para cada atributo. Los resultados dieron a conocer que integrales muestran que SVM ofrece un mejor equilibrio en la clasificación para datos con un margen claro entre clases, logrando un menor número de errores de clasificación (falsos positivos y negativos) y un F1-Score más alto en comparación con Random Forest y KNN, PCA es la técnica de reducción de dimensional dad presenta un impacto significativo en el rendimiento de los clasificadores por sus características de respuesta a la falla al tiempo. Se concluye que PCA es el método más eficaz para la reducción de la dimensionalidad y SVM el clasificador de alto desempeño.

Palabras clave: evaluación sísmica, PCA, SVM.

ABSTRACT

In this study, dimensionality reduction methods were compared to improve the accuracy of seismic evaluation. For this purpose, the basic principles of the PCA, LLA, SVM, and KNN algorithms were introduced, and a modeling process was subsequently established to analyze fault response characteristics for each attribute. The results revealed that integrals show that SVM offers better balance in classification for data with a clear margin between classes, achieving a lower number of classification errors (false positives and negatives) and a higher F1-Score compared to Random Forest and KNN. PCA stands out as the dimensionality reduction technique with a significant impact on the performance of classifiers due to its response characteristics to faults over time. It is concluded that PCA is the most effective method for dimensionality reduction, and SVM is the high-performance classifier.

Key words: Seismic evaluation, PCA, SVM.

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Dimensionality Reduction and Classification of Sismic Events at Cotopaxi Volcano

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***Resumen*—This study explored different dimensionality reduction methods to enhance the accuracy of seismic evaluations. The principles behind algorithms such as PCA, LLA, SVM, and KNN were introduced, followed by a modeling process to analyze how each attribute responds to faults. The findings showed that SVM stands out for its ability to classify data with clear class margins, resulting in fewer errors (both false positives and negatives) and a higher F1-Score compared to Random Forest and KNN. Among the dimensionality reduction techniques, PCA proved to be the most effective, significantly boosting classifier performance by capturing important fault response patterns over time. In summary, PCA emerged as the best method for reducing dimensionality, while SVM excelled as the top-performing classifier.**

***Index Terms*—Seismic evaluation, PCA, SVM.**

Introduction

According to information provided by the World Health Organization (WHO), between 1998 and 2017, around 750,000 people worldwide died due to earthquakes [11]. Given this scenario, it is necessary to predict earthquakes by implementing preventive measures, as seismology is capable of predicting severe earthquakes with a magnitude >5 [2]. Currently, there are volcanic seismology databases; however, these are often restricted, while publicly available data usually only provide seismograms without key information such as location, start points, or event endpoints. Restricted databases often involve a manual labeling process for seismic events, which is time-consuming and typically includes a small number of records (fewer than a thousand), lacking balance for certain types of events [11]. Nowadays, artificial intelligence enables better predictions of these phenomena through the use of learning algorithms [13].

The improvement in computer hardware has led to the emergence of machine learning methods based on waveform data in the field of seismology, significantly improving the extraction of features from input data samples [19]. Seismic signal processing can be classified into three stages: data acquisition, processing, and interpretation. During volcanic activity, the generated signals allow for the identification of different types of events [4].

Long-period events (LP) refer to periods longer than 2 seconds and occur during the eruptive phase of shield-type and stratovolcanoes with calderas. They are associated with fluid movement within conduits. A correlation has been found between gas emissions and VLP (very long period) events, as well as episodes of deformation caused by the accumulation and migration of molten material due to VLP occurrences. Observations from various volcanoes have confirmed a link between gas emissions and VLP events [9].

In the study by Jaramillo et al. (2014) [8], the characteristics of long-period seismic events generated by the Coto volcano were investigated to understand their evolution. In the frequency domain, it was determined that LP events occurred at frequencies below 10 Hz, while VT (volcano-tectonic) events evolved between 0 and 20 Hz. Additional records were also analyzed for the detection of zones unrelated to LP or VT events, showing evolution between 15 and 35 Hz. The results highlighted the need to improve the false alarm rate for detecting these events using a whitening processor (adaptive predictor) and a Bayesian processor based on likelihood ratios, which detects Gaussian processes of interest (seismic signals) amidst white and colored Gaussian noise.

Regarding volcano-tectonic events, Ortiz et al. (2019) [12] emphasized that methods based on characterizing background noise and detecting changes in the evolution of volcanic seismic signals often lack prior information regarding the sources and structures traversed by transient seismic waves. Additionally, new studies have adapted neuroscience methods such as Self-Organizing Maps (SOM), combined with decomposition techniques like Singular Spectrum Analysis, to identify specific evolutionary patterns.

