The Impact of Earthquakes on Air Pollution: Machine Learning-Based Air Quality Analysis Following the Kahramanmaraş Earthquakes

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***Abstract*—Air pollution is a significant environmental and societal problem that affects human health, wildlife, and ecological balance. While human activities such as industry, agriculture, traffic, and energy production are major contributors to air pollution, natural causes such as volcanic activities, forest fires, desert dust, and vegetation disruption also play a role. In this paper, we explore whether earthquakes can be considered natural factors contributing to air pollution. Specifically, we examine the effects of the magnitude 7.7 and 7.6 earthquakes centered in Kahramanmaraş that occurred on February 6, 2023, in Turkey. We collected data for the earthquake-affected province of Malatya for the five years before and 84 days after seismic events. We developed pollution prediction models by training artificial intelligence algorithms such as Facebook Prophet, LSTM(Long Short-Term Memory), and SVR(Support Vector Regression) on the collected data. These models aim to predict the expected normal air pollution levels in the absence of an earthquake. Then, post-earthquake air pollution measurements are taken and the predictions obtained from the developed models are compared with the actual measurements. The experimental results reveal a dramatic increase in air pollution, especially in the first month after the earthquake. This research contributes to our understanding of the complex interactions between seismic activity and air quality and emphasizes the importance of considering natural factors in the assessment of air pollution.**

***Index Terms*—Air pollution, air quality, time series prediction, earthquake effects**

I. Introduction

Today, air pollution has become one of the most important pollution problems that adversely affect public health with the increase in population, crowding of cities, individualization of motor vehicle use, and the expansion of industrialization and manufacturing. In order to monitor this situation and take necessary actions to protect public health, sensor networks are deployed in cities and measurements are performed at various time intervals and metrics [1]. The primary air pollution factors produced by pollutants that are hazardous to public health can be listed as PM10 (Particulate Matter ∼10 µm), PM2.5 (Particulate Matter ∼2.5 µm), SO2 (Sulfide Oxide), CO (Carbon Monoxide), NO2 (Nitrogen Peroxide), NOX and O3 (Ozone) [2]. The recognized metric for measuring air quality, based on air pollutants, is the AQI (Air Quality Index) [3].

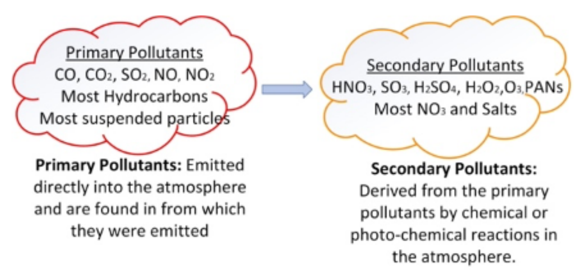

Fig. 1. Primary and Secondary Air Pollutants [4].

According to WHO (World Health Organization) statistics, air pollution is exceeding limits in areas where 99% of the world's population lives [5]. In general, inhaled pollutants increase cardiovascular and respiratory diseases [6].They are especially life-threatening for the elderly and children with lung and heart diseases [7]. On a pollutant basis, CO reduces oxygen levels in the blood, SO2, PM2.5, PM10, NO cause respiratory diseases, while Ozone affects breathing rates [3].

Data is continuously collected with sensors in residential areas to monitor air quality. These data can be used by public administrators to make decisions to protect public health in the short term, such as warnings to wear masks or curfews, depending on the level of pollution. In the long term,

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decisions such as population and infrastructure planning in the settlements, the impact of industrial zones on cities, and, if necessary, their relocation can be considered. However, for these long-term plans and actions, forecasts for future horizons should be calculated from the historical data.

Sensors measuring air pollution data capture this data in a time-dependent basis. In other words, measurements are performed deterministically in minute, hourly, or daily periods. This allows future forecasts to be made from the collected time series data using model-based or data-based methods. In addition, from the data as a function of time, missing data can be predicted by machine learning methods when stations cannot be measured for any reason.

