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Prediction of Drought - A Machine Learning Approach using Time Series Data

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***Abstract*—In order to forecast drought in a certain area, this research employed three different machine learning models, namely ARIMA (Auto Regressive Integrated Moving Average Model), VAR (Vector Auto Regressive model), and Prophet. These models are used to forecast upcoming drought occurrences and are trained using historical data on a variety of meteorological factors, including temperature, precipitation, humidity, and wind speed. Different statistical metrics, such as mean absolute error, root mean squared error, and coefficient of determination, are used to assess each model's performance. The findings indicate that all three models are capable of accurately and reliably forecasting drought episodes, with Prophet surpassing the other models. According to the findings of the study, machine learning models can be useful tools for forecasting drought episodes in a particular region, giving decision-makers a head start on taking the necessary actions to lessen the effects of drought on agriculture, water resources, and society. Among the three time series models experimented, Prophet model exhibited the accuracy of 92.01% which is the best when compared with the other two models. The choice of selecting a model for predicting the drought depends on the type of data being used for experimentation.**

Keywords—Drought prediction, ARIMA, VAR, Prophet, Time0series model.

I. INTRODUCTION

Drought is a natural phenomenon that happens when there is a protracted period of exceptionally dry weather that results in a shortage of water supplies. It is a complicated issue with many facets that has an impact on a variety of industries, including agriculture, water supply, energy generation, and the environment. According on the length, severity, and geographic scope of a drought, it can be divided into numerous different categories. A protracted period of excessively dry weather constitutes a meteorological drought, whereas an agricultural drought is characterised by a lack of soil moisture that has an impact on crop growth and yield. While socioeconomic drought refers to the effects of water shortage on human societies and their economic activities, hydrological drought is defined by a lack of water availability in rivers, lakes, and groundwater.

Drought and other natural calamities can have a significant effect on society. The main indicator of its consequences is lack of water. It is crucial to identify past droughts and predict future ones in order to decrease their effects. Droughts and other natural calamities happen when there is a considerable drop in precipitation relative to the long-term average. As drought causes are unexpected and nonlinear, accurate drought prediction remains a difficult scientific undertaking. It has a wide range of detrimental impacts on civilization and ramifications for all resources connected to water, with subsequent detrimental effects on the environment, and society and Many studies have recently suggested ways to enhance drought forecasts. The results of all of this research have favourable repercussions for drought predictions. The influence of change in the climate on these occurrences, especially in recent years, emphasizes the need for more advanced approaches for forecasting extreme weather events. A seasonal drought prediction model based on time series statistical models was used to find the area's drought.

Over the past 20 years, machine learning has made substantial advancements in the modelling of linear time series. The topic of drought forecasting utilizing forecasting algorithms is explored in this work. In this study machine learning-based time series models are developed to predict the drought and a comparison of the model's results has been presented. On the basis of previously demonstrated methods conventional linear genetic programming model is incapable of learning the nonlinear structure of drought with lead times of more than three months. In this research the draught is forecasted using an ARIMA model, VAR model, and a completely automated model Prophet, developed by Facebook. Three independent machine learning techniques, each one having its own methodology, architecture and algorithm are utilized to forecast long term droughts. The following section of the paper outlines the various methods of drought prediction.

II. RELATED WORK

In extreme circumstances, droughts may last for years more than expected, causing a very high disasters to agriculture and the water system. Drought is a slow phenomenon and its occurrence is a normal climate element. Yet, it is challenging to foresee the start and end of a drought. Droughts can be short-lived and end quickly, or drought is regarded as one of the most harmful natural calamities. It particularly has an impact on agriculture. The severe effects of drought have a variety of impacts on people and civilizations.

