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Earthquake Prediction on Spatio-Temporal Data Mining: An LSTM Based Approach

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ABSTRACT: The importance of seismological research around the globe is very clear. Therefore, new tools and algorithms are needed in order to predict magnitude, time, and geographic location, as well as to discover relationships that allow us to better understand this phenomenon and thus be able to save countless human lives. However, given the highly random nature of earthquakes and the complexity in obtaining an efficient mathematical model, efforts until now have been insufficient and new methods that can contribute to solving this challenge are needed. In this work, a novel earthquake magnitude prediction method is proposed, which is based on the composition of a known system whose behavior is governed according to the measurements of more than two decades of seismic events and is modeled as a time series using machine learning, specifically a network architecture based on LSTM (long short-term memory) cells. A variety of physical systems exhibit regular behavior in different time or space scales, such as the burst of the earthquakes on faults and crackling noise of paper crumpling . The behaviors are likely independent events, but there is universality for real systems which can be explained by simple models.

KEYWORDS: System Architecture, User Interface, Long short term memory cells, Gates, Exploratory data analysis, Data collection and cleaning,Convolutional Neural network, Recurrent Neural network, Supervised learning, Machine learning, Naive-Baiyes Algorithm, Random Forest Algorithm.

I. INTRODUCTION

In the seismic event classification, determining the seismic features of rockfall is significantly important for the automatic classification of seismic events because of the huge amount of raw data recorded by seismic stations in continuous monitoring. At the same time, the rockfall seismic features are still not completely understood. This study concentrates on the rockfall frequency content, amplitude (ground velocity), seismic waveform and duration analysis, of an artificial rockfall test at Torgiovannetto (a former quarry in Central Italy).

A total of 90 blocks were released in the test, and their seismic signals and moving trajectories were recorded by four tri-axial seismic stations and four cameras, respectively. In the analysis processing, all the artificial rockfall signal traces were cut separately and the seismic features were extracted individually and automatically. In this study, the relationships between a) frequency content and impacted materials, b) frequency content and the distance between block releasing position and seismic station (source-receiver distance) were discussed. As a result, we found that the frequency content of rockfall focuses on 10 – 60 Hz and 80 – 90 Hz within a source-receiver distance of 200 m, and it is well correlated with impacted material and source-receiver distance.

To evaluate the difference between earthquake and rockfall, 23 clear earthquake signals recorded in a seven month-long continuous seismic monitoring, carried out with the four seismic stations, were picked out, according to the Italian national earthquakes database (INGV). On these traces we performed the same analysis as in the artificial rockfall traces, and two parameters were defined to separate rockfall events from earthquake noise. The first one, the amplitude ratio, is related to the amplitude variation of rockfall between two stations and is greater than that of earthquakes, because of the higher attenuation occurring for rockfall events, which consists in high frequencies whereas for earthquakes it consists in low frequencies.

The other parameter, the shape of waveform of signal trace, showed a significant difference between rockfall and earthquake and that could be a complementary feature to discriminate between both. This analysis of artificial rockfall

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is a first step helpful to understand the seismic characteristics of rockfall, and useful for rockfall seismic events classification in seismic monitoring of slope.

II. RELATED WORK

In [1] In the mountain regions, seismic monitoring aids in assessing risks like rockfalls and debris flows. We employ supervised random forest algorithms to classify seismic data, considering challenges such as network coverage and data imbalance. Using data from the Swiss Alps, we achieve 70% accuracy in slope failure classification with low SNR and 80% accuracy with imbalanced data. Despite imbalance mitigation attempts, accuracy doesn't improve significantly. We further demonstrate successful classification of continuous seismic recordings, identifying slope failures alongside earthquakes. Integrating distant seismic stations enhances accuracy. Our study highlights the potential of machine learning in automated mass movement monitoring, even with limited data and suboptimal network setups.