The Republic of Turkey suffered one of the biggest earthquake disasters in its history on February 6, 2023 with magnitudes of 7.7 and 7.6 centered in the province of Kahramanmaras [8]. The effects of these massive earthquakes were reported as far as Syria, Lebanon, Cyprus, Iraq, Israel Jordan, and Egypt [9]. Thousands of buildings in the region collapsed with the earthquake. Most of the buildings that did not collapse were categorized as heavily damaged and demolished in a controlled process. The devices measuring air quality either did not take any measurements or collected insufficient data during/after the disaster. Collapsed buildings, the removal of rubble, and migration to other cities are considered to have significant impacts on the air quality data collected. In light of this information, investigating the air quality of cities affected by earthquakes emerges as a crucial issue concerning public health in the region. In this paper, we focus on predicting air quality during the 84 days following the earthquake, addressing the air pollution issue that arises after earthquakes. Additionally, we analytically compare measurements taken before and after the earthquake to understand the changes in air quality. The main contributions of the paper are summarized as follows.

- We develop ML(Machine Learning) and DL(Deep Learning) models for predicting air pollution before and after earthquakes.
- We provide a comprehensive analysis of the effects of seismic events on air pollution.

This paper is organized as follows: Section II presents related works on air quality prediction, Section III presents the research methodology including technical overviews of the used methods, data set, and data preprocessing, Section IV provides the experimental results. Finally, Section V summarises conclusions and future work.

II. Related Works

The IoT concept and the objectives of building smart cities have combined to monitor air pollution by connecting sensors with different architectures and network connections. As a function of time, these data help to protect public health and contribute to issues such as precautions to be taken and urban planning in forecasts for the future. For this challenge, several machine learning-based methods have been developed.

The authors [10] attempted to predict air pollution for the next 24 hours from historical hourly PM2.5 data with the CNN(Convolutional Neural Network)-LSTM hybrid model. Feature extraction with CNN and prediction tasks with LSTM were performed. Among CNN, LSTM, and CNN-LSTM models, the CNN-LSTM hybrid architecture achieved the best results according to MAE(Mean Absolute Error) and RMSE(Root Mean Square Error) implemented a distributed DNN(Deep Neural Network) architecture for 48-hour air pollution prediction from a heterogeneous data set (air quality data, weather forecast, meteorological data). With the method called DeepAir, they measured hourly periods in different cities for three years and achieved 63.2%, 2.4%, and 12.2% improvements in the instant, short and long term, respectively. The researchers [11] predicted PM10 by using RNN(Recurrent Neural Network), LSTM, and GRU(Gated Recurrent Unit) models using a dataset named AirNet, which contains meteorological time series data. The GRU model performed the best by the MAPE(Mean Absolute Percentage Error) metric.

In their study [12], the researchers proposed a hybrid model that predicts air quality from hourly data by combining CT (Chi-Square Test) and LSTM models. CT is utilized to analyze the factors affecting air quality. The hybrid model performed the best result among MLP(Multilayer Perceptron), BP(Back Propagate Neural Network), SVR, NN, and RNN models with 93.7% accuracy. The authors [13] aimed to forecast 24-hour PM2.5 data with the LightGBM(Ligth Gradient Boosting Machine) method using air pollution data collected from 35 different stations. Due to insufficient data, they applied the sliding window approach. Among the Adaboost, xGBoost, GBDT(Gradient Boosting Decision Tree), and DNN models, the LightGBM model performed the best according to SMAPE, RMSE, and MAE metrics. The authors [14] predicted 1-hour, 8-hour, and 24-hour AQI from 11 years of hourly air pollution and meteorological data using AdaBoost, ANN, SVM, and RF Stacking Ensemble methods. Stacking ensemble performed best in RSquare and RMSE metrics and AdaBoost model performed best in MAE metric.