The effectiveness of Holt-Winters, ARIMA, and exponential smoothing models for predicting drought in Nigeria and comparison of model outcome is presented in paper [1]. For their investigation, the authors used monthly Standardized Precipitation Index (SPI) data from 1961 to 2010. According to their findings, the ARIMA model surpasses the other two models in terms of predicting drought situations. Further findings in the same area demonstrated that the Random Forest algorithm performed better than the other two algorithms in terms of speed and accuracy [2]. The authors also discovered that as the number of features included for prediction increased, so did the model's accuracy. It shows that the suggested prediction model can accurately forecast both floods and droughts. To provide early warning of probable flooding or drought situations, the model can be connected with already-in-place water management systems. This suggested method may be able to alert farmers and policymakers of drought situations in advance, allowing them to take prompt action to lessen the effects of drought. To increase the precision and timeliness of drought predictions, the authors propose integrating the model with current drought monitoring systems [3]. To forecast the drought index, three different machine learning algorithms: Random Forest, Gradient Boosting, and Support Vector Regression (SVR). The Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) metrics were used to assess the performance of the models. Further study suggests a Convolutional Neural Network (CNN)-based method for exploiting satellite imagery to forecast agricultural dryness. Over a two-year period, the authors gathered satellite photos from the Sentinel-2 spacecraft of the European Space Agency. Authors pre-processed the photos and retrieved features such the Leaf Area Index (LAI), Soil Adjusted Vegetation Index (SAVI), and Normalized Difference Vegetation Index (NDVI) [4]. In addition, the authors discovered that adding satellite photos instead of just ground-based observations increased the model's accuracy.

Agana and Homaifar study show that a deep learning-based method for long-term drought prediction is presented in this study. In order to forecast the severity of a drought up to 12 months in advance, the scientists suggest using a Deep Belief Network (DBN). Based on historical climatic data such as temperature, precipitation, and soil moisture, the DBN is trained to forecast drought conditions in the future. The model's accuracy, they admit, could be impacted by variables including alterations in climatic patterns and land use, and more study is required to assess the model's robustness over longer time horizons [5].

The evaluation and forecasting of meteorological drought conditions using genetic programming models and time-series data are presented in the paper [6]. For 33 years, the authors gathered data from three stations in Iran on climate factors such precipitation, temperature, and humidity. To assess the severity of the meteorological drought, they pre-processed the data and developed the standardized Precipitation Index (SPI). The genetic programming model used a symbolic regression approach to create mathematical expressions that could predict drought conditions based on climate factors, whereas the time-series model was based on ARIMA. To find patterns and connections between climate factors and droughts and floods, the proposed framework analyses historical data on climate variables such precipitation, temperature, and humidity. The system comprises three modules: data preparation, feature selection, and prediction. The prediction module uses machine learning methods to forecast upcoming floods and droughts. Using historical climatic information from the Liao he River Basin in China, the scientists assessed the effectiveness of the suggested framework. They evaluated how well the framework worked in comparison to well-known machine learning algorithms like Random Forest and Support Vector Regression (SVR) and found that the suggested framework performed better in terms of accuracy. The suggested framework has the potential to offer insightful information on the patterns of drought and flooding, and it can assist farmers and policymakers in taking preventive steps to lessen the negative effects of drought and flooding on agriculture and water management [7]. The potential of machine learning techniques and remote sensing data to assist drought prediction and climate change mitigation initiatives is generally highlighted in this study. The model's accuracy, they admit, could be impacted by variables including alterations in climatic patterns and land use, and more study is required to assess the model's robustness over longer time horizons [8]. A drought prediction model based on echo state networks (ESNs) and data from remote sensing is proposed. The ESNs are improved by the authors in order to increase drought prediction precision. The potential of ESNs and optimization algorithms to aid in drought prediction and attempts to mitigate climate change is generally highlighted in this research [9]. The model's accuracy, they admit, could be impacted by variables including alterations in climatic patterns and land use, and more study is required to assess the model's robustness over longer time horizons. Using information from a vast ensemble of climate models, this research suggests a machine learning-based method for predicting drought. The scientists generate temperature and precipitation data using an ensemble of 35 global climate models and then train and test a variety of machine learning methods including gradient boosting, random forest and artificial neural networks using this data. Overall, this study emphasis's the potential of machine learning for climate simulation data-based drought prediction, and the findings imply that this strategy may offer useful information for drought management and climate change adaptation efforts [10]. Based on fuzzy theory and the analytical hierarchy process (AHP), suggest a novel risk prediction model. The model considers a variety of drought-related elements, such as precipitation, temperature, soil moisture, and crop growth status. The model is validated by the authors using historical data, which also serves to show how well the model predicts the likelihood of an agricultural drought [11]. Two case studies were employed in the study [12]. to test the suggested methodology. The first instance involved forecasting a drought in an area of India, while the second case involved estimating the water quality of a lake in Vietnam. The study's findings demonstrated that the Random Forest and SVM models were highly accurate and precise at predicting drought and estimating water quality metrics.