In the study by Bucio et al. (2022), a seismic alarm system was designed to detect P waves, capable of providing alerts tens of seconds in advance. Thanks to the characteristics of P waves, their low intensity, and greater capacity to propagate destructive waves over distances between Mexico City and the epicenter zone, seismic predictions were significantly improved [3].

Vaezi and Baan's research (2015) [14] evaluated seismic events when they reached seismological stations, finding distinct characteristics due to differing internal volcanic pathways. The acquisition system was studied using the STA/LTA algorithm, designed to detect seismic events within recorded seismograms. Each detected event was saved in a file containing a signal that extended 10 seconds before and after the detected event, enabling experts to estimate noise levels and thus reduce false positives.

To simplify data while retaining as much relevant information as possible, dimensionality reduction is a key process for managing data, as excessive data handling can lead to noise, overfitting in machine learning models, and other issues [10].

To reduce data dimensions, PCA is a multivariate analysis technique that, through axis rotation, decomposes eigenvalues and eigenvectors. This allows transforming high-dimensional data into lower dimensions while retaining original data classifications and reducing feature dimensions [17].

Similarly, for nonlinear dimensionality reduction, Locally Linear Embedding (LLE) is one of the most important techniques in data mining. It maintains as much key information as possible in a low-dimensional vector space. Its learning algorithm is local linear embedding (LLE) [17]. Chang et al. [16] used a series of SR methods based on LLE to predict HR image patches through the geometric structure captured from LR image space, using SR methods based on sparse representation. Spectral clustering methods are gaining popularity and are applied across various fields due to their high performance. However, they have limitations, such as spectral embedding and rotation not contributing to a globally optimal solution. These methods are also time-consuming and have high computational complexity [15].

Theoretical Framework

The analysis and classification of seismic signals generated by volcanic activity form the core of this study. To address the complexities inherent in seismic data, this project integrates advanced methodologies in signal processing, dimensionality reduction, and machine learning. The theoretical framework guiding this research is organized into four key components: seismic signal processing, dimensionality reduction techniques, classification algorithms, and evaluation metrics.

Seismic Signal Processing

Seismic signals contain rich information about the dynamic processes occurring within a volcano. Effective processing of these signals is essential for extracting meaningful patterns that differentiate between event types.

Long-Period (LP) Events: LP events are characterized by their low frequency and extended duration, commonly associated with the movement of fluids such as magma or volcanic gases. These events often precede eruptions, making their detection and classification critical for early warning systems. The unique spectral features of LP events, such as dominant low-frequency peaks, provide vital clues for their identification.

Volcano-Tectonic (VT) Events: VT events are high-frequency, short-duration signals caused by rock fracturing due to tectonic stress. These events are indicative of structural changes within the volcanic edifice and can be precursors to eruptive activity or shifts in volcanic dynamics.

Spectral Decomposition: Transform techniques like the Fourier Transform and the Wavelet Transform are used to analyze seismic signals in the frequency domain. While the Fourier Transform decomposes signals into their constituent frequencies, the Wavelet Transform allows multi-resolution analysis, capturing both time and frequency information.

These techniques enable the construction of descriptive features that serve as inputs for further analysis.

Dimensionality Reduction Techniques

Seismic datasets are typically large and high-dimensional, posing challenges for computational efficiency and model performance. Dimensionality reduction techniques simplify data representation while retaining critical information.

Principal Component Analysis (PCA): PCA is a linear technique that transforms correlated variables into a new set of uncorrelated variables, known as principal components. These components are ranked by the variance they capture, allowing the selection of a lower-dimensional representation that retains most of the data's information. PCA is particularly useful for reducing redundancy and noise in seismic data.

Locally Linear Embedding (LLE): LLE is a non-linear dimensionality reduction method that preserves local relationships among data points. By mapping the data into a lower-dimensional space, LLE captures complex structures that might be missed by linear methods. This is especially beneficial for the analysis of non-linear patterns in seismic signals.

Spectral Embedding: pectral Embedding leverages graph-based representations of data to identify clusters and relationships within high-dimensional spaces. This method excels at detecting intrinsic data structures and is instrumental in separating seismic event classes in a lower-dimensional space.

Classification Algorithms

Supervised machine learning algorithms are employed to classify seismic events based on the features extracted during signal processing and dimensionality reduction.

