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Deep Neural Networks for Predicting the Settlement of Earth Dams Based on the InSAR Outputs

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ABSTRACT Earth dams play a crucial role in water resource management, necessitating effective maintenance to ensure prolonged functionality and safety. Monitoring these dams traditionally involves methods such as surveying and instrumentation. However, challenges arise from equipment malfunctions and absences, especially in dams affected by environmental changes. In response to these challenges, the cost-effective and adaptable nature of Interferometric Synthetic Aperture Radar (InSAR) has made it a preferred choice for monitoring. Despite their advantages, traditional numerical models like finite element methods have limitations in predicting deformation comprehensively, particularly due to intricate, non-linear correlations involving material type and environmental conditions. To overcome these limitations, this research employs deep learning techniques, specifically Long Short-Term Memory (LSTM) network, to capture intricate relationships and accurately predict dam behavior. Time series data from InSAR, representing settlement, are decomposed into trend and seasonal components using Artificial Neural Networks (ANN) for trend prediction. Furthermore, an LSTM network is utilized to handle the complexity of the seasonal component and its correlation with environmental factors. This network incorporates settlement, precipitation, temperature, and reservoir water level time series as inputs, thereby enhancing prediction accuracy. The research outcome presents a robust solution that holds the promise of increased accuracy and efficiency in predicting, monitoring, and serving as an early warning system for earth dam deformations over time. Such advancements are crucial for ensuring the safety and integrity of critical infrastructure in the face of evolving environmental conditions.

KEYWORDS Earth Dam; Deep Learning; Health Monitoring; Climate Change; Remote Sensing

1 INTRODUCTION

The stability and integrity of earth dams are crucial for the safety of downstream communities and the efficient management of water resources. Earth dams, which are commonly used for water retention, irrigation, and hydroelectric power generation, are susceptible to settlement over time due to various factors, including soil consolidation, water seepage, and external loads. Predicting the settlement behavior of these structures is essential for maintenance, safety, and design purposes. Traditional methods for predicting settlement often rely on empirical formulas and numerical simulations, which may not fully capture the complex, nonlinear behavior of soil-structure interactions (Rana *et al.*, 2022).

Monitoring earth dam settlements with high precision is crucial for timely maintenance and ensuring the safety of these structures. Synthetic Aperture Radar (SAR) imagery has emerged as a powerful tool for this purpose. The SAR is an active remote sensing technology that transmits microwave signals towards the Earth surface and records the reflected signals to generate high-resolution images (Xiao *et al.*, 2022). One of the key advantages of SAR imagery is its ability to operate under all weather conditions, day or night, due to its independence from sunlight. This makes it particularly useful for continuous monitoring of large and remote areas. SAR imagery can detect minute ground deformations with millimeter-level accuracy, making it an invaluable resource for monitoring the settlement of earth dams (Bayik, Abdikan and Arıkan, 2021). By using techniques like Interferometric Synthetic Aperture Radar (InSAR), changes in the phase of the reflected signals over time can be analyzed to measure ground displacement.

In recent years, deep learning (DL) techniques have emerged as powerful tools for modeling and predicting complex systems in various engineering fields. Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks are among the widely used DL algorithms. These advanced computational methods offer significant potential in predicting the settlement of earth dams by learning from historical data and identifying underlying patterns that traditional methods might overlook. Compared to conventional numerical methods like the Finite Element Method (FEM), deep learning models can efficiently handle large, complex datasets, integrate diverse input features, and adapt to new data for continuous improvement. This enables more accurate and real-time monitoring and forecasting, capturing non-linear relationships and intricate patterns that are often challenging for traditional models (Ren *et al.*, 2021).

The primary objective of this study is to develop and compare predictive models for earth dam settlement using ANN, and LSTM algorithms. By leveraging historical settlement data obtained through the InSAR SBAS technique and other relevant factors, the study aims to provide accurate and reliable predictions that can assist engineers and decision-makers in monitoring and maintaining earth dam structures. The study also seeks to evaluate the performance of these models in terms of accuracy, robustness, and computational efficiency, providing insights into their applicability in geotechnical engineering.