In this study [15], the researchers predict AQI with LSTM and SVR models from the dataset (including pollution, weather, traffic, parking and parking, and cultural data). According to RMSE and MAE metrics, LSTM performed the best result. The researchers [16] predicted 24-hour nitrogen oxide pollution from 3 years of air pollution data by benchmarking LSTM, 1D-CNN and GRU models with SVM, Random Forest, and Lasso Regression models. LSTM, GRU models reinforced with 1D-CNN produced the best results according to the MAE evaluation metric. The authors [17] forecasted 48-hour PM2.5 air pollution with a hybrid model called ST (Spatial-Temporal)-DNN by combining LSTM, CNN, and ANN models. They highlighted that the station location is the most important factor affecting the prediction. It is concluded that the ST-DNN hybrid architecture always improves the result according to the MAE metric. The researchers [18] developed an AQI prediction model, PSO(Particle Swarm Optimization)-BP, robust to the local minimum problem by boosting BP with

PSO. According to the RMSE, MAPE, and EAS metrics, the proposed method gave the best results.

The researchers [19] implemented a transfer learning mechanism to the BLSTM algorithm for better air quality forecasts. The transfer learning is organized from small to high resolution. The insights from hourly air quality forecasts are transferred to weekly and monthly ones. According to the RMSE, MAE, and MAPE metrics, TL-BLSTM achieved significant improvements in the error rate for daily, weekly, and monthly forecasts. The authors [20] aim to predict air pollution for all pollutants using a method called STCNN-LSTM, which has three different processing steps. The first step involves considering regional air quality with equal importance, the second element fuses the time, space, and factor dimensions to create the necessary data package for the model, and the last step is the CNN-LSTM prediction. With this innovative method, improvements in Rsquare, MAE, RMSE, and MAPE metrics in time-dependent air quality forecasts have been achieved.

III. Methodology

In this study, the forecasting problem of air pollution - PM10 for the post-earthquake period is analyzed using three different approaches: Facebook Prophet, LSTM, and SVR. The time period that needs to be forecasted is an 84-day period covering February and March, which is right after the earthquake (February 6). Facebook Prophet and LSTM models are applied to forecast with a time series approach. In supervised learning, SVR is used, which performs effectively with this type of data. MAE metric is used to compare and evaluate the performance of the models.

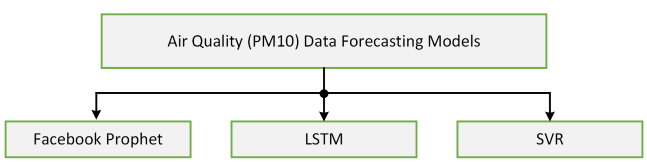

Fig. 2. PM10 Forecasting strategy.

A. Used Models

1) Facebook Prophet: FB Prophet is an additive regression model-based prediction library developed by the Facebook Data Science team for Facebook's time series data challenges, including missing values, outliers, seasonality (daily, monthly and weekly) and holidays [21]. It is open source and can be easily integrated into a wide problem domain. It performs effectively against outlier and missing data without distorting the trend [22].

Additive regression model equation consists of the following parameters: non-periodic changes i.e. trend, periodic changes, holiday effect and unique changes [21].

2) Long Short Term Memory (LSTM): LSTM is a deep learning approach derived by structurally modifying RNN architectures by adding a memory cell to the hidden layer and has succeeded in time series problems [23]. LSTM uses the memory cell for temporal connections throughout the entire life cycle [24]. These capabilities provide very efficient results in time series forecasting problems.

Improving the memory capabilities of LSTMs, They can process long input sequences that the short memory of the RNN cannot, and it is also robust to vanishing gradient problem [25]. The vanishing gradient problem is common in deep networks and is caused by the basis that at each training epoch, the weights are updated to gradient value during backpropagation. The value of gradient determined according to the activation function becomes very small and close to 0 in some functions and the network weights cannot be updated resulting in a saturation of the model's learning capability [26].

3) Support Vector Regression (SVR): Regression analysis is a statistical approach to extract the pattern between variables and transform it into a mathematical model, and predictions are performed with this mathematical model aiming for the lowest error rate between actual and predicted results in the machine learning domain [27]. The regression problems, which are generalized versions of classification problems, produce continuous outputs, while the outputs of classification problems are finite [28].

