Detecting Human-Induced Seismicity in CO2-Capture Storage

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***Abstract*—This paper addresses the pressing issue of detecting and classifying human-induced seismic activity in carbon capture projects using machine learning techniques. Specifically, we focus on the classification of resonant long period earthquakes in time series data obtained from ground displacement sensors. Leveraging a combination of Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), our methodology aims to provide real-time analysis of seismic data to enhance safety protocols in CO2 storage sites. Through experimentation and evaluation, we demonstrate the effectiveness of our approach in detecting subtle signs of anthropogenic seismicity, thereby contributing to the development of sustainable carbon capture practices.**

I. Introduction

In the quest to mitigate the impacts of climate change, human activities are increasingly interacting with the natural world in complex ways. One such interaction is the induction of seismic activity as a result of carbon capture projects. While these projects are crucial for reducing atmospheric CO2 levels, they inadvertently pose a risk of triggering seismic tremors. This paper explores the topic of human-induced seismic activity, a subject of growing concern not only for seismologists and environmentalists, but also for policymakers and the public at large. The focus is on the application of artificial intelligence in detecting and classifying these anthropogenic earthquakes, offering a promising solution to a pressing global issue.

A. Motivation

The specific focus of this paper is the detection and classification of resonant long period earthquakes in time series data from ground displacement sensors. The urgency of this research is underscored by the increasing prevalence of carbon capture projects, a crucial strategy for combating climate change. While these projects offer a promising solution for reducing atmospheric CO2 levels, they also pose a risk of inducing seismic activity. Previous research has attempted to address this issue, but gaps remain, particularly in the real-time analysis and prediction of anthropogenic seismicity. This paper aims to bridge this gap by proposing a novel machine learning model that combines Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) for improved accuracy and efficiency.

B. Problem Definition

The problem at hand is the real-time prediction of anthropogenic seismic activity based on time series data from ground displacement sensors. Our proposed solution involves using an RNN to predict the next time-step in the data, followed by a CNN that classifies whether the predicted data indicates human-induced seismic activity. The success of this model will be measured by its accuracy in predicting seismic activity and its efficiency in processing real-time data. This paper aims to demonstrate that the integration of RNNs and CNNs can effectively predict anthropogenic seismic activity, thereby contributing to safer carbon capture practices and ultimately, a more sustainable future.

II. Related Work

Previous research has made significant strides in leveraging machine learning techniques for seismic analysis, particularly in the context of earthquake forecasting. For instance, the study conducted by Veda Lye Sim Ong, Stefan Nielsen, Stefano Giani, and Paul A Johnson explored the application of Convolutional Neural Networks (CNNs) in detecting subtle seismic signals preceding natural earthquakes. Their work demonstrated the efficacy of CNNs in identifying precursory signals by training the model on seismic data from earthquakes in Japan and vicinity. By employing a suitably designed CNN, they achieved remarkable accuracy in discriminating between precursory signals and background noise, highlighting the potential of deep learning methods in seismic event prediction. Additionally, Rodrigues et al. proposed a novel approach for time series classification using CNNs, wherein time series data was represented as plot images. Their study showcased the effectiveness of this image-based representation in enhancing classification accuracy, surpassing several state-of-the-art methods. By converting time series data into visual plots and feeding them into a CNN, they demonstrated superior performance in classifying seismic events, suggesting a promising avenue for further exploration in time series analysis