2 CASE STUDY

The biggest embankment dam in Iran is the Karkheh Dam, which is situated on the Karkheh River in the Khuzestan Province (Figure 1). The Karkheh dam was built in the region with a medium occurrence level of land subsidence (Sadeghi *et al.*, 2023), around 22 kilometers northwest of the city of Andimeshk. The dam is 127 meters elevation, giving it a commanding presence. Its impressive reservoir capacity of 7.8 billion cubic meters in its greatest condition is reflected in its crest length of 3030 meters and its elevation of 234 meters above sea level (Shafiee, 2008).

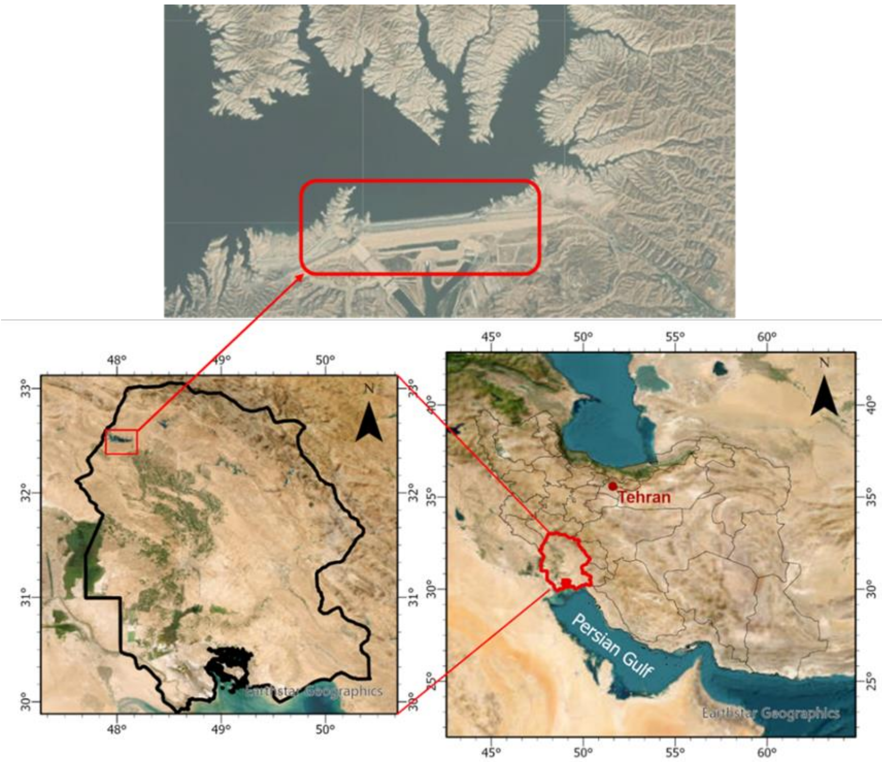

Figure 1. The location of Karkheh dam

3 METHODS

3.1 Dataset

For this study, settlement data is obtained using the Interferometric Synthetic Aperture Radar (InSAR) Small Baseline Subset (SBAS) technique. The redundant interferogram network of picture pairs with a short spatial baseline and a moderate temporal baseline are the foundation of the Small Baseline InSAR (SB-InSAR) technology. It enhances the geographical coverage and tracks the temporal history of ground displacement, particularly over rural and agricultural areas where the persistent scatterer density may be low. The procedures of master picture selection, topographic phase removal, and interferogram creation were used to carry out the interferometric process. By employing SRTM DEM (30m) data, the research area's topographic phase impact was eliminated. To estimate the displacement value of each pixel in the Karkhe dam, the entire set of interferometric networks is then inverted for incremental displacements between the capture dates using the least-squares approach (X. Chen *et al.*, 2021; Ghorbani *et al.*, 2022).