SVR is an extension of the SVM model for solving nonlinear problems and is used in forecasting analysis [29]. The SVR model is based on the support vectors of the Vapnik-Chervonenkis theory [28]. Kernel functions and support vectors are the most important elements of the model. The kernel function maps the inputs into high-dimensional space [27]. One of the strengths of SVR is that its high dimensionality is not coupled with computational complexity [28].

B. Dataset, Preprocessing and Parameter Optimization

1) Dataset: The air quality data is collected from the National Air Quality Monitoring Portal of the Ministry of Environment, Urbanization and Climate Change [30]. The national monitoring system measures air pollutants in hourly and daily periods at many points across the country. Air pollution data from Malatya, which is one of the most affected cities among the provinces affected by the earthquake, is used to detect the post-earthquake effect of the given gases. This earthquake effect the area which consists of 11 provinces. We focus on one province called Malatya that processes these data for analyzing post effect of the earthquake. The data are collected from Malatya provenience for dates between 01/01/2018 and 30/04/2023. The data has 1946 samples that contain both nan and missing values which are eliminated in the pre-processing step (Table I).

TABLE I
Air Quality Dataset

Time Tag of Dataset	***Features***	***Number of Total Records***	***NaN Values***	***Missing Value Ratio***
Last 5 Years	Time Tag,PM10	1946	124	6%

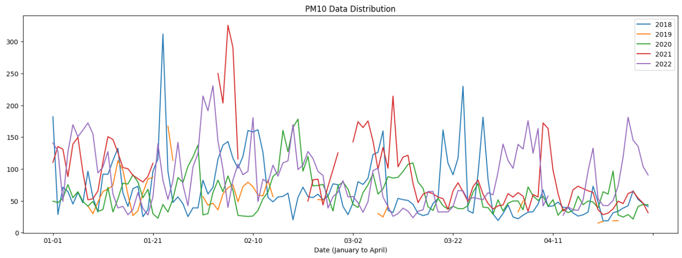

Fig. 3. PM10 distribution between January and May for the last 5 years.

2) Preprocessing: As stated in Table I, there is 6% missing data in the dataset. The effect of missing data on the data distribution can be visualized in Fig. 3. The BoxPlot approach is used for outlier data analysis. The data set is segmented on an annual basis and each outlier is defined according to the statistical distribution for that year.

To eliminate missing data in terms of the time series problem, the missing data day has been filled by the average of Malatya's adjacent provinces. Furthermore, these neighboring provinces can be listed as Sivas, Elazığ, Tunceli, Diyarbakır, Adıyaman, Kahramanmaraş and Kayseri that are influenced by the earthquake. Then, MinMaxScaler is applied to improve the performance of the algorithms.

3) Parameter Optimization: We practice numerous experiments to get the best parameters We adopt grid search technique to find the optimum parameters. For example, in order to achieve better results in SVR, the dataset is augmented by extracting dayofweek, quarter, month, year, dayofyear, dayofmonth and weekofyear features from the time tag. With the SVR method, the time series problem is converted into a supervised learning problem. C, gamma and kernel parameters were tuned for better results in SVR. The GridSearchCV function of the Sklearn library is used for this task.

TABLE II
SVR PARAMETER TUNING VALUES

Parameter	***Values***
C	0.1, 1, 10, 100, 1000
Gamma	1, 0.1, 0.01, 0.001, 0.0001
Kernel	'rbf', 'poly', 'sigmoid'

After varying parameters, we get the best hyper-parameters to use in the model which is shown at Table III.
FB Prophet: Model training is conducted with the following parameters configuration: growth: linear, holidays: ignored, seasonality mode: additive, seasonality: weekly and annual, seasonality prior scale: no regularization (10), change point prior scale (Trend):0.05.
LSTM: In this model, training is performed in 50 epochs with layer size(16,16,16), 30-day lags and no shuffling in the dataset. The ScaleCast-Forecaster [31] library is used for the LSTM model.
SVR: The parameters tested with are shown in Table II. As a result of these tests, the best SVR configuration is defined as C:1, 'gamma':0.1 and kernel = 'rbf'.