Utilizing Multilayer Perceptron (MLP) neural networks, a drought forecasting model. It explains the limitations of conventional statistical models in effectively forecasting drought and the necessity of drought forecasting for efficient management of water resources. In order to forecast drought, authors suggest employing MLP neural networks, a variety of artificial neural networks [13]. collection of real-time data on climate factors including temperature, humidity, and soil moisture using various IoT devices, such as sensors and weather stations. After that, a cloud-based platform receives the data collection for processing and analysis. the idea of a "green framework," which alludes to the utilization of cloud computing resources and energy-efficient IoT devices to lessen the framework's environmental impact [14]. Another System [15]. gathers information from a variety of sources, such as social media, satellite imagery, and weather stations, and stores the information in a distributed file system. They collect and analyze the data using Apache Hadoop and Spark, and they apply machine learning algorithms such as decision trees and random forests to forecast the occurrence of droughts. An approach to drought forecasting that combines Bayesian Model Averaging (BMO) and convolutional neural networks (CNN)has been employed in [15]. An approach to drought forecasting that combines Bayesian Model Averaging (BMO) and convolutional neural networks (CNN). By fusing the advantages of CNN and BMO, the suggested method seeks to overcome the problem of uncertainty and variability in drought prediction. The Standard Precipitation Index (SPI) values are first extracted from the historical data by the authors as part of the pre-processing of the input data. The CNN model extracts the pertinent features and generates a prediction using the SPI values as input. Then the use of BMO to correct for model uncertainty and variability in the CNN model's output. The resulting ensemble model offers a more reliable and accurate drought prediction [16].

In paper [17]. authors made use of Sentinel-2 satellite data to forecast dryness in India's western region. To examine the satellite data and create prediction models, the researchers employed deep learning techniques like convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. The study used a variety of criteria, including accuracy, precision, recall, and F1 score, to assess the performance of the models. The study's findings demonstrated that the deep learning models created therein could successfully foretell agricultural drought using satellite remote sensing data. In order to help farmers and policymakers take preventive steps to lessen the impact of drought on agricultural productivity, the study demonstrates the potential of deep learning techniques to increase the accuracy and reliability of drought prediction models. In some cases [18]. the application of ANNs, a kind of machine learning algorithm inspired by the design and operation of the human brain, for drought prediction. The researchers gathered information on several environmental factors from multiple meteorological stations located around India, including temperature, rainfall, humidity, and wind speed. An ANN model was trained using the pre-processed data to forecast drought. Using a variety of criteria, including accuracy, sensitivity, specificity, and the area under the receiver operating characteristic (ROC) curve, the study assessed the effectiveness of the ANN model. The findings demonstrated that the ANN model had an accuracy of over 90% in predicting drought. It also examined how each meteorological factor affected the likelihood of drought. The findings indicated that the most crucial factors in forecasting drought were temperature, rainfall, and humidity. In another research [19]. the primary focus of the work is on the application of SARIMA, a time series forecasting model, to forecast monsoon rainfall in Tamil Nadu. The Indian Meteorological Department (IMD) provided the researchers with historical information on monsoon rainfall in Tamil Nadu for the years 1901 to 2019. The SARIMA model was trained using the pre-processed data to forecast upcoming rainfall patterns. Various statistical metrics including root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) have been used in the study to assess the effectiveness of the SARIMA model. The outcomes demonstrated that the SARIMA model was capable of correctly forecasting Tamil Nadu's monsoon rainfall patterns. The main purpose of the study in [20]. focuses on the application of transfer learning, a machine learning technique that leverages a model created for one activity to predict drought using a model created for a separate but related task. The researchers gathered climate data from the Climate Forecast System Reanalysis (CFSR) and remote sensing data from the Moderate Resolution Imaging Spectroradiometer (MODIS) for the years 2001 to 2019. The pre-processed data was used to extract useful characteristics for drought prediction using a feature-based transfer learning approach. In order to capture spatiotemporal patterns, time series data is translated into 2D images in the study's unique time series imaging method. The patterns in the remote sensing and climatic data were visualized using the time series imaging method.