We employed 300 SLC format Sentinel-1A in band C, interferometric wide swath (IW) mode, and VV polarization in this investigation. The coverage range is up to 250 km^2, and the pixel resolution is up to 5×20 m^2. The study ran from October 25, 2015, to December 30, 2022. Images were received every 12 days using Sentinel-1A data from descending orbit 20.

Based on the Hydrostatic-Seasonal-Time (HST) model, which is widely used in dam health monitoring, temperature and precipitation are considered as components of the seasonal factor (Sigtryggsdóttir, Snæbjörnsson and Grande, 2018; Alonso, Olivella and Pinyol, 2005). To capture the effect of seasonal factors on earth dam settlement, an LSTM network was employed, using precipitation, temperature, and historical settlement data as input features. The model's performance in predicting settlements was then evaluated. Therefore, statistics on precipitation and air temperature were collected between 2016 and 2023, as shown in Figure 2.

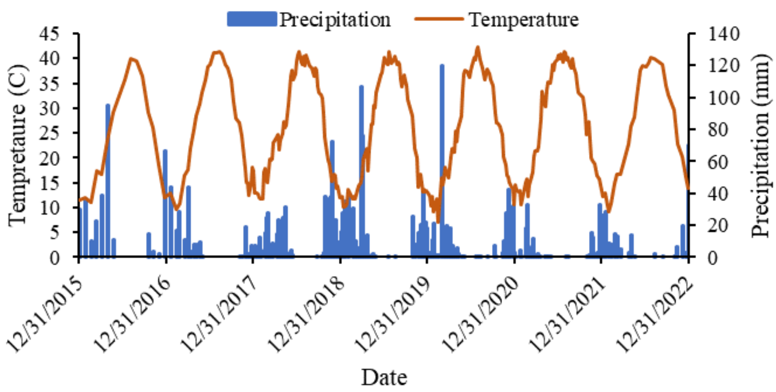

Figure 2. The time series of precipitation and temperature

3.2 Data Preprocessing

Raw data collected from various sources often contain inconsistencies, missing values, and noise, which can adversely affect the performance of deep learning models. Therefore, data preprocessing is an essential step to clean and prepare the data for analysis. The following sub-steps are involved in data preprocessing:

3.2.1 Data Cleaning

Data was enhanced by removing or imputing missing values, correcting errors, and addressing outliers in the dataset. Techniques such as mean or median imputation for missing values and z-score analysis for outlier detection can be employed.

3.2.2 Normalization

The data was scaled to ensure that all features contribute equally to the model. Normalization techniques such as min-max scaling and standardization are applied to transform the data into a suitable range. This step is critical for the convergence of neural network training algorithms.

3.2.3 Data Splitting

Data were divided into training, validation, and test sets. Typically, 60% of the data is used for training, 20% for validation, and 20% for testing. The training set is used to train the models, while the validation set is used to tune the model parameters, with the goal of minimizing validation loss and preventing overfitting. Finally, the test set was employed to assess the model's performance on unseen data.

3.3 Decomposition

The Seasonal-Trend decomposition using Loess (STL) is a robust and versatile method for decomposing time series data into three main components according to Equation (1): seasonal (s_i), trend (t_i), and residual (r_i), such a way that sum of the three components Equals to the original series (Theodosiou, 2011).

$$y_i = t_i + s_i + r_i \tag{1}$$

In the context of earth dam settlement, the seasonal component could capture periodic variations due to factors like seasonal rainfall or temperature changes. In the other hand, the trend component can highlight the general pattern of settlement over time, reflecting the cumulative effects of soil consolidation and external loads.

