

Time-Series Forecasting of the Pazarcık Earthquake Using LSTM, Transformer and RNN Models

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Anahtar Kelimeler

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Graphical/Tabular Abstract (Grafik Özet)

This study investigates deep learning models (LSTM, Transformer, RNN) for earthquake time-series forecasting using USGS teleseismic data (Figure 2). LSTM Transformer+RNN achieved highest accuracy ($R^2=0.9999987$) for seismic waveform prediction following Pazarcık earthquake. / Bu çalışma, USGS telesismik verileri kullanarak deprem zaman serisi tahmini için derin öğrenme modellerini (LSTM, Transformer, RNN) araştırmaktadır (Figure 2). LSTM Transformer+RNN, Pazarcık depremi sonrası sismik dalga formu tahmini için en yüksek doğruluğu ($R^2=0.9999987$) elde etmiştir.

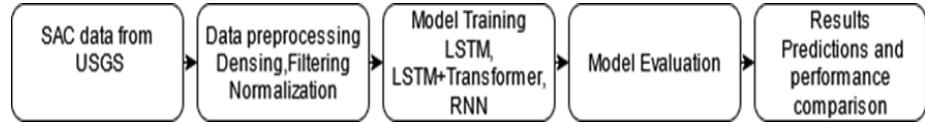


Figure 2. General diagram of the study (Çalışmanın genel diyagramı)

Highlights (Önemli noktalar)

- LSTM Transformer+RNN model achieved superior performance with MSE of 3.5691×10^{-9} and R^2 score of 0.9999987 for earthquake time-series forecasting. / LSTM Transformer+RNN modeli, deprem zaman serisi tahmini için 3.5691×10^{-9} MSE ve 0.9999987 R^2 skoru ile üstün performans elde etti.
- Global broadband teleseismic dataset from USGS containing 1000 seismic records was utilized for comprehensive model training and validation. / Kapsamlı model eğitimi ve doğrulama için 1000 sismik kayıt içeren USGS küresel geniş bant telesismik veri seti kullanıldı.
- Novel integration of Transformer architecture with LSTM and RNN demonstrates effectiveness in capturing long-range dependencies in seismic data. / Transformer mimarisinin LSTM ve RNN ile yeni entegrasyonu, sismik verilerdeki uzun menzilli bağımlılıkları yakalamada etkinlik gösterdi.
- Results provide significant implications for earthquake early warning systems and real-time seismic monitoring applications. / Sonuçlar, deprem erken uyarı sistemleri ve gerçek zamanlı sismik izleme uygulamaları için önemli çıkarımlar sunmaktadır.

Aim (Amaç): To develop and evaluate deep learning models for earthquake time-series forecasting using global teleseismic data, specifically analyzing the Pazarcık earthquake sequence. / Küresel telesismik verileri kullanarak deprem zaman serisi tahmini için derin öğrenme modelleri geliştirmek ve değerlendirmek, özellikle Pazarcık deprem dizisini analiz etmek.

Originality (Özgünlük): This study presents the first comprehensive comparison of LSTM, Transformer, and hybrid architectures for earthquake waveform prediction using global USGS teleseismic data. / Bu çalışma, küresel USGS telesismik verileri kullanarak deprem dalga formu tahmini için LSTM, Transformer ve hibrit mimarilerin ilk kapsamlı karşılaştırmasını sunmaktadır.

Results (Bulgular): LSTM Transformer+RNN model achieved the lowest error rates (MSE: 3.5691×10^{-9} , MAE: 4.5421×10^{-5}) and highest accuracy (R^2 : 0.9999987) among tested architectures. / LSTM Transformer+RNN modeli, test edilen mimariler arasında en düşük hata oranlarını (MSE: 3.5691×10^{-9} , MAE: 4.5421×10^{-5}) ve en yüksek doğruluğu (R^2 : 0.9999987) elde etti.

Conclusion (Sonuç): The hybrid LSTM Transformer+RNN architecture demonstrates superior capability for seismic waveform prediction, offering promising applications for earthquake early warning systems. / Hibrit LSTM Transformer+RNN mimarisi, sismik dalga formu tahmini için üstün yetenek göstererek deprem erken uyarı sistemleri için umut verici uygulamalar sunmaktadır.



