ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Vol 11, Issue 8, August 2024

Mobile Application for Drought Forecasting with Vulnerability Scale Indexing using Machine Learning Algorithm

[1] Akhila Vignesh, [2] Anagha Nambiar, [3] Ananthi S, [4] K Anand

[1] [2] [3] UG Students, Computer Science and Engineering, Rajalakshmi Engineering College, Tamil Nadu, India.
[4] Associate Professor ,Rajalakshmi Engineering College, Tamil Nadu, India.
Corresponding Author Email: [1] akhila.vignesh.2019.cse@rajalakshmi.edu.in,
[2] anagha.nambiar.2019.cse@rajalakshmi.edu.in, [3] ananthi.s.2019.cse@rajalakshmi.edu.in, [4] anand.k@rajalakshmi.edu.in[4]

Abstract— There can be no clear origin or finish to the beginning of drought because of its gradual development and withdrawal. This can be decreased by creating an algorithm based on the crisis analysis framework suggested in the National Crisis Management Plan for Drought (2019), which rates the vulnerability of each state on a scale from 0 to 10. The drought forecast is then fabricated by looking at trends in various metrics, comprising soil moisture, precipitation, water table levels, and surface water levels. A mobile application is then created that gives users a forecast that is displayed on a map with colors based on the scale of the vulnerabilities. The best accurate approach for predicting this drought was determined by contrasting numerous algorithms.

Index Terms— soil moisture, rainfall, groundwater level, and surface water level.

I. INTRODUCTION

Drought is the term used to denote frequent precipitation on terrain that has remained below average over many years or months. There are four types of drought: social, agricultural, and meteorological. Each year, drought has a devastating impact on the economy, politics, and culture. Thus, it is essential to anticipate droughts and take the necessary steps. Planning, managing, and mitigating the effects of drought may all be accomplished with the help of a great drought forecasting model. For this, numerous models have been created.

In order to display drought risk using a mobile application, this study intends to give a forecasting approach. A vulnerability index based on the NCMP framework is created to identify the drought-prone states by ranking them from 0 to 10, taking into account soil moisture, precipitation, and surface and groundwater levels.

On a map of India, the predicted colours for the drought are shown. The best drought outcome prediction algorithm is used to determine and implement these predictions. Through a mobile application, the forecasting system is incorporated.

II. RELATED WORK

Abhirup Dikshit, et al.[1] predict the SPEI, a commonly used drought indicator using LSTM. R2 and MSE are two statistical measures used to assess the model's capacity to forecast drought intensity. The threat assessment technique was used to examine the fluctuation in the number of dry months. Following that, the model was used to predict weather patterns in the region of New South Wales utilizing the climatic and hydro-meteorological data. Data from 2001–2018 were used for testing and training the architecture, respectively. The study's findings demonstrated that the LSTM stacking model can anticipate accurately for both short- and long-term lead times.

A system was developed by Alfredo Huete, Biswajeet Pradhan, and Abhirup Dikshit [2] to exemplify the merits of using a DL model over conventional approaches to ML. The Climatic Research Unit dataset (1901–2018) was compiled upon the variables and indicators. The SPEI on the SPEI 1 and SPEI 3 time scales is used for drought assessments, and LSTM approach were both utilized. This forecasting R2 values beyond 0.99 and AUC values of 0.83 and 0.82, correspondingly, for the SPEI 1 and SPEI 3 cases.

Using random forest machine learning algorithm, Abhirup Dikshit, Biswajeet Pradhan, and Abdulla M. Alamri [3] carried out their research on drought prediction and the factors influencing it for the Australian state of New South Wales. There were three distinct phases to this study. Using a global climate data set from the Climate Research Unit from 1901 to 2018, the SPEI was first determined. The data was then trained and tested using Random Forest. The model's performance is then evaluated using statistical metrics and drought classifications.

Writers Sankaran Adarsh and Manne Janga Reddy [4] performed a pattern assessment of droughts in the Indian meteorology sections of Kerala, Telangana, and Orissa with the use of EMD-based prediction. A multimodal solution for anticipating short-term droughts was created using MEMD, SLR, and GP approaches. The MEMDGP hybrid model performed better than the MEMDSLR model because of its ability to detect the variance of higher - frequency modes.