3.4 Model Development

The core of the methodology involves developing predictive models using ANN and LSTM algorithms. The trend component exhibited a relatively simple and smooth progression, making it suitable for prediction using an ANN model, which excels in capturing such straightforward patterns. Conversely, the seasonal component demonstrated a complex and intricate behavior influenced by various environmental factors (C. Chen *et al.*, 2021). Displacement is influenced by historical patterns, and LSTMs are specifically designed to handle time-series data where the order of inputs is crucial. While Artificial Neural Networks (ANN) are powerful for modeling complex relationships, they do not inherently consider the sequence of inputs, which is a key limitation when dealing with time-dependent data. As shown in Figure 3, in LSTM models, each unit is connected to others within the hidden layers across various time steps. LSTMs retain past information and incorporate it into the current output. Through loops in the hidden layer, information is transferred from one step of the network to the next. Therefore, LSTM was chosen over ANN to leverage its memory cell structure, which allows the model to learn long-term dependencies, making it more suitable for the predictive task (Xu and Niu, 2018). By integrating these models, we leveraged the ANN's strength in trend prediction and the LSTM's proficiency in handling seasonal variations, thus providing a comprehensive and accurate predictive framework for the settlement time series of the earth dam.

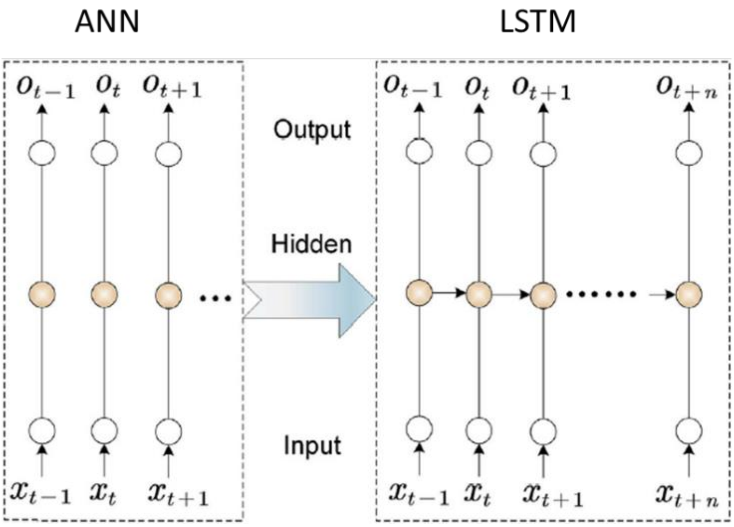

Figure 3. The difference between the architecture of ANN and LSTM (Xu and Niu, 2018).

3.4.1 ANN Model

An ANN is a computational model inspired by the human brain. It consists of interconnected units called neurons arranged in layers: an input layer, one or more hidden layers, and an output layer (Figure 4). Each neuron in a layer receives inputs, processes them, and passes the output to the next layer. In an ANN, each connection between neurons has an associated weight that determines the strength and direction of the signal. Each neuron also has a bias that adjusts the weighted sum of the inputs before passing it through an activation function. The input to each neuron is multiplied by the corresponding weights, summed up along with the bias, and then passed through the activation function to produce the neuron's output (Hosseini, Mojtahedi and Sadeghi, 2020; F. Mojtahedi, Ahmadihosseini and Sadeghi, 2023).

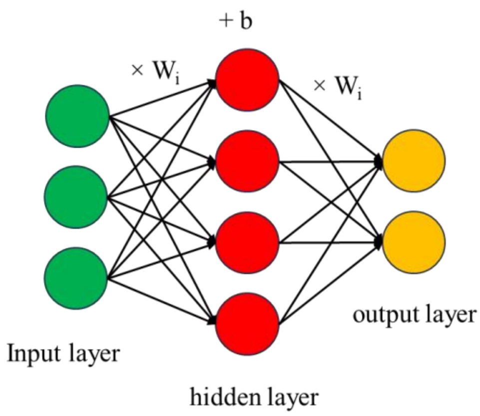

Figure 4. An ANN architecture

3.4.2 LSTM Model

LSTM networks are a type of Recurrent Neural Network (RNN) designed to handle sequential and time series data. LSTMs are particularly effective for capturing long-term dependencies within data, which is crucial for tasks like predicting time series trends. LSTM networks consist of a series of repeating modules called LSTM cells. As shown in Figure 5 each containing three main components: input gates (i_t), forget gates (f_t), and output gates (o_t). These gates regulate the flow of information through the cell (Yang *et al.*, 2020).