Support Vector Machines (SVM): SVM identifies an optimal hyperplane that maximizes the margin between data points of different classes. It is particularly effective for linearly separable data and can be extended to non-linear problems using kernel functions such as radial basis or polynomial kernels.

K-Nearest Neighbors (KNN): KNN classifies a data point based on the majority class of its nearest neighbors. While simple and intuitive, KNN provides a valuable benchmark for comparing the performance of more complex models.

Logistic Regression: Logistic Regression models the probability of a data point belonging to a specific class. Its probabilistic nature and simplicity make it a reliable choice for binary classification tasks, such as distinguishing between LP and VT events.

Random Forest: Random Forest is an ensemble learning algorithm that combines multiple decision trees to improve classification accuracy and robustness. By aggregating predictions from individual trees, it mitigates overfitting and adapts well to noisy seismic datasets.

Evaluation Metrics

To ensure the reliability and effectiveness of the classification models, several evaluation metrics are used:

F1 Score: The F1 Score balances precision and recall, making it a critical metric for imbalanced datasets where false positives and false negatives carry significant consequences.

Area Under the Curve (AUC): AUC measures the model's ability to distinguish between classes, providing a comprehensive assessment of classification performance across various decision thresholds.

Accuracy: Accuracy evaluates the proportion of correct predictions in all instances, serving as a general indicator of the performance of the model.

Integration of Concepts

The combination of these techniques creates a robust framework for the detection and classification of seismic events. Signal processing extracts relevant features, dimensionality reduction simplifies data representation, and machine learning models leverage these processed features for accurate classification. Together, these components enable real-time monitoring and enhance the predictive capabilities of volcanic early warning systems, contributing to the safety and preparedness of communities surrounding Cotopaxi Volcano.

Materials

The project is based on two critical seismic datasets sourced from the Cotopaxi Volcano, Ecuador, developed and curated under the ESeismic repository. These datasets provide a comprehensive basis for analyzing volcanic seismic events, facilitating advanced signal processing, feature extraction, and machine learning classification tasks. The details of the databases are outlined below.

MicSigV1 Dataset (Volcanic Seismic Signals)

MicSigV1 is a raw seismic signal dataset containing discrete seismic events recorded at the Cotopaxi Volcano. It is designed to enable foundational research in signal processing and detection of volcanic events. **Content**The dataset includes 1187 seismic records divided into five classes of events:

- **Long-Period (LP)**: 1044 samples (87.9 %).
- **Volcano-Tectonic (VT)**: 101 samples (8.5 %).
- **Regional (REG)**: 27 samples (2.3 %).
- **Hybrid (HB)**: 8 samples (0.7 %).
- **Icequake (ICE)**: 7 samples (0.6 %).

SeisBenchV1 Dataset (Feature Benchmark)

SeisBenchV1 is a feature-based dataset derived from MicSigV1. It includes feature vectors calculated from the original seismic signals to benchmark classification algorithms.

ContentEach seismic event is represented by a feature vector comprising 84 descriptors extracted from:

- **Time Domain (13 features)**:Metrics such as mean, variance, kurtosis, and energy.
- **Frequency Domain (21 features)**:Computed using power spectral density and periodogram analysis.
- **Scale Domain (50 features)**: Derived using Wavelet transforms (db10 Daubechies family up to level 6).

Analysis The dataset highlights the relevance of features for separating classes such as LP and VT. Visualization techniques like t-SNE show distinct clusters corresponding to different stations and event types, though some overlap remains, reflecting real-world complexities.//

PurposeThis dataset supports advanced research in feature selection, dimensionality reduction, and machine learning classification for seismic events.