In [2] A case study with seismic geophone data from the unstable Åknes rock slope in Norway is considered. This rock slope is monitored because there is a risk of severe flooding if the massive-size rock falls into the fjord. The geophone data is highly valuable because it provides 1000 Hz sampling rates data which are streamed to a web resource for real-time analysis. The focus here is on building a classifier for these data to distinguish different types of microseismic events which are in turn indicative of the various processes occurring on the slope. There are 24 time series from eight 3-component geophone data for about 3500 events in total, and each of the event time series has a length of 16 s. For the classification task, novel machine learning methods such as deep convolutional neural networks are leveraged. Ensemble prediction is used to extract information from all-time series, and this is seen to give large improvements compared with doing immediate aggregation of the data. Further, self-supervised learning is evaluated to give added value here, in particular for the case with very limited training data.

In [3] A convolutional neural network (CNN) was implemented to automatically classify 15 years of seismic signals recorded by an eight-geophone network installed around the back scarp of the Åknes rock slope in Norway. Eight event classes could be identified and are adapted from the typology proposed by Provost et al. (2018), of which five could be directly related to movements on the slope. Almost 60 000 events were classified automatically based on their spectrogram images. The performance of the classifier is estimated to be near 80 %. The statistical analysis of the results shows a strong seasonality of the microseismic activity at Åknes with an annual increase in springtime when snow melts and the temperature oscillates around the freezing point, mainly caused by events within classes of low-frequency slope quakes and tremors. The clear link between annual temperature variations and microseismic activity could be confirmed, supporting thawing and freezing processes as the origins. Other events such as high-frequency and successive slope quakes occur throughout the year and are potentially related to the steady creep of the sliding plane. The huge variability in the annual event number cannot be solely explained by average temperatures or varying detectability of the network. Groundwater recharge processes and their response to precipitation episodes are known to be a major factor of sliding at Åknes, but the relationship with microseismic activity is less obvious and could not be demonstrated.

In [4] Ensemble learning combines several individual models to obtain better generalization performance. Currently, deep learning architectures are showing better performance compared to the shallow or traditional models. Deep ensemble learning models combine the advantages of both the deep learning models as well as the ensemble learning such that the final model has better generalization performance. This paper reviews the state-of-art deep ensemble models and hence serves as an extensive summary for the researchers. The ensemble models are broadly categorised into bagging, boosting, stacking, negative correlation based deep ensemble models, explicit/implicit ensembles, homogeneous/heterogeneous ensemble, decision fusion strategies based deep ensemble models. Applications of deep ensemble models in different domains are also briefly discussed. Finally, we conclude this paper with some potential future research directions.

In [5]In the seismic event classification, determining the seismic features of rockfall is significantly important for the automatic classification of seismic events because of the huge amount of raw data recorded by seismic stations in continuous monitoring. At the same time, the rockfall seismic features are still not completely understood. This study concentrates on the rockfall frequency content, amplitude (ground velocity), seismic waveform and duration analysis, of an artificial rockfall test at Torgiovannetto (a former quarry in Central Italy). A total of 90 blocks were released in the test, and their seismic signals and moving trajectories were recorded by four tri-axial seismic stations and four

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III. PROPOSED ALGORITHM

LONG SHORT TERM MEMORY ALGORITHM:

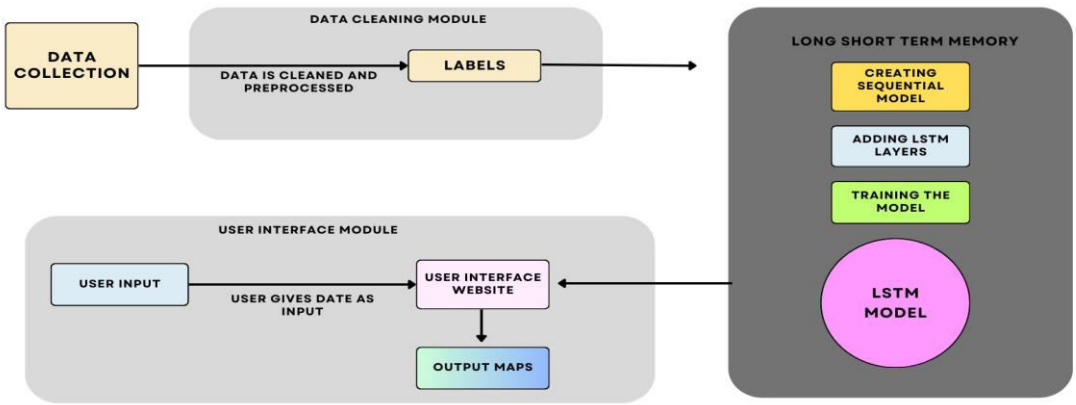
Long Short Term Memory is a kind of recurrent neural network. In RNN output from the last step is fed as input in the current step. LSTM was designed by Hochreiter & Schmidhuber. It tackled the problem of long-term dependencies of RNN in which the RNN cannot predict the word stored in the long-term memory but can give more accurate predictions from the recent information. As the gap length increases RNN does not give an efficient performance. LSTM can by default retain the information for a long period of time. It is used for processing, predicting, and classifying on the basis of time-series data.

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) that is specifically designed to handle sequential data, such as time series, speech, and text. LSTM networks are capable of learning long-term dependencies in sequential data, which makes them well suited for tasks such as language translation, speech recognition, and time series forecasting.

A traditional RNN has a single hidden state that is passed through time, which can make it difficult for the network to learn long-term dependencies. LSTMs address this problem by introducing a memory cell, which is a container that can hold information for an extended period of time. The memory cell is controlled by three gates: the input gate, the forget gate, and the output gate. These gates decide what information to add to, remove from, and output from the memory cell.

The input gate controls what information is added to the memory cell. The forget gate controls what information is removed from the memory cell. And the output gate controls what information is output from the memory cell. This allows LSTM networks to selectively retain or discard information as it flows through the network, which allows them to learn long-term dependencies.

LSTMs can be stacked to create deep LSTM networks, which can learn even more complex patterns in sequential data. LSTMs can also be used in combination with other neural network architectures, such as Convolutional Neural Networks (CNNs) for image and video analysis.



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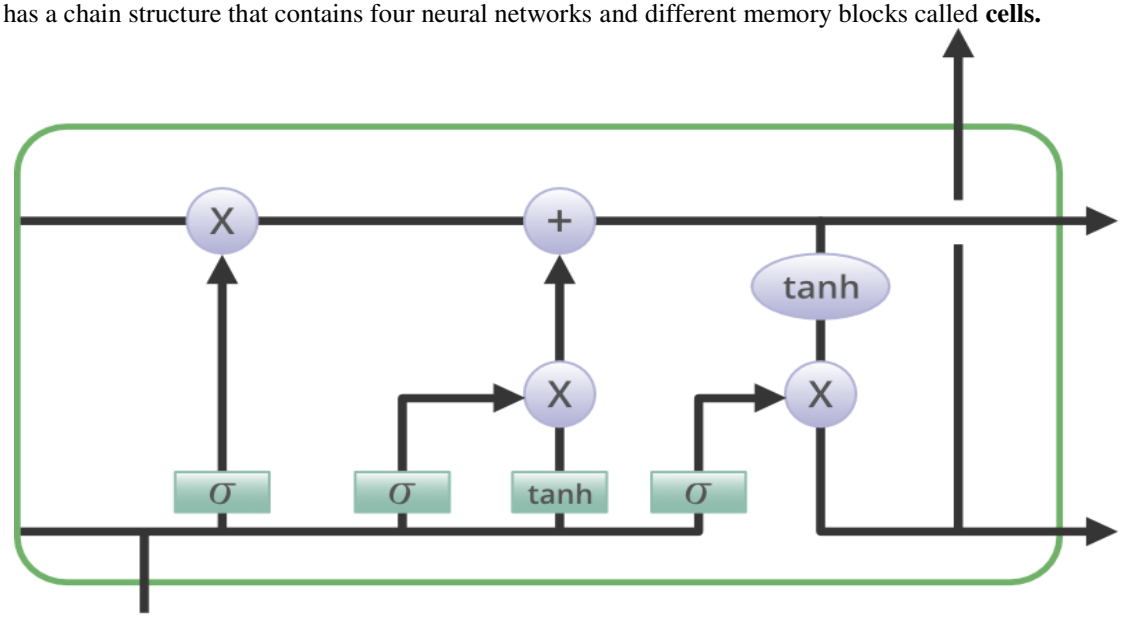
STRUCTURE OF LSTM:

LSTM has a chain structure that contains four neural networks and different memory blocks called **cells.**



Information is retained by the cells and the memory manipulations are done by the **gates.**
There are three gates –

1. FORGET GATE: The information that is no longer useful in the cell state is removed with the forget gate. Two inputs *x_t* (input at the particular time) and *h_t-1* (previous cell output) are fed to the gate and multiplied with weight matrices followed by the addition of bias. The resultant is passed through an activation function which gives a binary output. If for a particular cell state the output is 0, the piece of information is forgotten and for output 1, the information is retained for future use.

2. INPUT GATE: The addition of useful information to the cell state is done by the input gate. First, the information is regulated using the sigmoid function and filter the values to be remembered similar to the forget gate using inputs *h_t-1* and *x_t*. Then, a vector is created using *tanh* function that gives an output from -1 to +1, which contains all the possible values from h_t-1 and *x_t*. At last, the values of the vector and the regulated values are multiplied to obtain the useful information

3. OUTPUT GATE: The task of extracting useful information from the current cell state to be presented as output is done by the output gate. First, a vector is generated by applying tanh function on the cell. Then, the information is regulated using the sigmoid function and filter by the values to be remembered using inputs *h_t-1* and *x_t*. At last, the values of the vector and the regulated values are multiplied to be sent as an output and input to the next cell.

SOME OF THE FAMOUS APPLICATIONS OF LSTM INCLUDES:

1. Long Short-Term Memory (LSTM) is a powerful type of Recurrent Neural Network (RNN) that has been used in a wide range of applications. Here are a few famous applications of LSTM:
2. Language Modeling: LSTMs have been used for natural language processing tasks such as language modeling, machine translation, and text summarization. They can be trained to generate coherent and grammatically correct sentences by learning the dependencies between words in a sentence.
3. Speech Recognition: LSTMs have been used for speech recognition tasks such as transcribing speech to text and recognizing spoken commands. They can be trained to recognize patterns in speech and match them to the corresponding text.
4. Time Series Forecasting: LSTMs have been used for time series forecasting tasks such as predicting stock prices, weather, and energy consumption. They can learn patterns in time series data and use them to make predictions about future events.

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5. Anomaly Detection: LSTMs have been used for anomaly detection tasks such as detecting fraud and network intrusion. They can be trained to identify patterns in data that deviate from the norm and flag them as potential anomalies.
6. Recommender Systems: LSTMs have been used for recommendation tasks such as recommending movies, music, and books. They can learn patterns in user behavior and use them to make personalized recommendations.
7. Video Analysis: LSTMs have been used for video analysis tasks such as object detection, activity recognition, and action classification. They can be used in combination with other neural network architectures, such as Convolutional Neural Networks (CNNs), to analyze video data and extract useful information.

Algorithm code:

```
input1 = Input(shape=(3,1))

x = LSTM(units = 64, return_sequences=True)(input1)

x = Dropout(0.2)(x)

x = LSTM(units = 64, return_sequences=True)(x)

x = Dropout(0.2)(x)

x = LSTM(units = 64)(x)

x = Dropout(0.2)(x)

x = Dense(32, activation='softmax')(x)

dnn_output = Dense(1)(x)

model = Model(inputs=input1, outputs=[dnn_output])

model.compile(loss='mean_squared_error', optimizer='Nadam')

model.summary()

return model
```

LAYERS DESCRIPTION:

The LSTM model defined in this code has three LSTM layers and two dense layers. The three LSTM layers are stacked on top of each other, with the output of each LSTM layer being fed as input to the next LSTM layer.