III. METHODOLOGY

The system requirement for the proposed method includes hardware requirements such as a computer with sufficient processing power and memory to handle the data and computations involved in the modeling process, operating systems like Windows, macOS, or Linux and software requirements such as Python, Python Libraries like Pandas, NumPy, Prophet, Mat-plot and Seaborn.

Fig 1 shows the methodology used for the drought prediction.

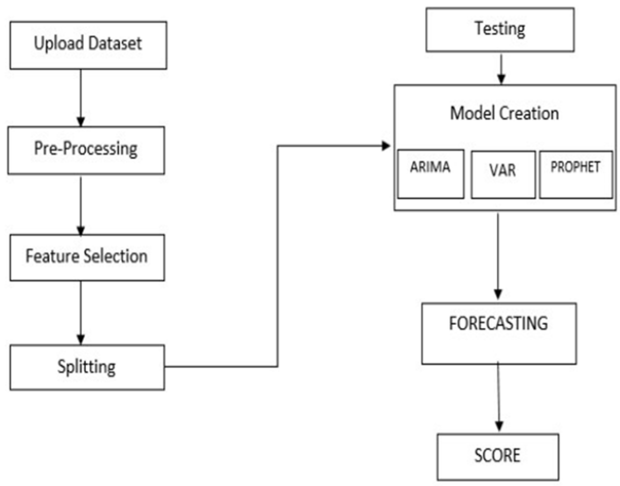

Fig. 1. Methodology used for Drought Prediction

A. *Dataset Collection And Pre-Processing*

1) Dataset: The first step is to collect relevant data on drought related variables such as rainfall, temperature, soil moisture, and other meteorological and hydrological data. This data can be obtained from government agencies, research institutes, and other sources. The dataset contains the occurrence of drought in specific areas during specific period (Date) and SPI index along with ground water level of that area and the previous drought score.

2) Pre-processing: The collected data may contain missing values, outliers, or other errors that can affect the accuracy of the models. Therefore, the data should be cleaned by removing or imputing missing values, detecting and correcting outliers, and dealing with other anomalies in the data. In this study the dataset is organized based on the date and then all the null values present are removed along with outlier. The dataset is partitioned into training and testing sets in 60:40 ratio.

B. Arima Model

The renowned time-series forecasting technique known as the ARIMA model can be used to anticipate droughts. ARIMA models use an amalgamation of autoregressive (AR) and moving average (MA) components to capture the patterns and trends in the time series data. The moving average component represents the correspondence between the variable's present value and its historical values, whereas the autoregressive component models the correspondence between the variable's present value and historical forecasting errors.

In this method, an ARIMA model is fitted using historical time-series data of drought-related variables like rainfall, temperature, and soil moisture, which can then be used to predict the future Values. This model contains mainly 3 parameters (p, d, q) where

p: the number of autoregressive terms (AR).

d: the number of differences (I).

q: the number of moving average terms (MA)

The resultant graph in fig 2 suggest that ARIMA (2,0,1) model seems to predict a correct forecast. The observed value lies within 90% confidence band. So, in this case we have the correct average value for the data and iteratively increase of p and q values to certain number to see the better results.

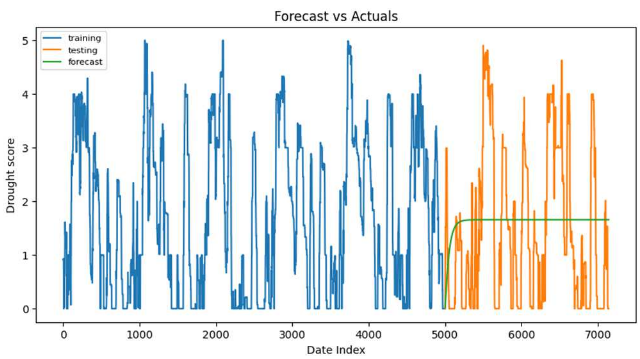

Fig. 2. ARIMA Results

C. Var Model

A statistical model called a vector autoregression model is used to examine the dynamic relationships between several time series variables. In VAR model each variable is represented as a linear mixture of both its own historical values and the historical values of other variables in the system.