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Abstract

The Earth's internal structure and mitigating seismic hazards are significant for understanding earthquake prediction and seismic wave analysis. In this study, we studied with different deep learning models for earthquake time series prediction using Broadband Teleseismic Data from the USGS database. This dataset consists of 1000 seismic records in SAC format with long-period seismic waves from global earthquakes. This study aimed to test LSTM and RNN models with LSTM Transformer to predict the next time step based on previous seismic waves. In this study, model performances was evaluated with Mean Square Error (MSE), Mean Absolute Error (MAE) and R² Score. In conclusion, the LSTM Transformer+RNN model achieves the lowest error rates and presents its effectiveness in learning both short-term dependencies and long-term correlations in seismic data. At the same time, this study can also contribute to the advancement of deep learning applications in seismology and the improvement of the prediction capabilities of earthquake monitoring systems.

LSTM, Transformer ve RNN Modellerini Kullanarak Pazarcık Depreminin Zaman Serisi Tahmini

Makale Bilgisi

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Öz

Dünya'nın iç yapısını anlamak ve sismik tehlikeleri azaltmak için deprem tahmini ve sismik dalga analizlerinin yapılması büyük önem taşımaktadır. Bu çalışmada, USGS veritabanından elde edilen Geniş Bant Teleseismik Veriler kullanılarak deprem zaman serisi tahmini için farklı derin öğrenme modelleri uygulanmıştır. Veri seti, küresel depremlerden gelen uzun dönemli sismik dalgaları yakalayan 1000 adet SAC formatında sismik kayıttan oluşmaktadır. Çalışmanın amacı, önceki sismik dalgaları temel alarak bir sonraki zaman adımını tahmin etmek için LSTM, LSTM-Transformer ve LSTM-Transformer-RNN modellerinin performansını karşılaştırmaktır. Model performansları, Ortalama Karese Hata (MSE), Ortalama Mutlak Hata (MAE) ve R² skoru kullanılarak değerlendirilmiştir. Elde edilen sonuçlar, LSTM-Transformer-RNN modelinin en düşük hata oranlarına ulaştığını ve sismik verilerde hem kısa vadeli bağımlılıkları hem de uzun vadeli korelasyonları öğrenmede etkin olduğunu göstermektedir. Bu çalışma, derin öğrenme uygulamalarının sismolojide ilerlemesine ve deprem izleme sistemlerinin tahmin yeteneklerinin geliştirilmesine katkı sağlayabilir.

1. INTRODUCTION (GİRİŞ)

Earthquakes are disasters that cause major destructive disasters with seismic signals caused by sudden ground oscillations [1]. On February 6, 2023, at 04:17 local time, a devastating earthquake with a magnitude of 7.7 struck Kahramanmaraş,

Turkey. Approximately nine hours later, another 7.6-magnitude earthquake occurred in the same region, followed by over 1,000 aftershocks, some exceeding magnitude 6. According to official reports from AFAD and USGS, these earthquakes are among the most destructive in Turkey's history,

causing severe damage with over 50,000 casualties and hundreds of thousands of injuries [2,3].

The global significance of this problem is further highlighted by similar large-scale earthquakes, such as the 2011 Tōhoku earthquake in Japan (Mw 9.0) and the 2010 Maule earthquake in Chile (Mw 8.8), both of which resulted in severe human and economic losses [4,5]. These events demonstrate the universal need for more accurate prediction methods. Traditional approaches for earthquake magnitude prediction are based on physical models and statistical methods; however, these techniques often have difficulty capturing nonlinear and complex patterns in seismic activities. Recent advancements in deep learning have introduced more robust predictive models capable of learning from large-scale seismic datasets. In particular, Recurrent Neural Networks (RNNs) and Transformer-based architectures can give promising results in capturing temporal dependencies in seismic signals.

This study contributes to the literature by utilizing Broadband Teleseismic Data obtained from the USGS to train deep learning-based regression models for earthquake magnitude prediction. Unlike prior studies that rely on region-specific data or shallow learning methods, our approach leverages a global dataset and advanced architectures, thereby offering improved generalization and accuracy in magnitude estimation.