The first two LSTM layers have return_sequences=True, which means they return the full sequence of output values for each input time step, rather than just the output for the final time step. This allows the LSTM layers to capture the temporal dynamics of the input data more effectively.

The third LSTM layer does not have return_sequences=True, which means it only returns the output for the final time step. This output is then fed into two dense layers, one with a softmax activation function and one with no activation function. The softmax layer produces a probability distribution over the 32 possible output classes, while the final dense layer produces a single output value.

So in total, this LSTM model has three LSTM layers and two dense layers.

Softmax activation function:

In the defined LSTM model, the last dense layer uses the softmax activation function. The softmax function is commonly used in the output layer of a classification model to produce a probability distribution over the output classes.

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In this case, the output of the LSTM layers is fed into a dense layer with 32 units, which represents the number of possible output classes. The softmax activation function then produces a probability distribution over these 32 classes, where each output value represents the probability that the input sequence belongs to a particular class.

Function of layers:

Input(shape=(3,1)): This is the input layer, which defines the shape of the input data. In this case, the input is a three-dimensional tensor, where the first dimension is the sequence length (3), the second dimension is the number of features in the sequence (1), and the third dimension is the batch size (which is not specified here).

LSTM(units = 64, return_sequences=True): This is the first LSTM layer. It takes the input tensor from the input layer and applies a set of 64 LSTM cells to it. The return_sequences=True argument specifies that the output of this layer should be a sequence rather than a single value.

Dropout(0.2): This is a dropout layer, which randomly drops out 20% of the units in the previous LSTM layer during training. This is a regularization technique that helps prevent overfitting.

LSTM(units = 64, return_sequences=True): This is the second LSTM layer. It takes the output sequence from the previous LSTM layer and applies another set of 64 LSTM cells to it.

Dropout(0.2): This is another dropout layer, which again randomly drops out 20% of the units in the previous LSTM layer during training.

LSTM(units = 64): This is the third and final LSTM layer. It takes the output sequence from the previous LSTM layer and applies another set of 64 LSTM cells to it. However, this time the return_sequences argument is not specified, so the output of this layer will be a single value rather than a sequence.

Dropout(0.2): This is another dropout layer, which again randomly drops out 20% of the units in the previous LSTM layer during training.

Dense(32, activation='softmax'): This is a fully connected layer with 32 units and a softmax activation function. It takes the output of the previous dropout layer and applies a linear transformation to it, followed by a softmax function. The softmax function ensures that the output values are normalized and represent a probability distribution.

Dense(1): This is the final output layer, which takes the output of the previous layer and applies a linear transformation to it. The output of this layer is a single value, which represents the predicted value for the target variable.

IV. RESULTS

The project embarked on a pioneering quest to transform earthquake prediction methodologies by harnessing the power of LSTM network architecture, an advanced form of recurrent neural networks (RNNs), to analyze seismic data spanning over two decades. The intricate interplay between seismic parameters such as Modified Mercalli Intensity (MMI), earthquake depth, distance from the epicenter, and Richter scale magnitude was meticulously scrutinized to develop robust predictive models. Through rigorous experimentation, both naive Bayes and LSTM algorithms demonstrated remarkable efficacy in forecasting earthquake magnitudes, showcasing their prowess in handling complex and dynamic temporal data. Nevertheless, the endeavor showcased the segmentation of the observation period into hourly windows, particularly in windows devoid of seismic activity, necessitating innovative solutions to ensure model robustness and accuracy.

The algorithms devised were leveraged to power a cutting-edge website poised to ease the accessibility of earthquake prediction data. This dynamic online platform empowers users with real-time insights into imminent seismic events, bolstering disaster preparedness and mitigation efforts worldwide. Utilizing sophisticated data visualization techniques and intuitive user interfaces, the website provides seamless access to critical information, enabling individuals to stay informed and take proactive measures in the face of potential seismic threats. By seamlessly integrating advanced machine learning algorithms with web-based technologies, this initiative not only exemplifies the convergence of data science and geoscience but also underscores the pivotal role of technological innovation in safeguarding lives and infrastructure against natural disasters.