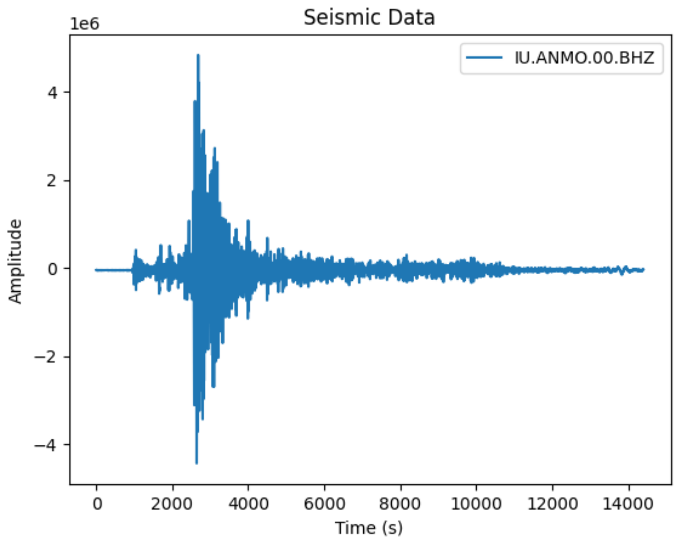

Fig. 1. Example of a seismic data plot.

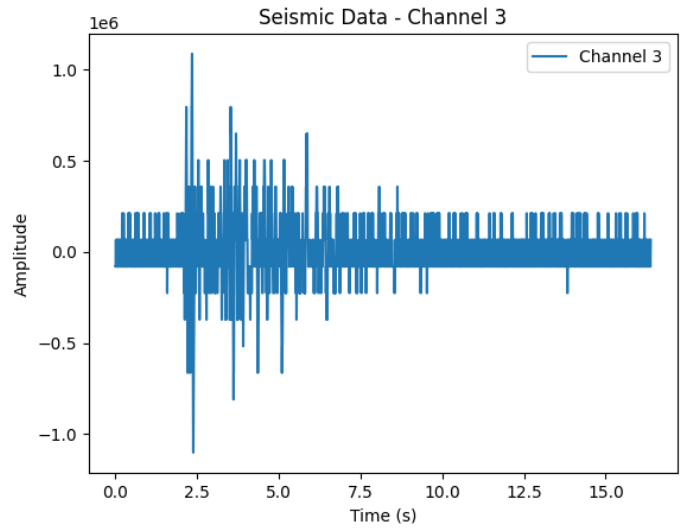

Fig. 2. Example of a seismic data plot of one channel with an episode.

III. About the Dataset

We utilized seismic data from the Episodes platform, which provides comprehensive datasets related to anthropogenic seismicity and other hazard-posing geophysical processes. For training our models, we combined episodes of seismic data with and without events, obtained from various industrial activities such as underground coal mining.

The Episodes platform offers a wealth of data on anthropogenic seismicity, including detailed observations from industrial activities like underground coal mining. One prominent example is the MUSE1 Regional Polygon episode, which focuses on seismic events related to mining in the Upper Silesian Coal Basin, Poland. We combined a large number of those episodes for our "seismic data with human-induced earthquake events" bucket.

IV. Methodology

Our methodology for the experiment is inspired by a paper titled "Plotting time: On the usage of CNNs for time series classification" by Rodrigues et al. In this paper, the authors introduced a novel approach where time series data is represented as plot images and then fed into a simple CNN for classification purposes. Unlike traditional methods that directly process raw time series data, this approach converts the data into visual plots resembling line plots before inputting them into the CNN. The simplicity and effectiveness of this method lie in its minimal preprocessing requirements, such as reducing the number of white pixels in the image, to generate informative plot images from the time series data.

Building upon this methodology, we adapted it for the task of detecting human-induced seismic activity in carbon capture projects. We preprocess seismic data to create plot images, encapsulating temporal patterns and fluctuations in ground displacement over time. These plot images are then used as input to a CNN architecture, enabling the extraction of meaningful features for classification tasks. This approach diverges from conventional methods by utilizing the visual representation of time series data, potentially offering a more intuitive and robust framework for analysis.