2. MATERIALS AND METHODS (MATERYAL VE METOD)

In this study, we used a dataset of seismic waveforms recorded during the Mw 7.8 Pazarcık earthquake on February 6, 2023, consisting of 1,000 SAC-formatted seismic records obtained from the USGS, primarily collected through the Global Seismographic Network (GSN) and selected ANSS stations were used in this study [6]. It was in SAC (Seismic Analysis Code) format which includes broadband teleseismic waveforms and the SAC files contain time-series data representing ground motion with metadata such as station information, sampling rate and the details of events.

2.1. DATASET AND PREPROCESSING (Veriseti ve Önışleme)

The raw seismic data were preprocessed to remove noise and normalize the amplitude values. A band-pass filter (0.1 Hz to 1.0 Hz) was applied to eliminate low-frequency and high-frequency noise. Then, the MinMaxScaler from the scikit-learn

library was used to normalize to ensure that all values were scaled between 0 and 1. This normalization step is crucial for improving the convergence of the deep learning model during training.

In this study, all measurements and data are processed using the International System of Units (SI). The parameters of the data used in the study are given in the Table 1. The seismic data, which are read from the SAC files, are represented in amperes per meter (A/m) for magnetic field strength and teslas (T) for magnetic flux density. The time-series data extracted from the seismic recordings are normalized using the MinMaxScaler, where the data values are scaled between 0 and 1. The deep learning models (LSTM, RNN) use these normalized data for training and prediction and the evaluation metrics (e.g., Mean Squared Error - MSE, Mean Absolute Error - MAE) are computed without changing units, as the data is already normalized. For data storage, both SI and English units are used when required (e.g., "10 Gb/cm² (100 Gb/in²)").

Table 1. Key parameters of the seismic dataset (Sismik verisetindeki anahtar parametreler)

Parameter	Value
Network	IU
Station	MACI
Location	00
Channel	BH2
Start Time	2023-02-06T01:17
End Time	2023-02-06T02:07
Sampling Rate	40.0Hz
Sample Interval	0.025 seconds
Number of samples	120,000
Calibration Factors	1.0
Station Latitude	28.2502°
Station Longitude	-16.5082°
Station Elevation	1674.0 meters
Component Azimuth	81.0°
Component Inclination	90.0°

For the seismic data processing, the Matplotlib library is used for visualization of the seismic waveforms, where the plots are saved in PNG format which is represented in Figure 1.

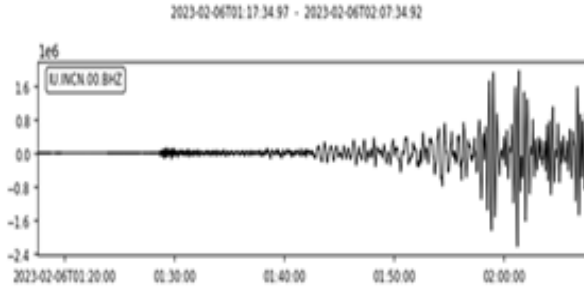


Figure 1. Sample seismic waveforms with PNG format (PNG formatında örnek sismik dalga formları)

Each plot corresponds to a seismic recording file and the output is stored in a specified directory. The training and testing of the machine learning models, such as LSTM and RNN are performed with input data in the form of 3D arrays (samples, time steps, features).

2.2. PROPOSED SYSTEM (Önerilen Sistem)

The overall framework of the proposed system is illustrated in Figure 2.) Three different deep learning architectures were implemented and compared in this study: LSTM, LSTM + Transformer and LSTM + Transformer+RNN. The details of each architecture are described below.

SAC data provided by the United States Geological Survey (USGS) is used in this study. This dataset consists of seismic waveform time series that represent ground motion generated by the Mw 7.8 Pazarcık earthquake. The dataset serves as the primary source for model training and evaluation. The proposed deep learning-based framework shows significant potential for improving earthquake magnitude prediction.

Furthermore, the evaluation results are presented in a comparative format, supported by quantitative metrics such as RMSE, MAE and R^2 which are summarized in Table 2. This comparative discussion highlights the relative strengths of different models and provides a clearer understanding of the performance improvements achieved.

Data Preprocessing (Densifying, Filtering, Normalization): Densifying: Filling in missing data or condensing the dataset. Filtering: Noisy or anomalous data is cleaned. Normalization: Scaled the data to a specific range (e.g. 0-1). Purpose: To make the data suitable for model training.