TABLE III
PARAMETER CONFIGURATIONS OF MODELS

Model	***Hyperparameters***
FB Prophet	Growth: Linear, Seasonality Mode: Additive, Holidays: Ignored, Change Point Prior Scale:0.05
LSTM	Epoch: 50, layer size(16,16,16),Shuffling: False, Lags:30
SVR	Kernel:rbf, C:1, Gamma:0.1

IV. EXPERIMENTAL RESULTS

In this study, we use the earthquake dataset which dates between 01/01/2018 and 30/04/2023. The dataset is divided into two groups to detect the earthquake effects of air pollution. On Feb. 6, 2023, the earthquake occurred in southern Turkey the earthquake magnitude is calculated 7.8 by officials. Similarly, after nine hours after the first earthquake, a magnitude 7.5 earthquake occurred in the same area. From this point, for detecting the post-earthquake effect of the air pollution, we divide the dataset into two: after and before February 6 of 2023. In this paper, we use three algorithms as FB prophet, LSTM and SVR for training. We evaluate the prediction performance of the given algorithms in terms of MAE(Mean Absolute Error), MSE(Mean Square Error), and RMSE(Root Mean Square Error) which are given in Eq. 1, Eq. 2, Eq. 3.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

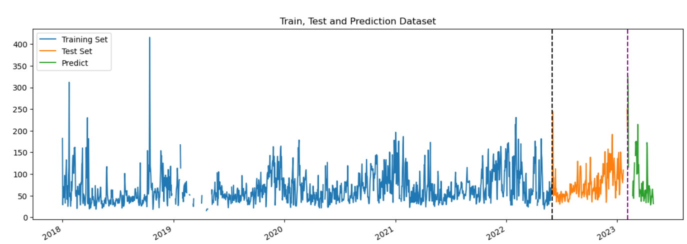

Fig. 4. Training and test set.

The results of the models are given in Table IV. According to Table IV, the SVR model shows better performance than the other models as LSTM and FB Prophet. Furthermore, LSTM shows similar results in terms of evaluation metrics. But FB Prophet demonstrates the lowest performance in comparison to the other models. Here, It is seen that the traditional

SVR model provides more accurate predictions. However, we expect that the deep learning models are superior in prediction problems in various areas. The data set size appears as a factor that affects the performance of the models. Considering the data set size and the problem, it seems reasonable that the results of SVR are better than the other methods.

TABLE IV
PERFORMANCE METRICS FOR ALL MODELS

Model	***Mean Absolute Error***	***Mean Square Error***	***Root Mean Square Error***
FB Prophet	0.26	0.08	0.29
LSTM	0.1114	0.0258	0.16
SVR	0.1110	0.0203	0.14

To see the earthquake effect of the air quality and prediction performance, the prediction results of the models are visualized in Fig. 5, Fig. 6 and Fig. 7. We want to observe the PM10 values by using historical information to find the question of ”What the air quality would have been like if the earthquake had not happened?”. Furthermore, we also noted that some of the sensors could not take any measurements in some time intervals after the earthquake. we expect that a decrease in activities such as traffic and heating due to the population and the shutdown of the industry. Although we expect to have more healthy and normal conditions of air quality, we have seen the peaks that were recorded after the earthquake. Due to debris of the buildings, removal and rescue operations give rise to serious peaks. we infer from the Figure that the removal operations of the buildings is the main cause of the peaks of the PM10 values after the earthquake.