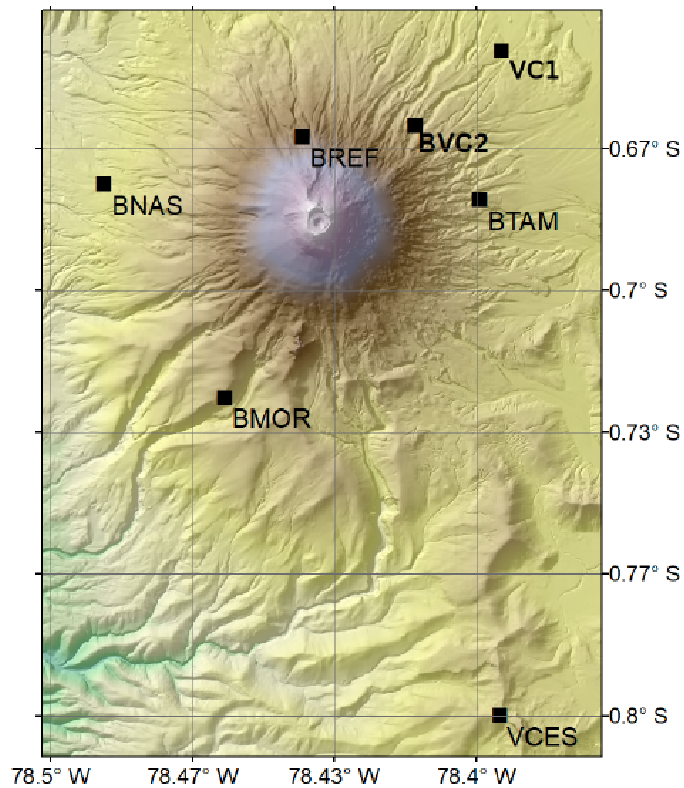

Figura 1. Some of the stations from the seismological network deployed at Cotopaxi volcano. Data for this study have been recorded at the VC1 and BREF stations. Image provided by IGEPN.

Contribution and Relevance

The ESeismic repository, developed by the Instituto Geofísico de la Escuela Politécnica Nacional (IGEPN), marks a significant advancement in making Ecuadorian volcanic seismic data publicly accessible. It provides a well-curated and expertly labeled dataset for global research, overcoming traditional barriers of data privacy. Both datasets serve complementary roles:

- **MicSigV1** enables foundational signal processing and detection research.
- **SeisBenchV1** facilitates machine learning applications, especially for feature-based classification.

Methodology

The methodology employed in this project is designed to handle the complexity and high dimensionality of seismic data, ensuring accurate classification of volcanic seismic events. The process follows a systematic workflow comprising several stages: data collection, preprocessing, dimensionality reduction, classification, and evaluation. Below is a detailed explanation of each stage:

Data Collection

The initial step involves acquiring raw seismic data from various sources, including repositories and sensors deployed near the Cotopaxi Volcano. These datasets often contain noise, outliers, and high-dimensional features that require preprocessing for subsequent analysis.

Preprocessing

Normalization: The data is scaled to a common range to prevent features with larger magnitudes from dominating the model training process.
Outlier Removal: Extreme values are identified and filtered to minimize distortion in model performance. This ensures that the dataset accurately represents the underlying signal characteristics.

Dimensionality Reduction

Given the high dimensionality of seismic data, dimensionality reduction techniques are applied to extract meaningful features while minimizing computational complexity:

- **PCA (Principal Component Analysis):** A standard PCA technique is applied, retaining 95 % of the dataset's variance. This method simplifies data structure while preserving essential information.
- **Locally Linear Embedding (LLE)** This non-linear method captures intricate, local relationships among data points, respecting their neighborhood structure.
- **Spectral Embedding:** This graph-based technique maps data into a lower-dimensional space, maintaining relationships between points even in noisy conditions..

Data Transformation

After dimensionality reduction, the data is projected into a transformed space with fewer dimensions (e.g., 2D or 3D) for improved interpretability and enhanced classifier performance. This stage also ensures that critical patterns in the data are retained for classification.

Classification

The reduced dataset is then fed into classification models that assign seismic events into predefined categories:

- **SVM (Support Vector Machines):** This algorithm identifies an optimal hyperplane that maximizes the margin between data classes, ensuring high classification accuracy.
- **KNN (K-Nearest Neighbors):** A simple yet effective algorithm that assigns classes based on proximity to neighboring data points.
- **Logistic Regression:** A probabilistic model used to classify events into binary categories, making it a versatile tool for distinguishing event types.
- **Random Forest:** An ensemble-based method that utilizes multiple decision trees to classify seismic events with robustness and resilience to noise.

Evaluation of Results

The performance of the classification models is rigorously assessed using the following metrics:

- **F1-Score:** Measures the harmonic mean of precision and recall, balancing false positives and false negatives in imbalanced datasets.
- **AUC (Area Under the Curve):** Quantifies the model's ability to distinguish between classes over a range of thresholds.
- **Accuracy:** Represents the proportion of correctly predicted instances among all predictions, offering a general measure of model performance.

Results and Discussion

To ensure the robustness of the methodology, the performance of dimensionality reduction techniques (PCA, Spectral Embedding, and LLE) is compared based on their impact on classification metrics. This comparative analysis provides insights into the effectiveness of each method under different conditions and highlights the most suitable approach for seismic event classification.