Model training: LSTM: Used to learn long dependencies in time series data.

LSTM+Transformer: Used to capture both local (LSTM) and global (Transformer) dependencies and to use in time series data. **RNN:** Used for time series problems.

Model evaluation: MSE (Mean Squared Error): Measures how far the predictions are from the true values. MAE (Mean Absolute Error): Gives the absolute average of the prediction errors. R^2 (R-squared): It presents how well the model explains the data. Purpose: To compare the performance of the models quantitatively.

Results: LSTM Model: It achieved 2.669×10^{-9} MSE and 3.01×10^{-5} MAE values. LSTM + Transformer Model: It achieved 3.63×10^{-8} MSE, 1.20×10^{-4} MAE and 0.99999 R^2 score. LSTM Transformer+RNN Model: It recorded 3.57×10^{-9} MSE, 3.48×10^{-5} MAE and 0.999999 R^2 score.

The results indicate that hybrid models combining recurrent and transformer-based architectures can effectively capture complex patterns in seismic data. These findings highlight the substantial potential of deep learning approaches in earthquake magnitude estimation and contribute to advancing research in seismic prediction.

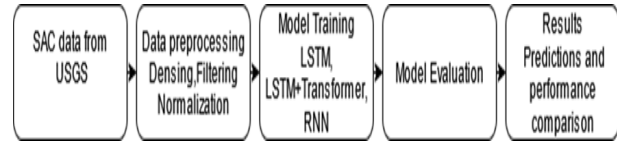


Figure 2. General diagram of the study (Çalışmanın genel diyagramı)

2.3. MODEL TRAINING AND EVALUATION (Model eğitimi ve değerlendirilmesi)

In this study, the Adam optimizer with Mean Squared Error (MSE) as the loss function was used to train all models. Early stopping and learning rate reduction mechanisms were implemented to prevent overfitting to improve training efficiency: **Early Stopping:** It shows the validation loss and stops training if no improvement is observed for 5 consecutive epochs. **ReduceLROnPlateau:** It reduces the learning rate by a factor of 0.5 if the validation loss does not improve for 3 consecutive epochs. The data set of this study was split into training and testing sets as 80% of the data used for training and 20% for testing procedure. Each model was trained for a maximum of 50 epochs with a batch size of 32. The training process was presented using validation loss to ensure generalization. After training process, the models' performance was evaluated using the test dataset. As a result, the predicted values were compared to the actual

values, then the following performance metrics were calculated: Mean Absolute Error (MAE): It is the average absolute difference between predicted and actual values. Mean Squared Error (MSE): It is the the average squared difference between predicted and actual values. R^2 Score: It is the proportion of variance in the dependent variable that is predictable from the independent variable.

2.3.1. LSTM MODEL (LSTM modeli)

The LSTM model was designed to capture temporal dependencies in the seismic time-series data. The architecture consists of the following layers. Figure 3. shows the LSTM model architecture. Input Layer: It accepts input with shape (None, 20, 1), where 20 is the window size and 1 is the number of features. LSTM L1: 100 units with return_sequences=True. LSTM L2: 50 units with return_sequences=False. Dense Layer: A single unit for regression output. The total number of trainable parameters in this model is 71,051.

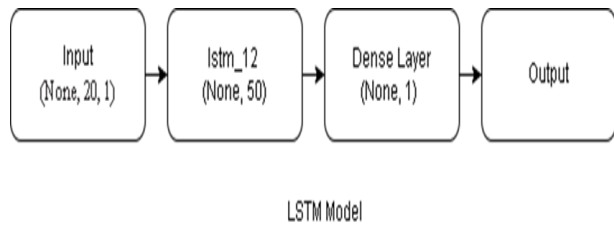


Figure 3. LSTM Diagram (LSTM diyagramı)

2.3.2. LSTM + TRANSFORMER MODEL (LSTM+TRANSFORMER)

To enhance the model's ability to capture long-range dependencies, a hybrid architecture combining LSTM and Transformer was implemented. Figure 4. shows the LSTM model architecture. Input Layer: Accepts input with shape (None, None, 1). LSTM Layer: 64 units with return_sequences=True. Multi-Head Attention Layer: 64 units with 8 attention heads. Layer Normalization: Applied after the attention layer. Global Average Pooling 1D: Reduces the sequence dimension. Dense Layer: A single unit for regression output. The total number of trainable parameters in this model is 83,457.