IFERP
Explore Your Research Journey...
ISSN (Online) 2394-2320
International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 11, Issue 8, August 2024

The goal of the study [5] by Pouya Aghelpour, et al is to predict and assess hydrological droughts along the western Caspian Sea margin. For this reason, time windows of 1, 3, 6, 9 and 12 months are used to calculate the multiscalar hydrological drought indicator known as SDI. In this work, two black-box ML techniques—ANFIS and GMDH—were evaluated for the first time in terms of their ability to predict SDI. The study area includes the southern Caspian Sea coast and the Iranian province of Guilan in the north. The complex nonlinear ML was drastically outperformed by the linear stochastic models in comparison with the models.

The Internet of Things (IoT) was utilised by Amandeep Kaur and Sandeep K. Sood [6] to continuously monitor, record, and analyse various environmental phenomena. The data gathered on the elements that cause drought, including climate, dew, precipitation, evapotranspiration, groundwater, soil moisture at various depths, current, and season, are made less dimensional using PCA at the fog layer. ANN is used in the cloud layer to evaluate the drought severity. A meticulous structure is formed as a result of the optimization of the parameters using GA. The prediction of drought over varying time period was done using ARIMA.

A general paradigm for the evaluation and forecasting of droughts utilizing IoT, fog computing, and cloud computing is constructed by authors Amandeep Kaura and Sandeep K. Sood [7]. With excellent precision, the system gauges the extent of the drought conditions. The performance of the three methodologies—ANN, ANN-GA, and DNN—used in the system is assessed. For three distinct climatic blocks and three different time spans, the SVR methodology evaluates the drought conditions. It was discovered that the DNN model has the highest accuracy (95.361%).

Ali Haidar and Brijesh Verma [8] projected average rainfall for a defined site in eastern Australia that used a deep CNN. In comparison to the first version of the Simulator, the proposed CNN model fared better. Monthly precipitation in Australia's geographically defined regions is examined and used as a dataset. The RMSE differed from ACCESS by 37.006 mm and from conventional MLP by 15.941 mm. Further analysis revealed that whereas ACCESS performs better in months with low yearly averages, CNN performs better on average in months with high annual averages.

In this work, J. Drisya D., et al. [9] discuss drought index prediction for a semi-arid watershed in southern India, Kalpathy using a wavelet-capable precipitation runoff-based modelling technique. FFNN and WHEN are the methods employed. The most effective transfer function for representing the current flow of forecasts turns out to be the hyperbolic tangent sigmoid function. The WHEN prediction model was deemed adequate for hydrological drought evaluation by stream flow forecasts due to its accuracy of 75 to 86%.

Heri Kuswanto and Achmad Naufal assessed the effectiveness of a three-month SPI created from TRMM and MERRA-2 [10]. Random Forest is used for classification, whereas CART is utilised. CART and RF revised its performance with SMOTE. The study concludes that utilising the Random Forest predicted MERRA-2 dataset, a more accurate drought forecast for East Nusa Tenggara, Indonesia, may be produced.

Kit Fai Fung, et al. [11] evaluated the potency of the various SVR-based models in forecasting an agricultural drought with a 1-month lead time at the downstream end of the Langat River basin. A Research of Tropical Climate Patterns independently used fuzzy logic principles with the boosting ensemble approach with the SVR model to increase forecasting accuracy of SPEIs. SVR, F-SVR, and BS-SVR were the approaches employed. It was demonstrated that the combined F-SVR and BS-SVR models produced more accurate forecasts than the solo SVR model.

Ling Du et al. [12] developed a novel approach based on maximum rain-use efficiency to determine global losses of ecosystem function. Three global GPP datasets using MODIS remote sensing imagery (MOD17), ground upscaling FLUXNET data (MPIBGC), process-based models (BESS), and a global gridded precipitation product (CRU) were merged to construct yearly global RUE datasets for 2001-2011. Large, well-known severe drought occurrences, including the 2003 European, 2002 and 2011 American, and 2010 Russian droughts, were found.

In order to build ML-based models for projecting moderate, severe, and extreme droughts in Pakistan, Najeebullah Khana, et al. [13] employed SPEI. SVM, ANN, and KNN were the 3 methods used. A brand-new feature selection technique called RFE is also applied to drought forecasting. According to data from the NCEP/NCAR reanalysis database, it is predicted that SVM will have better temporal and spatial features.