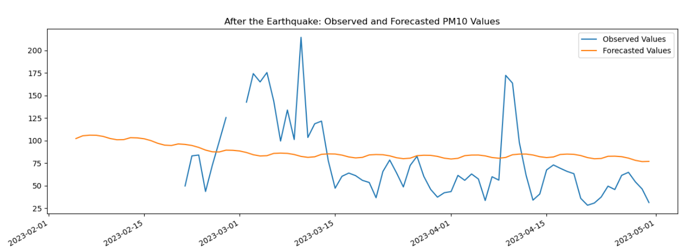

Fig. 5. Facebook Prophet prediction results. (*Observed values are the ones collected from the sensors after the earthquake. Predicted values are the ones predicted in the non-earthquake scenario using the pre-earthquake sensor data.*)

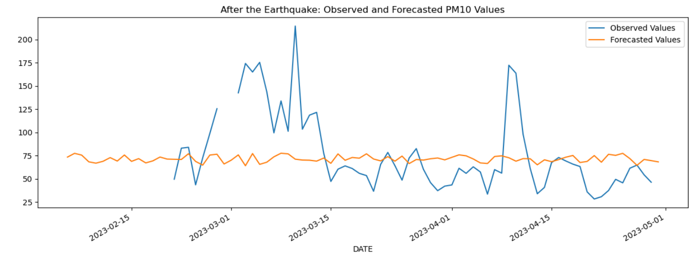

Fig. 6. LSTM forecast results. (*Observed values are the ones collected from the sensors after the earthquake. Predicted values are the ones predicted in the non-earthquake scenario using the pre-earthquake sensor data.*)

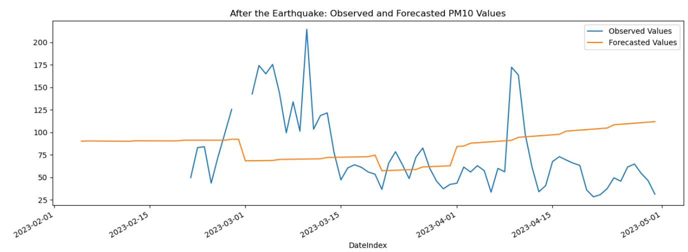

Fig. 7. SVR forecast results. (*Observed values are the ones collected from the sensors after the earthquake. Forecasted values are the ones predicted in the non-earthquake scenario using the pre-earthquake sensor data.*)

In particular, we evaluate Fig 7, and it is seen that the observed PM10 values until the second week of March are above the predicted values. At the beginning of April, this trend changes and observed PM10 values decrease while they were predicted to increase. The reason for this decrease is assumed to be the completion and pause of the removal of debris. Furthermore, we also add the reason of this decrease that activities such as traffic, heating, population and the shutdown of the industry. The second peak in April is considered to be related to rubble removal operations.

V. CONCLUSION AND FUTURE WORKS

This study focuses on investigating the impact of the Kahramanmaraş earthquakes that occurred on February 6, 2023 on air quality in the region. In this context, 5 years of PM10 data is collected for the cities affected by the earthquake. We aim to see the effect of the earthquake on air pollution. In this context, FB Prophet, LSTM, and SVR models are used to predict air pollution. Experimental results show that SVR and LSTM models show better performance in comparison to FB Prophet model. Especially during the initial one-month period following the earthquake, we notice a significant increase in air pollution. We can list possible reasons for this increase may include disruption of industrial facilities, increased vehicular traffic due to rescue and recovery work, and changes in atmospheric conditions triggered by seismic events. Further investigation is required to pinpoint the specific contributors to the observed spike in air pollution during this post-earthquake period. Also, Future investigations may consider employing different classification models or exploring diverse hyperparameters to further refine results.

Additionally, integrating air quality data with measurements from various areas within smart cities could enhance the comprehensiveness of predictions and analyses, especially in monitoring values within natural water resources.

REFERENCES

[1] I. Kok, M. Guzel, and S. Ozdemir, "Recent trends in air quality prediction: An artificial intelligence perspective," in *Intelligent Environmental Data Monitoring for Pollution Management*. Elsevier, 2021, pp. 195–221.

[2] M. S. Ram, C. Reshmasri, S. Shahila, and J. V. P. Saketh, "Air quality prediction using machine learning algorithm," in *2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*. IEEE, 2023, pp. 316–321.