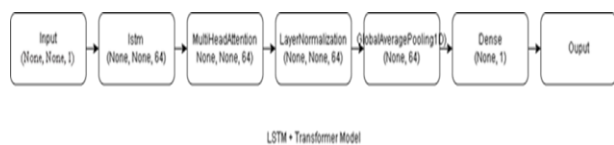


Figure 4. LSTM + Transformer model diagram (LSTM+Transformer modeli diyagramı)

2.3.3. RNN MODEL (RNN modeli)

Recurrent neural networks (RNN) is one of the most widely used method for time series forecasting. RNN is an artificial neural network in which nodes are connected in a loop and the internal state of the network can display dynamic temporal behavior [7]. Figure 5. shows the LSTM model architecture Input Layer: Accepts input with shape (None, None, 1). Simple RNN Layer: 64 units with return_sequences=True. Multi-Head Attention Layer: 64 units with 8 attention heads. Layer Normalization: Applied after the attention layer. Global Average Pooling 1D: Reduces the sequence dimension. Dense Layer: A single unit for regression output. The total number of trainable parameters in this model is 70,785.

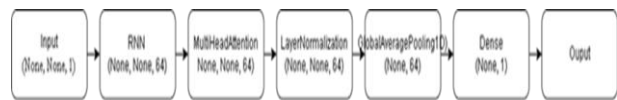


Figure 5. RNN MODEL (RNN modeli)

3. FINDINGS AND DISCUSSION (BULGULAR VE TARTIŞMA)

In this study, three deep learning models LSTM, LSTM + Transformer and LSTM + Transformer+RNN were developed and evaluated for predicting seismic waveforms following the Mw7.8 Pazarcık earthquake. The models were trained on broadband teleseismic data obtained from the USGS, preprocessed to remove noise and normalize amplitude values. The key findings are as follows:

Model Performance: The LSTM model achieved a Mean Squared Error (MSE) of 2.6694e-09, a Mean Absolute Error (MAE) of 3.0116e-05 and an R^2 score of 0.9999993 on the test dataset. The LSTM + Transformer model demonstrated slightly lower performance, with an MSE of 3.6322e-08, an MAE of 0.0001200 and an R^2 score of 0.9999950. The LSTM+RNN model showed the best performance among the three, with an MSE of 3.5691e-09, an MAE of 4.5421e-05 and an R^2 score of 0.9999987. The LSTM Transformer+RNN model the extremely low MSE and MAE values, along with the high R^2 scores, indicate that all models are highly accurate in predicting seismic waveforms.

Training Dynamics: LSTM model converged in 18 epochs, LSTM + Transformer model converged in 21 epochs and LSTM + Transformer+RNN model converged in 13 epochs. This also shows that LSTM+Transformer+RNN model trained faster.

Learning rate was kept at $1.0e-04$ throughout the training process and no significant fluctuation was observed. Visualization of Predictions: Predicted waveforms closely matched the actual waveforms for all models, especially for LSTM+Transformer+RNN model. For example, RNN model achieved a nearly perfect R^2 score of 0.9999987 indicating almost perfect match between predicted and actual values. LSTM model also showed an outstanding performance with an R^2 score of 0.9999993, while LSTM + Transformer model achieved an R^2 score of 0.9999950. The results of this study are consistent with previous research demonstrating the effectiveness of deep learning models in seismic data analysis. Time series prediction features are usually obtained by shifting the time window and the prediction results are influenced by the sequence of events. The use of LSTM for time series prediction in seismology has been widely documented with studies such as [8] reporting similar success in capturing temporal dependencies. The deep NN model has a recurrent Long Short Term Memory (LSTM) part that accounts for temporal dependencies between earthquakes and a convolutional part that accounts for spatial dependencies. The results demonstrate that NNs-based models outperform baseline feature-based models, which also account for spatio-temporal dependencies between different earthquakes. The other benefit of combining LSTM and RNNs is to achieve both high accuracy and computational efficiency [9]. Time series prediction is a critical component in many fields, such as the geosciences [10]. However, due to limited measurement conditions, we can usually only obtain short-term time series samples. On the one hand, since a short-term data set does not have enough information, accurate multi-step forward prediction using a short-term time series becomes a challenging task [11]. Transformer, RNN, and LSTM models are therefore used in the study.