Narjes Nabipour, Majid Dehghani, Shahaboddin, Shamshirband, and Amir Mosavi [14] used ANN in combination with novel, nature-inspired optimization methods to provide short-term hydrological drought forecasts. Recently suggested optimization methods GOA, SSA, BBO, and PSO hybridized with ANN were employed for SHDI forecasting, and the outcomes were compared to that of the conventional ANN. The hydrometric and precipitation data were gathered by the Iranian Water Resources Management and Iran Meteorological Organization. From October 1963 through September 2017, data was available monthly. The results show that the hybridized model performs better. PSO outperformed the other optimizers. The best model predicted SHDI1.

For the purpose of predicting various time scales, Ozgur Kisi, et al.[15] examined the effectiveness of 4 evolutionary neuro-fuzzy methods: ANFIS-PSO, ANFIS-GA, and ANF. The RMSE, MSE, and index of agreement were applied in the case study to examine the semi-annual rainfall data from the Abbasabad, Biarjmand, and Ebrahim-Abad Iranian stations.

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Vol 11, Issue 8, August 2024

Paula Ramos-Giraldo, Steven Mirsky, Chirs Reberg-Horton, Edgar Lobaton, and Anna M. Locke [16] executed real-time drought stress detection and its substantial through implications to prevent crop yield losses caused by variable weather conditions and recurring climate variability. They used CNN and DenseNet-121 and computer vision combined with machine learning algorithms. The cameras took 40,000 photographs of soybeans over a 70-day span.

The historical drought index, meteorological measurements, and climatic signals from various stations in Shaanxi Province, China, from over 55 years were utilised in this work by Rong Zhang, et al. [17] to build a novel model for drought forecasting. The method used in the estimation techniques is the DLNM and XGBoost model. The two models were validated by projecting the SPEI one to six months in ahead. The XGBoost model's overall drought accuracy rate ranged from 89% to 97%.

U. Ashwini, et al. [18] were capable of demonstrating the stationary nature of the time-series flow via the precipitation forecast and by assessing the seasonal correlogram through the seasonal ARIMA strategy. Using MSE and RMSE, the output of this model is examined. The figures come from the Indian Meteorological Department and contains about 117 recordings of constant updates on precipitation taken between January 1901 and December 2017. The results unequivocally states that the ARIMA model predicts precipitation the most accurately and with minimum errors.

SPEI was utilised by Wan tian, et al. [19] to measure and predict drought on four different time scales (3,6,9,12). Predictions were done based on the resulting features which were extracted from the SPEI series using Time-series imaging and Feature-Based Transfer Learning. To encrypt SPEI sequences into pictures, time-series imaging techniques GASF/GADF, MTF, and RP were applied. The feature extraction network was also trained using the image data sets and CNNs such ResNet and VGG. To model the recalled features for drought prediction, the final four regressors were WNN, RF, LSTM Networks, and SVR.

Authors Yang Liu and Lihu Wang [20] address that By using the extreme value delay technique and the orthogonal triangle (QR) decomposition, authors Yang Liu and Lihu Wang [20] are able to minimise the output matrix solution method of broad learning (BL) and increase the computing efficiency of BL. The comparison model is the Drought Prediction Model (EMD-SVR), which is created by combining EMD and SVR. According to the test findings, CEEMDAN-QR-BL has 11.84% more accuracy and 29.57% more dependability than EMD-SVR. Additionally, compared to only BL, QR-prediction BL's accuracy is increased by 62.29%.

III. SYSTEM ARCHITECTURE

At first, information about rainfall, soil moisture, surface water levels, and groundwater levels is collected from a variety of sources made available by the Government of India (India-WRIS). Following data cleansing, the raw data is preprocessed. Data cleansing involves deleting useless and inaccurate data. Fig. 1 depicts the links between the system's many parts and lists the functions that each one serves.