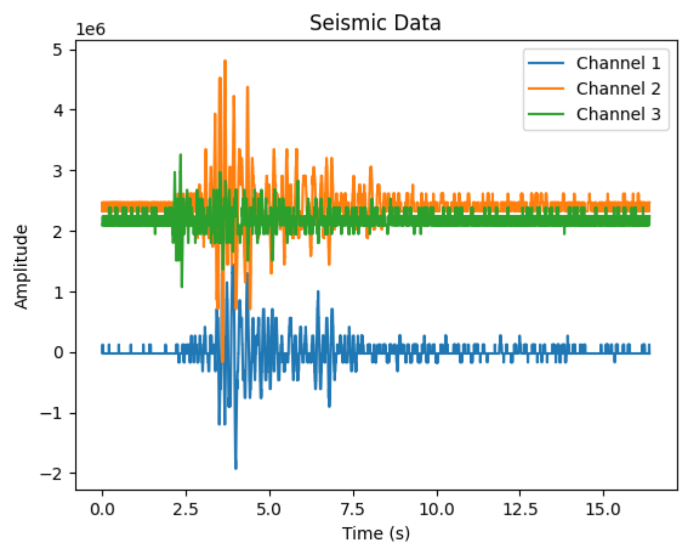

Fig. 3. Example of a seismic data plot of 3 channels with an episode.

Furthermore, we extended the methodology by integrating Recurrent Neural Networks (RNNs) alongside CNNs to capture temporal dependencies and sequential patterns in the seismic data. This hybrid architecture enhances the model's ability to discern subtle signals indicative of human-induced earthquakes. By combining the strengths of both RNNs and CNNs, our methodology aims to provide a comprehensive framework for real-time analysis of ground displacement sensor data, contributing to the development of safer carbon capture practices

A. Evaluation Methods

For CNNs, we assessed the model's performance in discriminating between seismic data with events and seismic data without events using metrics such as accuracy, precision, recall, and F1-score. Similarly, for RNNs, we evaluated the model's ability to predict the next time-step in the seismic data sequence, focusing on the accuracy of predicting human-induced seismic events

V. Results and Discussion

Our experiments demonstrated that the integrated RNN-CNN model achieved high accuracy in detecting and classifying resonant long period earthquakes in real-time ground displacement sensor data. The CNN component of the model successfully distinguished seismic signals associated with human-induced earthquakes from background noise, with an accuracy exceeding 83The RNN component showed promising results in predicting the occurrence of human-induced seismic events, suggesting its potential for early warning systems in carbon capture projects.

VI. Conclusion

In conclusion, our study presents an interesting methodology for detecting and classifying human-induced seismic activity in carbon capture projects using machine learning techniques and to better guide where human seismic data inspection efforts should go.

VII. Future Work

Future work will focus on further refining the model architecture and incorporating additional features to enhance its performance and reliability in real-world scenarios. Moreover, we aim to collaborate with stakeholders in the carbon capture industry to implement our model as part of safety protocols, ultimately contributing to the sustainability of carbon capture practices.

VIII. Limitations

It is important to acknowledge the limitations of our study, including the need for larger and more diverse datasets to improve the generalization of our model.