PCA stands out as the most reliable and effective option in this analysis. Similarly, the classifiers Logistic Regression and Random Forest demonstrated more consistent performance in combination with different dimensionality reducers.

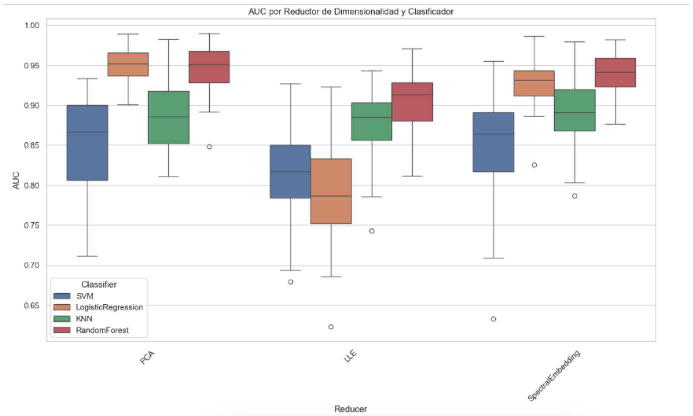

Figura 2. AUC Comparison for Different Classifiers and Dimensionality Reduction Techniques.

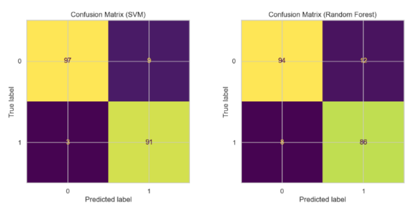

Figura 3. Confusion matrix comparison: SVM outperforms Random Forest with fewer false positives and more true positives, excelling in accuracy for seismic signal classification.

Confusion matrices reveal that SVM offers better balance in classification for data with a clear margin between classes, achieving fewer classification errors (false positives and negatives) and a higher F1-Score compared to Random Forest and KNN. LLE is effective in capturing nonlinear structures in the data and projecting them into a two-dimensional space, providing a better visual understanding of the distribution and relationships between classes, which is valuable for exploratory analysis.

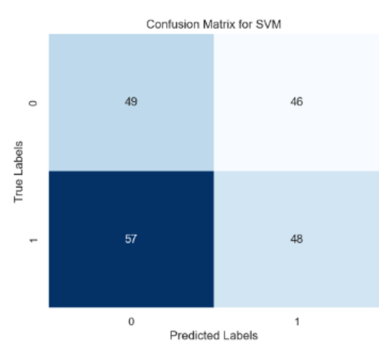

Figura 4. A balance of errors between classes can be observed, suggesting that the model could benefit from hyperparameter adjustments, class balancing techniques, or even a change in the classification approach.

A balance of errors between classes can be observed, suggesting that the model could benefit from hyperparameter adjustments, class balancing techniques, or even a change in the classification approach.

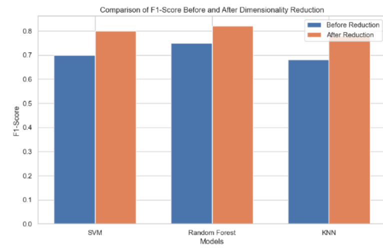

Figura 5. In the comparative analysis, dimensionality reduction is observed to improve the performance of the Random Forest and KNN models. These results help to understand how feature reduction can impact outcomes.

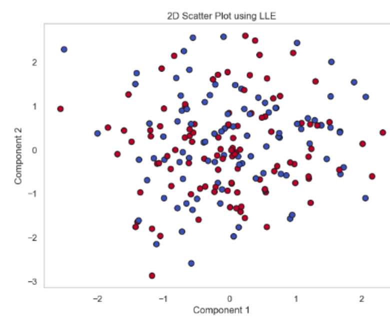

Figura 6. The scatter plot shows the grouping of data within a two-dimensional space using LLE (Locally Linear Embedding). LLE is useful for reducing the dimensionality of complex data with nonlinear structures, providing a visualization in a two-dimensional space that preserves the local relationships between the data.

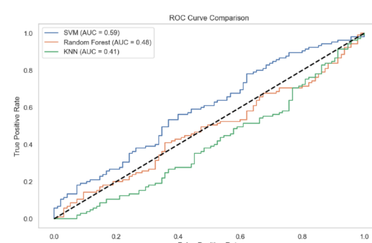

Figura 7. Regarding the performance of the models and their ability to differentiate between classes, it was found that SVM presents advantages over the three compared models. However, it could be improved with hyperparameter adjustments or additional techniques.