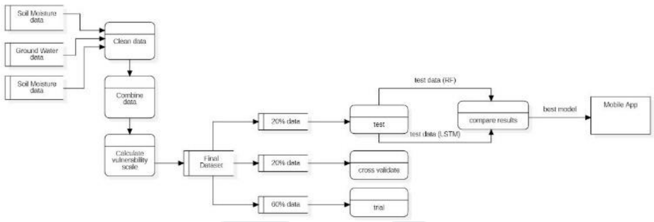

Fig-1. System Architecture

IV. METHODOLOGY

A. Development of Vulnerability Index

Using a framework that accounts for the parameters of soil moisture, precipitation, and surface and groundwater levels, the vulnerability index is constructed in this module. The core process in the machine learning pipeline is data collection to train the ML model. The precision of predictions made by machine learning algorithms can only be ensured by the data utilised to train those algorithms. Individual regional data sets for these traits are gathered, and over time, they are compiled. A single dataset has all of these cumulative traits. The drought's severity is then predicted using this measure.

B. Prediction of the Drought using Vulnerability Index

When an algorithm is used to estimate the likelihood of a specific event after it has been trained on previous data and applied to new data, the term "prediction" is used. Based on the estimated vulnerability index, this module forecasts the drought. LSTM and Random Forest models are used for the prediction in the R programming language using Firebase as the database.

C. Deployment of Mobile Application

This lesson shows how to create a mobile application in Kotlin that shows a color-coded map of India according to the severity of the drought. Users of this program may view the drought prognosis for individual Indian states, and they will receive notifications when the scale for their chosen state changes.

V. CONCLUSIONS

Based on all the research and analysis that has been done, this project aims to create a smartphone application that would anticipate drought in all of India. This forecasting can help the average user, the State Drought Monitoring Centers (DMCs), and the inter-ministerial Crop Weather Watch Group (CWWG), in forecasting and controlling droughts by using the Vulnerability Scale from the National Crisis Management Plan for Drought (2019).

REFERENCES

[1] Abhirup Dikshit, Biswajeet Pradhan, Abdullah M. Alamri, "Long lead time drought forecasting using lagged climate variables and a stacked long short- term memory model", Science of The Total Environment, Volume 755, Part 2, 2021, 142638, ISSN0048-9697, Available at: https://doi.org/10.1016/j.scitotenv.2020.142638.

[2] Abhirup Dikshit, Biswajeet Pradhan, Alfredo Huete, "An improved SPEI drought forecasting approach using the long short-term memory neural network", Journal of Environmental Management, Volume 283, 2021,1 11979, ISSN 0301-4797. Available at: https://doi.org/10.1016/j.jenvman.2021.111979.

[3] Abhirup Dikshit, B. Pradhan, and A. M. Alamri, “Short-Term Spatio- Temporal Drought Forecasting Using Random Forests Model at New South Wales, Australia,” Applied Sciences, vol. 10, no. 12, p. 4254, Jun. 2020. Available: http://dx.doi.org /10.3390/app10124254.

[4] Adarsh S, Janga Reddy M, "Evaluation of trends and predictability of short- term droughts in three meteorological subdivisions of India using multivariate EMD-based hybrid modeling", Hydrological Processes, 2019; 33: 130– 143. Available at: https://doi.org/10.1002/hyp.13316

[5] Aghelpour, P., Bahrami-Pichaghchi, H. & Varshavian, V, "Hydrological drought forecasting using multi-scalar streamflow drought index, stochastic models and machine learning approaches, in northern Iran", Stoch Environ Res Risk Assess 35, 1615–1635 (2021). Available at: https://doi.org/10.1007/s00477-020-01949-z.

[6] Amandeep Kaur & Sandeep K. Sood (2020), "Cloud-Fog based framework for drought prediction and forecasting using artificial neural network and genetic algorithm", Journal of Experimental & Theoretical Artificial Intelligence, 32:2, 273-289, Available at: 10.1080/0952813X.2019.1647563.

[7] Amandeep Kaur, Sandeep K. Sood, "Deep learning based drought assessment and prediction framework", Ecological Informatics, Volume 57, 2020, 101067, ISSN1574-9541, Available at: https://doi.org/10.1016/j.ecoinf.2020.101067.

[8] A. Haidar and B. Verma, "Monthly Rainfall Forecasting Using One- Dimensional Deep Convolutional Neural Network," in IEEE Access, vol. 6, pp. 69053-69063, 2018, Available at: 10.1109/ACCESS.2018.2880044.