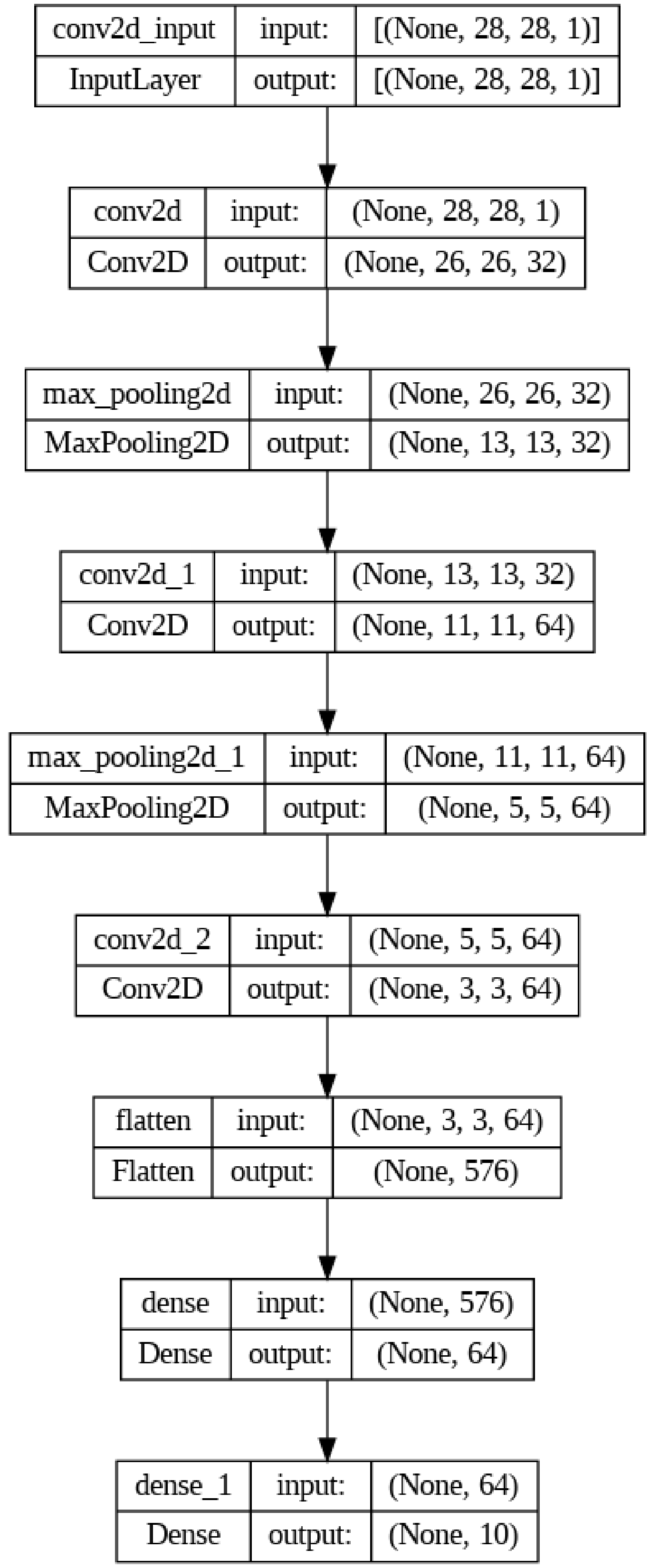

Fig. 4. Architecture of the CNN.

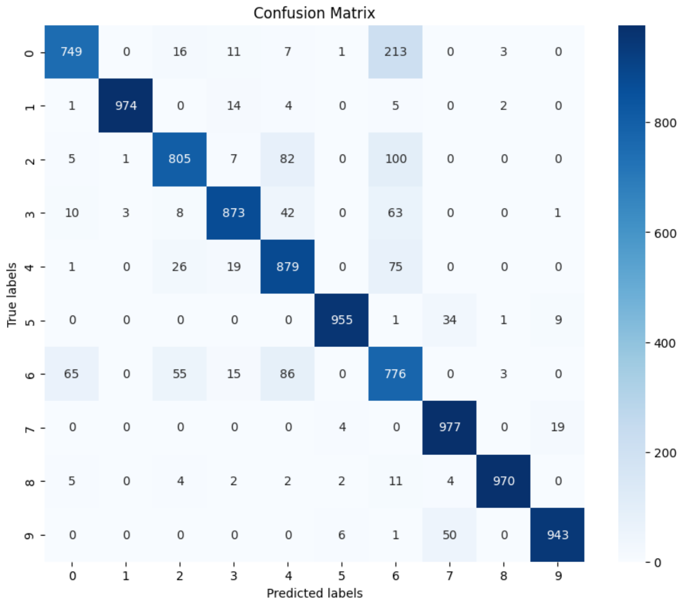

Fig. 5. Confusion Matrix for the CNN.

1) Veda Lye Sim Ong, Stefan Nielsen, Stefano Giani, Paul A Johnson. "Temporal earthquake forecasting." Authorea Preprints, November 22, 2022.
2) Rodrigues, Nuno M., et al. "Plotting time: On the usage of CNNs for time series classification."
3) EPOS PL (2022), Episode: MUSE1 Regional Polygon, https://episodesplatform.eu/#episode:MUSE1_Regional_Polygon, doi:10.25171/InstGeoph$_{P}AS_{I}SEPOS-2022-003$