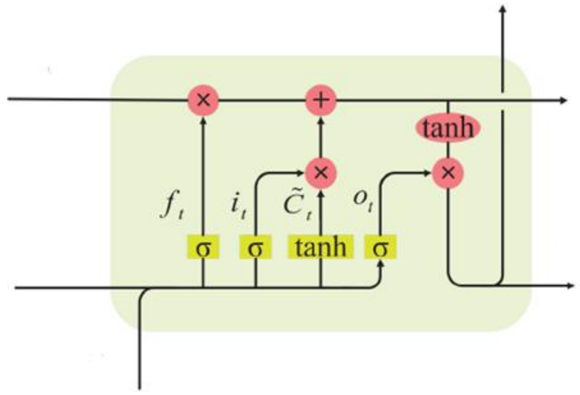

Figure 5. An LSTM cell architecture (Yang *et al.*, 2020)

Input Gate: Determines how much of the new input should be added to the cell state.
Forget Gate: Decides how much of the past information should be retained or forgotten.
Output Gate: Controls the output that is passed to the next LSTM cell and the hidden state.

Each LSTM cell maintains a cell state that carries important information across the sequence, allowing the network to remember or forget information as needed. This architecture helps LSTM networks to avoid issues like vanishing or exploding gradients, which are common in traditional RNNs.

3.5 Evaluation

To evaluate the performance of the predictive models, Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) described in Equations (2) and (3), respectively were utilized as the primary metrics.

$$MSE = \frac{1}{n}\sum_i^n (y_i - \hat{y})^2 \quad (2)$$

$$MAPE = \frac{1}{n}\sum_i^n \left|\frac{y_i - \hat{y}}{y_i}\right| \quad (3)$$

4 RESULTS AND DISCUSSION

The mean velocities across the dam crest attained by the SBAS method are shown in Figure 6. The dam crest has fifteen control stations. P6 has the greatest settlement rate, measuring -12.5 mm/year. Furthermore, the minimum settlement velocities at abutment sites p1 and p15 are approximately -2 mm/y and -4.5 mm/y, respectively.

Since point P6 exhibited the greatest settlement, it was selected as the critical point. Therefore, the time series corresponding to this point was decomposed into trend and seasonal time series using the STL algorithm. As shown in Figure 7, Seasonal displacement varies with a decreasing approach, ranging from -2.5 to 1. In the meantime, there is a declining tendency in the cumulative displacement, which has settled down to -80 mm.

In this study, an ANN model was employed to predict the trend displacement time series of an earth dam. To this end, a three-layer artificial neural network with 5, 50, and 1 neuron in each layer, respectively, was considered. The input to this model was solely the trend displacement, which was fed into the model with 5 past time steps to predict one future time step. The results of the model are illustrated in Figure 8, which demonstrates the predicted versus actual displacement values. This figure highlights the accuracy and effectiveness of the ANN model in capturing the displacement trends, as evidenced by the achieved MSE and MAPE scores of 0.06 and 0.004, respectively.