[3] M. Kulkarni, A. Raut, S. Chavan, N. Rajule, and S. Pawar, "Air Quality Monitoring and Prediction using SVM," in *2022 6th International Conference On Computing, Communication, Control And Automation (ICCUBEA*. Pune, India: IEEE, Aug. 2022, pp. 1–4. [Online]. Available: https://ieeexplore.ieee.org/document/10010942/

[4] "Types of air pollutants (Primary & Secondary) and their Meas." [Online]. Available: https://www.clarity.io/blog/how-measuring-different-types-of-air-pollutants-creates-a-more-holistic-picture-of-air-pollution

[5] "Air pollution data portal." [Online]. Available: https://www.who.int/data/gho/data/themes/air-pollution

[6] K. Hu, X. Guo, X. Gong, X. Wang, J. Liang, and D. Li, "Air quality prediction using spatio-temporal deep learning," *Atmospheric Pollution Research*, vol. 13, no. 10, p. 101543, Oct. 2022. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1309104222002240

[7] H. Zheng, Y. Cheng, and H. Li, "Investigation of model ensemble for fine-grained air quality prediction," *China Communications*, vol. 17, no. 7, pp. 207–223, Jul. 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9147144/

[8] "Kahramanmaraş'ta Meydana Gelen Depremler Hk. – 34." [Online]. Available: https://www.afad.gov.tr/kahramanmarasta-meydana-gelen-depremler-hk-34

[9] "2023 Kahramanmaraş depremleri," May 2023, page Version ID: 29780190. [Online]. Available: https://tr.wikipedia.org/w/index.php?title=2023_Kahramanmara%C5%9F_depremleri&oldid=29780190

[10] T. Li, M. Hua, and X. Wu, "A Hybrid CNN-LSTM Model for Forecasting Particulate Matter (PM2.5)," *IEEE Access*, vol. 8, pp. 26 933–26 940, 2020. [Online]. Available: https://ieeexplore.ieee.org/document/8979420/

[11] A. V, G. P, V. R, and S. K P, "DeepAirNet: Applying Recurrent Networks for Air Quality Prediction," *Procedia Computer Science*, vol. 132, pp. 1394–1403, 2018. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1877050918308007

[12] J. Wang, J. Li, X. Wang, J. Wang, and M. Huang, "Air quality prediction using CT-LSTM," *Neural Computing and Applications*, vol. 33, no. 10, pp. 4779–4792, May 2021. [Online]. Available: https://link.springer.com/10.1007/s00521-020-05535-w

[13] Y. Zhang, Y. Wang, M. Gao, Q. Ma, J. Zhao, R. Zhang, Q. Wang, and L. Huang, "A Predictive Data Feature Exploration-Based Air Quality Prediction Approach," *IEEE Access*, vol. 7, pp. 30 732–30 743, 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8637825/

[14] Y.-C. Liang, Y. Maimury, A. H.-L. Chen, and J. R. C. Juarez, "Machine Learning-Based Prediction of Air Quality," *Applied Sciences*, vol. 10, no. 24, p. 9151, Dec. 2020. [Online]. Available: https://www.mdpi.com/2076-3417/10/24/9151

[15] I. Kok, M. U. Simsek, and S. Ozdemir, "A deep learning model for air quality prediction in smart cities," in *2017 IEEE International Conference on Big Data (Big Data)*. Boston, MA, USA: IEEE, Dec. 2017, pp. 1983–1990. [Online]. Available: http://ieeexplore.ieee.org/document/8258144/

[16] R. Espinosa, J. Palma, F. Jiménez, J. Kamińska, G. Sciavicco, and E. Lucena-Sánchez, "A time series forecasting based multi-criteria methodology for air quality prediction," *Applied Soft Computing*, vol. 113, p. 107850, Dec. 2021. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1568494621007729