[9] Drisya, J., Kumar, D.S. & Roshni, T, "Hydrological drought assessment through streamflow forecasting using wavelet enabled artificial neural networks", Environ Dev Sustain 23, 3653–3672 (2021). Available at: https://doi.org/10.1007/s10668-020-00737-7.

[10] Heri Kuswanto, Achmad Naufal, "Evaluation of the performance of drought prediction in Indonesia based on TRMM and MERRA-2 using machine learning methods", MethodsX, Volume 6, 2019, ISSN 2215-0161. Available at: https://doi.org/10.1016/j.mex.2019.05.029.

[11] Kit Fai Fung, Yuk Feng Huang, Chai Hoon Koo, Majid Mirzaei, "Improved SVR machine learning models for agricultural drought prediction downstream of Langat River Basin", Malaysia, Journal of Water and Climate Change, 1 December 2020; 11 (4): 1383–1398. Available at: https://doi.org/10.2166/wcc.2019.295.

[12] Ling Du, Nathaniel Mikle, Zhenhua Zou, Yuanyuan Huang, Zheng Shi, Lifen Jiang, Heather R. McCarthy, Junyi Liang, Yiqi Luo, "Global patterns of extreme drought-induced loss in land primary production: Identifying ecological extremes from rain-use efficiency, Science of The Total Environment", Volumes 628–629,2018, ISSN 0048-9697. Available at: https://doi.org/10.1016/j.scitotenv.2018.02.114.

[13] Najeebullah Khan, D.A. Sachindra, Shamsuddin Shahid, Kamal Ahmed, Mohammed Sanusi Shiru, Nadeem Nawaz, "Prediction of droughts over Pakistan using machine learning algorithms", Advances in Water Resources, Volume 139, 2020, 103562, ISSN 0309-1708. Available at: https://doi.org/10.1016/j.advwatres.2020.103562.

[14] N. Nabipour, M. Dehghani, A. Mosavi and S. Shamshirband, "Short-Term Hydrological Drought Forecasting Based on Different Nature-Inspired Optimization Algorithms Hybridized With Artificial Neural Networks," in IEEE Access, vol. 8, pp. 15210-15222, 2020, Available at: 10.1109/ACCESS.2020.2964584

[15] Ozgur Kisi, Alireza Docheshmeh Gorgij, Mohammad Zounemat-Kermani, Amin Mahdavi-Meymand, Sungwon Kim, "Drought forecasting using novel heuristic methods in a semi-arid environment", Journal of Hydrology, Volume 578, 2019, 124053, ISSN 0022-1694, Available at: https://doi.org/10.1016/j.jhydrol.2019.124053.

[16] P. Ramos-Giraldo, C. Reberg-Horton, A. M. Locke, S. Mirsky, and E. Lobaton, "Drought Stress Detection Using Low-Cost Computer Vision Systems and Machine Learning Techniques," in IT Professional, vol. 22, no. 3, pp. 27-29, 1 May-June 2020, Available at: 10.1109/MITP.2020.2986103.

[17] Rong Zhang, Zhao-Yue Chen, Li-Jun Xu, Chun-Quan Ou, "Meteorological drought forecasting based on a statistical model with machine learning techniques in Shaanxi province, China", Science of The Total Environment, Volume 665, 2019, ISSN 0048-9697, Available at: https://doi.org/10.1016/j.scitotenv.2019.01.431.

[18] U. Ashwini, K. Kalaivani, K. Ulagapriya, and A. Saritha, "Time Series Analysis based Tamilnadu Monsoon Rainfall Prediction using Seasonal ARIMA," 2021 6th International Conference on Inventive Computation Technologies (ICICT), 2021, pp. 1293-1297, Available at: 10.1109/ICICT50816.2021.9358615.

[19] W. Tian, J. Wu, H. Cui, and T. Hu, "Drought Prediction Based on Feature- Based Transfer Learning and Time Series Imaging," in IEEE Access, vol. 9, pp. 101454-101468, 2021, Available at: 10.1109/ACCESS.2021.3097353.

[20] Y. Liu and L. Wang, "Drought Prediction Method Based on an Improved CEEMDAN-QR-BL Model," in IEEE Access, vol. 9, pp. 6050-6062, 2021, Available at: 10.1109/ACCESS.2020.3048745.