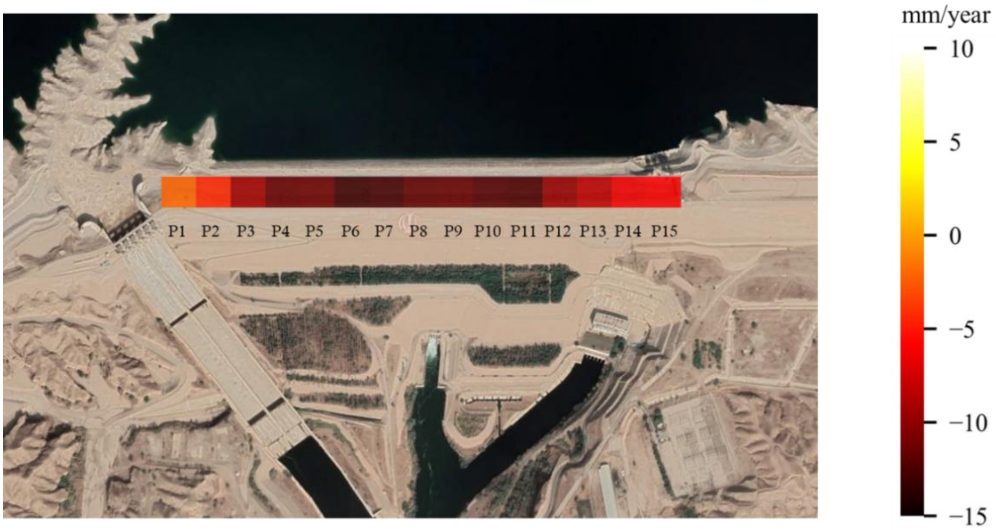

Figure 6. The mean velocity of uniformly distributed points along the crest

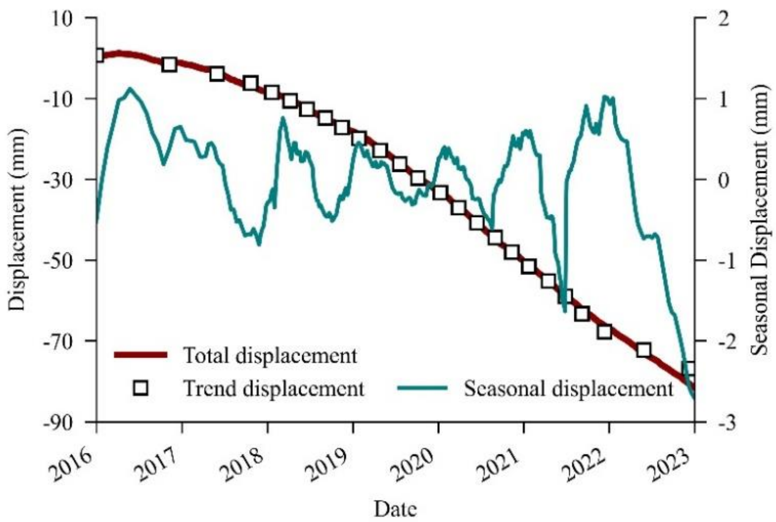

Figure 7. Components of the decomposed time series

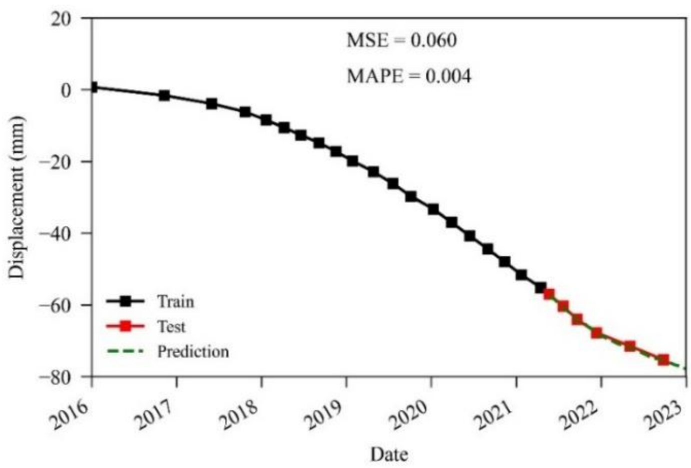

Figure 8. Results of prediction by the ANN model

Additionally, a LSTM network was used for forecasting seasonal displacement. The model was structured with three layers containing 100, 100, and 40 neurons, respectively, and used precipitation, temperature, and seasonal displacement as input features. The LSTM network achieved a Mean Squared Error MSE of 0.144 and a MAPE of 1.115. The results of the LSTM model are presented in Figure 9, which illustrates its performance in predicting seasonal displacement.