The choice of dimensionality reduction technique has a significant impact on classifier performance, and PCA has stood out as the most reliable and effective option in this analysis. Similarly, the classifiers Logistic Regression and Random Forest have shown more consistent performance in combination with different dimensionality reducers, standing out as the most robust in this context.

Cuadro I
F1 Score Results and p-values by Dimensionality Reduction Technique and Classifier.

Reducer	Classifier	F1 Scores (Range)	p-value F1
4*PCA	SVM	0.885 - 0.942	0.463344
	Logistic Regression	0.913 - 0.947	*NaN (Base)*
	KNN	0.913 - 0.959	1.000000
	Random Forest	0.906 - 0.972	0.916563
4*LLE	SVM	0.897 - 0.913	0.249153
	Logistic Regression	∼0.476	0.009701
	KNN	0.879 - 0.913	0.249153
	Random Forest	0.924 - 0.942	0.916563
4*Spectral Embedding	SVM	∼0.476	0.009701
	Logistic Regression	∼0.476	0.009701
	KNN	0.467 - 0.475	0.011159
	Random Forest	0.466 - 0.474	0.007937

These results align with the study by Babiki et al. (2022) [18], who used a series of correlation coefficients such as Pearson, Rank, and Mutual Information (MI) to reduce the attribute set. These coefficients allowed mapping the relationship between input and output features for three classes. When calculating seismic attributes, they found that the Gray Level Co-Occurrence Matrix (GLCM) and the spectral group of attributes enabled high seismic prediction accuracy.

Espinoza et al. (2020) analyzed the principal components of seismic evaluation and determined that the high dimensionality of the feature vector caused significant data dispersion. To address this issue, PCA was used to reduce dimensionality and computational complexity, achieving an improvement in response time supported by a vector with features within a smaller dimensional subspace [15].

To study daily variations in geomagnetism, Han Peng [5] applied principal component analysis after harmonic approximation in three stations. The results revealed that the proportion of the second component showed concurrent variations a month before the 2000 Izu Islands earthquake. Similarly, Guo et al. (2021) [5] conducted a series of statistical studies on electromagnetic data within the AETA station using a modified PCA method. The results showed that 80 % of AETA stations have a significant relationship between electromagnetic anomalies and local earthquakes.

Bavikir et al. (2022) [6] concluded that PCA is more effective when similar types of attributes are analyzed together. This allows quantifying the importance of seismic attributes for unsupervised learning. Thus, PCA has high effectiveness in measuring the contribution of each seismic attribute to data variability.

In this study, SVM was found to offer better balance in classification for data with a clear margin between classes, achieving fewer classification errors (false positives and negatives) and a higher F1-Score compared to Random Forest and KNN after dimensionality reduction. Harirchian (2020) [1] found that the SVM method achieved 52 % accuracy in detecting earthquake-induced damage. A total of 22 performance modifiers were implemented using machine learning, showing 52 % accuracy. To improve this rate, it is recommended to use a k-fold cross-validation technique to verify the classifier's model performance.

To reduce the dimensionality of complex data with nonlinear structures, this research found that LLE provides a visualization in a two-dimensional space that preserves local relationships between the data. Similarly, in the study by Guangui et al. (2023) [7], seismic attributes in the training dataset were analyzed, finding that the LLE algorithm has a better dimensionality reduction effect for nonlinear data volumes. SVM can effectively highlight fault response characteristics over time by allowing the elimination of redundant information, improving the efficiency of fault interpretation.

Conclusion

This research aimed to integrate advanced techniques of signal processing, dimensionality reduction, and supervised classification to improve the detection and classification of volcanic seismic events. The study found that SVM and PCA demonstrated the best performance in dimensionality reduction and as classifiers in seismic evaluation.

Recommendation

For future studies, it is recommended to explore advanced dimensionality reduction techniques such as t-SNE, UMAP, or deep autoencoders, while integrating traditional methods like PCA to achieve more robust representations. It is also essential to implement modern classifiers, such as deep neural networks and Transformers, to enhance seismic event classification and reduce dependency on feature engineering. Additionally, hyperparameter optimization and data balancing techniques like SMOTE should be applied to address class imbalance issues. Finally, it is suggested to integrate these models into real-time monitoring systems, ensuring continuous updates and dynamic adaptability to improve early detection and risk management for seismic events in contexts such as the Cotopaxi Volcano.

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