[17] P.-W. Soh, J.-W. Chang, and J.-W. Huang, "Adaptive Deep Learning-Based Air Quality Prediction Model Using the Most Relevant Spatial-Temporal Relations," *IEEE Access*, vol. 6, pp. 38 186–38 199, 2018. [Online]. Available: https://ieeexplore.ieee.org/document/8392677/

[18] Y. Huang, Y. Xiang, R. Zhao, and Z. Cheng, "Air Quality Prediction Using Improved PSO-BP Neural Network," *IEEE Access*, vol. 8, pp. 99 346–99 353, 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9102994/

[19] J. Ma, J. C. Cheng, C. Lin, Y. Tan, and J. Zhang, "Improving air quality prediction accuracy at larger temporal resolutions using deep learning and transfer learning techniques," *Atmospheric Environment*, vol. 214, p. 116885, Oct. 2019. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1352231019305151

[20] G. Zhao, G. Huang, H. He, H. He, and J. Ren, "Regional Spatiotemporal Collaborative Prediction Model for Air Quality," *IEEE Access*, vol. 7, pp. 134 903–134 919, 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8842551/

[21] S. J. Taylor and B. Letham, "Forecasting at Scale," *The American Statistician*, vol. 72, no. 1, pp. 37–45, Jan. 2018. [Online]. Available: https://www.tandfonline.com/doi/full/10.1080/00031305.2017.1380080

[22] R. Gupta, A. K. Yadav, S. Jha, and P. K. Pathak, "Time Series Forecasting of Solar Power Generation Using Facebook Prophet and XG Boost," in *2022 IEEE Delhi Section Conference (DELCON)*. New Delhi, India: IEEE, Feb. 2022, pp. 1–5. [Online]. Available: https://ieeexplore.ieee.org/document/9752916/

[23] K. V. Kumar and R. Anitha, "A Novel Ensemble Model by Combining LSTM, BiLSTM, and Facebook Prophet Algorithm to Forecast Stock Prices," in *2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT)*. Kannur, India: IEEE, Aug. 2022, pp. 1044–1047. [Online]. Available: https://ieeexplore.ieee.org/document/9917634/

[24] W. Kong, Z. Y. Dong, Y. Jia, D. J. Hill, Y. Xu, and Y. Zhang, "Short-term residential load forecasting based on lstm recurrent neural network," *IEEE transactions on smart grid*, vol. 10, no. 1, pp. 841–851, 2017.

[25] G. Singhal, "Introduction to LSTM units in RNN," Sep. 2023. [Online]. Available: https://www.pluralsight.com/guides/introductionto-lstm-units-in-rnn

[26] S. Basodi, C. Ji, H. Zhang, and Y. Pan, "Gradient amplification: An efficient way to train deep neural networks," *Big Data Mining and Analytics*, vol. 3, no. 3, pp. 196–207, 2020.

[27] M. Wajid, F. Alam, S. Yadav, M. A. Khan, and M. Usman, "Support vector regression based direction of arrival estimation of an acoustic source," in *2020 International Conference on Innovation and Intelligence for Informatics, Computing and Technologies (3ICT)*. IEEE, 2020, pp. 1–6.

[28] M. Awad and R. Khanna, *Support Vector Regression*. Berkeley, CA: Apress, 2015, pp. 67–80. [Online]. Available: https://doi.org/10.1007/978-1-4302-5990-9_4

[29] F. Miao, Y. Wu, Y. Xie, and Y. Li, "Prediction of landslide displacement with step-like behavior based on multialgorithm optimization and a support vector regression model," *Landslides*, vol. 15, no. 3, pp. 475–488, Mar. 2018. [Online]. Available: http://link.springer.com/10.1007/s10346-017-0883-y

[30] "Sim (surekli İzleme merkezi - t.c. Çevre, Şehircilik ve İklim değişikliği bakanlığı." [Online]. Available: http://havaizleme.gov.tr

[31] "Scalecast-forecaster." [Online]. Available: https://scalecast.readthedocs.io/en/latest/Forecaster/Forecaster.html