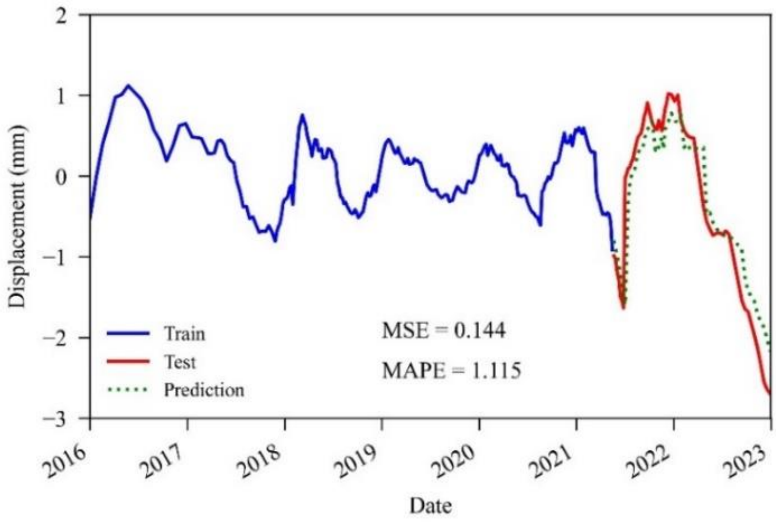

Figure 9. Results of prediction by the LSTM model

To prevent overfitting, the Adam optimizer was employed with the learning rate of 0.0009, the batch size was set to 10, and a bias-variance trade-off analysis was conducted. As shown in Figure 10, the validation loss and training loss converge during the final learning epochs, indicating that the model is reaching a stable state and learning effectively without overfitting.

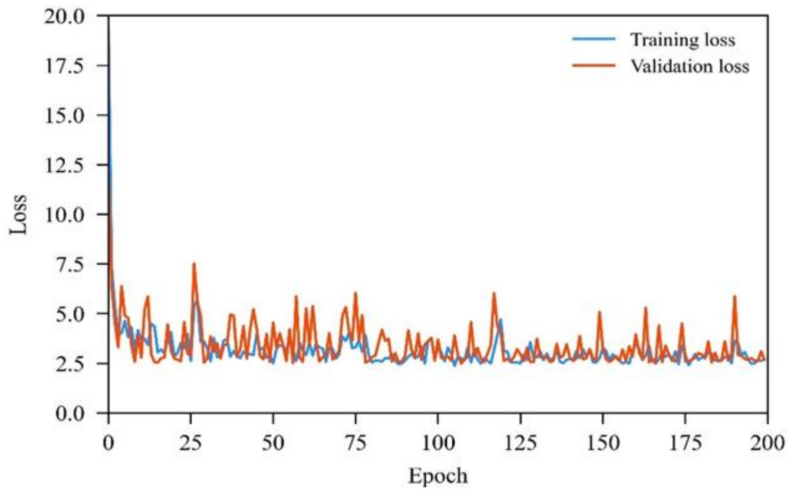

Figure 10. Validation and training loss during the learning epochs

5 CONCLUSION

The application of deep learning models, specifically Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks, in conjunction with remote sensing data, has demonstrated significant potential for effective earth dam monitoring.

In this study, an ANN model was employed to predict the trend displacement time series of an earth dam. Utilizing the trend displacement as the sole input feature over five past time steps to predict one future time step, the ANN model achieved an accuracy of 99.6% in capturing the displacement trends.

Additionally, an LSTM network was utilized to forecast the seasonal displacement, incorporating precipitation, temperature, and seasonal displacement as input features. The LSTM model achieved an accuracy of 97% in capturing the seasonal variations and dependencies within the data.

These results underscore the effectiveness of deep learning models in processing and analyzing complex time series data obtained from remote sensing technologies. The integration of remote sensing data allows for continuous and accurate monitoring of earth dams, providing critical insights into their structural health and potential risk factors.

DISCLAIMER

The authors declare no conflict of interest.

AVAILABILITY OF DATA AND MATERIALS

All data are available on request from the corresponding author.

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