3.1. MODEL PERFORMANCE (Model performansı)

The LSTM Transformer+RNN model achieved the best performance, with an MSE of $3.5691e-09$, an MAE of $4.5421e-05$ and an R^2 score of 0.9999987. This indicates that the hybrid architecture combining LSTM Transformer and RNN is highly effective in capturing both local and global dependencies in seismic data. The Actual and Estimated Values graph is shown in Figure 6 and the training graph is shown in Figure 7.

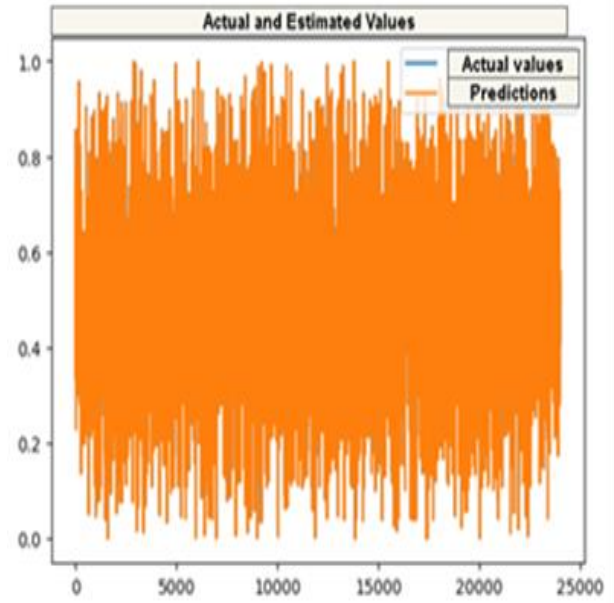


Figure 6. Actual and Estimated Values graph +RNN for LSTM T. + RNN model (Gerçek ve Tahmini Değerler grafiği +LSTM T için RNN. + RNN modeli)

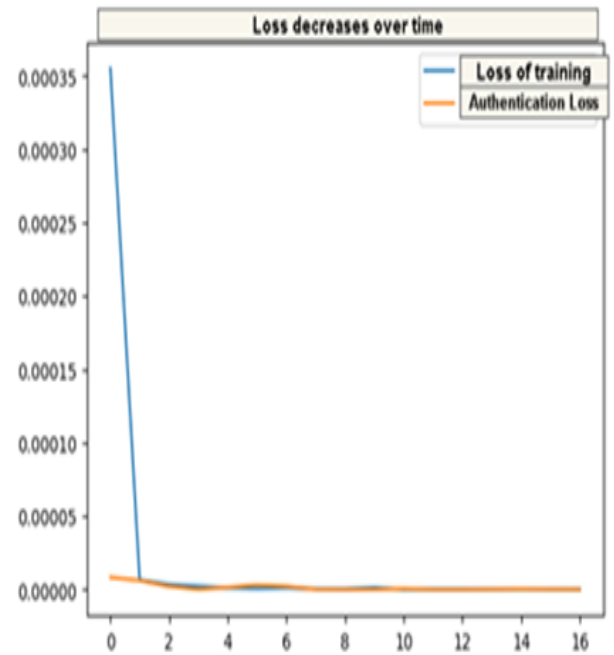


Figure 7. Training graph of LSTM T.+RNN Model (LSTM T+RNN. Modelinin eğitim grafiği)

The LSTM model also performed exceptionally well, with an MSE of $2.6694e-09$, an MAE of $3.0116e-05$ and an R^2 score of 0.9999993, demonstrating the robustness of LSTM in handling temporal dependencies. The Actual and Estimated Values graph is shown in Figure 8 and the training graph is shown in Figure 9.