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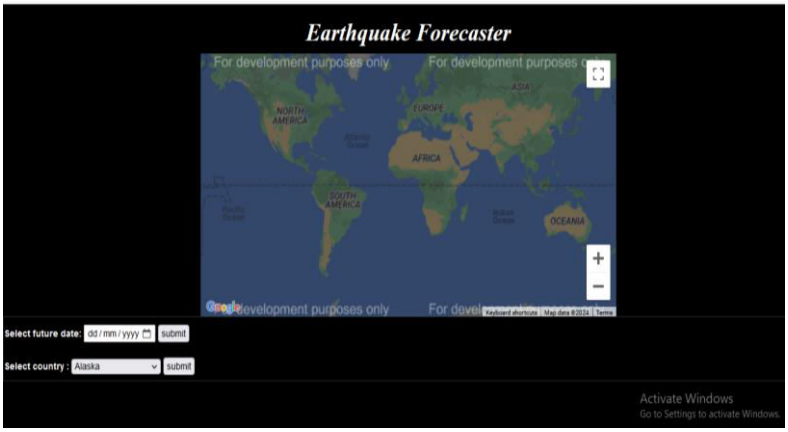

Fig 1:The user interface that will be facing the end user

Fig 2: The model predicting the earthquake after its given the location

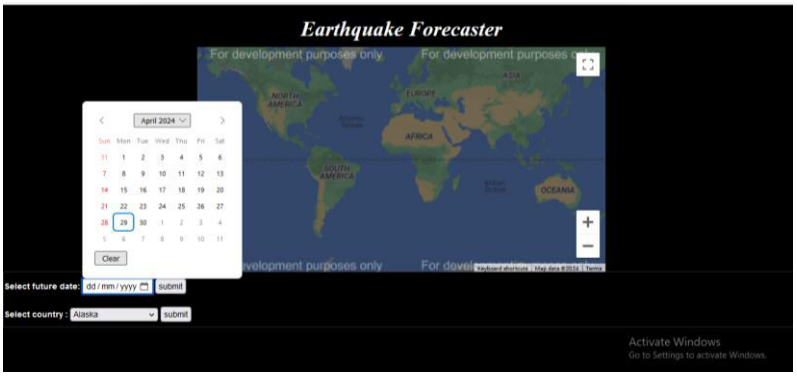

Fig 3: The selection of dates and location

V. CONCLUSION AND FUTURE WORK

In paving the way for future advancements in earthquake prediction, this project lays a solid foundation for several avenues of potential exploration and refinement. One promising direction for future work involves further optimizing the LSTM network architecture to enhance prediction accuracy and robustness, perhaps by incorporating additional features or refining existing ones. Additionally, exploring the integration of other advanced machine learning

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techniques, such as convolutional neural networks (CNNs) or ensemble methods, could yield insights into improving predictive performance and overcoming challenges posed by data segmentation. Furthermore, delving into the realm of ensemble learning approaches, which combine multiple models to achieve superior predictive capabilities, holds immense promise for advancing earthquake prediction methodologies. By harnessing the collective intelligence of diverse models, researchers can mitigate the limitations of individual algorithms and enhance overall prediction accuracy. Additionally, leveraging emerging technologies such as deep reinforcement learning (DRL) could offer novel insights into optimizing earthquake prediction strategies and adapting models in real-time to evolving seismic dynamics.Moreover, the project's integration of predictive algorithms into a user-friendly website opens up avenues for enhancing public engagement and disaster preparedness. Future endeavors could focus on expanding the website's functionalities, incorporating real-time data streams, and developing interactive visualization tools to provide users with comprehensive insights into seismic activity. Additionally, exploring partnerships with governmental agencies, research institutions, and humanitarian organizations could facilitate the integration of predictive models into broader disaster management frameworks, enabling proactive mitigation efforts and timely response strategies.

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