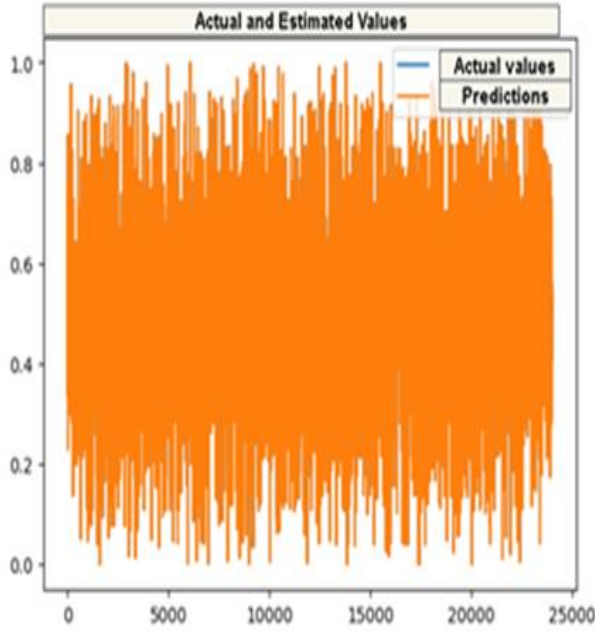


Figure 8. Actual and Estimated Values graph for LSTM model (LSTM modu için Gerçek ve Tahmini Değerler grafiği)

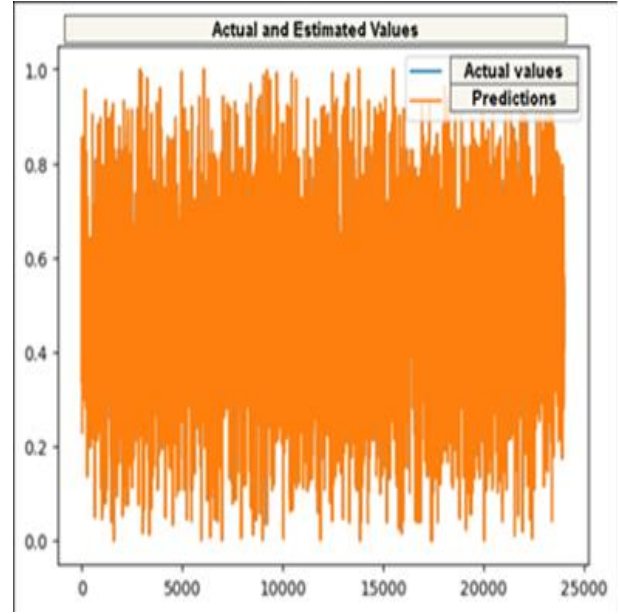


Figure 10. Actual and Estimated Values LSTM T. model (Gerçek ve Tahmini Değerler LSTM T. modeli)

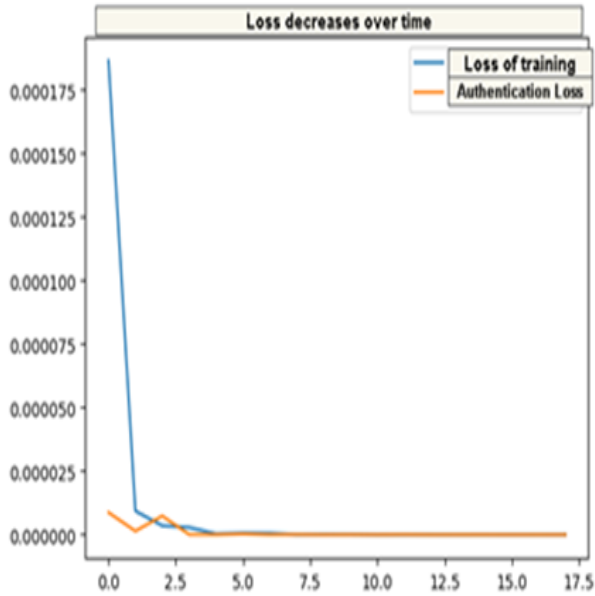


Figure 9 Training graph of LSTM model (LSTM eğitim grafiği)

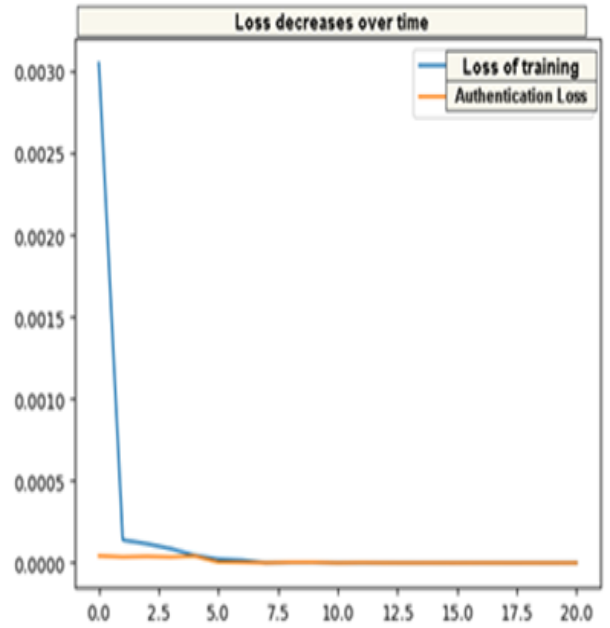


Figure 11. Training graph of LSTM T. model (LSTM eğitim grafiği)

The LSTM + Transformer model showed slightly lower performance, with an MSE of 3.6322e-08, an MAE of 0.0001200 and an R^2 score of 0.9999950, but still provided accurate predictions, highlighting the potential of Transformer-based approaches for seismic data analysis. The Actual and Estimated Values graph is shown in Figure 10 and the training graph is shown in Figure 11.

3.2. TRAINING EFFICIENCY (Eğitim performansı)

The LSTM + Transformer+RNN model not only achieved the highest accuracy but also demonstrated faster convergence, requiring only 13 epochs to train, compared to 18 epochs for the LSTM model and 21 epochs for the model. This suggests that the LSTM Transformer+RNN architecture is both efficient and effective for seismic waveform prediction. The Model Values graph is shown in Table 2.

Table 2. Different Deep Learning Models Result Values (Farklı Derin Öğrenme Modelleri Sonuç Değerleri)

Model	MSE	MAE	R ²	Epoch
LSTM	2.6694e-09	3.0116e-05	0.9999993	18
LSTM + Transfor mer	3.6322e-08	0.0001200	0.9999950	21
LSTM Transfor mer+ RNN	3.5691e-09	4.5421e-05	0.9999987	13

4. CONCLUSION (SONUÇLAR)

This study investigates the effectiveness of three deep learning models—LSTM, LSTM + Transformer and LSTM Transformer+RNN—for forecasting seismic waveforms following the Mw 7.8 Pazarcık earthquake. The models were trained on broadband teleseismic data from the USGS which were preprocessed to remove noise and normalize amplitude values. The results of this study have significant implications for earthquake early warning systems and seismic data analysis. The LSTM Transformer+RNN model demonstrated the highest accuracy and efficiency, making it a strong candidate for real-time applications as it achieved the lowest MSE (3.5691×10^{-9}) and MAE (4.5421×10^{-5}) values, along with the highest R² score (0.9999987), outperforming both the LSTM and LSTM + Transformer models. Furthermore, the integration of Transformers with LSTM and RNN models presents a novel approach for capturing long-range dependencies in seismic data. In conclusion, this study highlights the considerable potential of deep learning models for seismic waveform prediction. Future research could focus on enhancing these models using explainable AI (XAI) techniques [12, 13] to enable accurate and reliable automatic detection of seismic processes.

DECLARATION OF ETHICAL STANDARDS (ETİK STANDARTLARIN BEYANI)

The author of this article declares that the materials and methods they use in their work do not require ethical committee approval and/or legal-specific permission.

Bu makalenin yazarı çalışmalarında kullandıkları materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel bir izin gerektirmediğini beyan ederler.

AUTHORS'

(YAZARLARIN KATKILARI)

Seda ŞAHİN: She conducted the software, program experiments, analyzed the results and performed the writing process.

Yazılım ve program uygulamalarını yapmış, sonuçlarını analiz etmiş ve makalenin yazım işlemini gerçekleştirmiştir.

Emine ÇANKAYA: She conducted the software, program experiments, analyzed the results.

Yazılım ve program uygulamalarını yapmış, sonuçlarını analiz etmiştir.

CONFLICT OF INTEREST (ÇIKAR ÇATIŞMASI)

There is no conflict of interest in this study. Bu çalışmada herhangi bir çıkar çatışması yoktur.

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