The general form of a VAR model with p lags is shown in equation 1:

$$y_t = C + B_1 y_{t-1} + B_2 y_{t-2} + ---- + B_p y_{t-p} + e_t \quad (1)$$

where Yt is a K x 1 trajectory of endogenous variables at time t, c is a K x 1 trajectory of constants, B1, B2, ..., Bp are K x K coefficient matrices, and et is a K x 1 vector of error terms. The number of lags p is chosen based on model selection criteria such as Bayesian information criterion (BIC) or Akaike information criterion (AIC). VAR model that is being developed not only considers the past values along with them it considers all the variables that are responsible for the cause of drought. After estimating the VAR model, one can use it to forecast future values of the system variables.

The result of VAR model is textual table type data which indicates the forecast of drought score between 0 and 1 where 0 indicates no drought and 1 says probability of occurrence of drought is more. All the meteorological parameters responsible for the drought that are present in the dataset are considered and their effect on the calculation of drought score is given in the table.

D. Prophet Model

Prophet is a technique for forecasting time series data that applies an additive model for nonlinear seasonal trends that occur on holidays, weekends, daily, monthly and yearly. It performs the best for time series data that are greatly seasonal and historical data that stretches several seasons. Prophet usually better handles outliers and withstands missing data and trend changes in the data.

1) Accurate forecast: Numerous Facebook applications use Prophet to produce precise projections for planning and goal-setting. We've found that it works better than any alternative method in the majority of cases. We fitte d models in Stan so that you might receive forecasts in only a few seconds.

2) Fully automatic: There are many choices available to Prophet method users for changing and adjusting forecasts. Our subject knowledge will let us use human-interpretable criteria to improve our forecast.

3) Tunable forecasts: There are many choices available to Prophet method users for changing and revamping forecasts. You can improve your forecast by using human-interpretable criteria by incorporating your subject knowledge. The developed Prophet model result shown in fig 3 obtained by only considering the date and drought index like drought score of the area during past years and based on those two past values it predicts the future occurrence of drought by estimating gap between the dates and the drought score with their impact on the present condition.

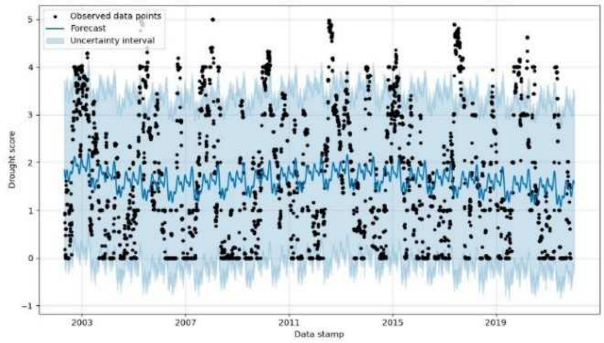

Fig. 3. Results of Prophet mode

IV. Results And Discussion

Time-series forecasting models like ARIMA [21], Prophet, and VAR may all be used to examine and forecast future patterns in a given dataset.

The statistical model ARIMA calculates future values of a variable based on its previous time lags. It is frequently applied to assess trends in data from stationary time series. ARIMA models data autocorrelation and generates predictions.

The VAR model calculates the future values of a variable based on the previous time lags and the previous lags of some other dependent variable and it is frequently used to examine how one variable affects another in a set of time-series data in order to generate predictions. It is suitable not only for stationary data but also for all the different kinds of data available.

Prophet model that is intended primarily for time series data with seasonal patterns. Prophet can handle missing data and outliers and employs a combination of linear and non-linear models to create predictions. The developed prophet model gives the better precision and accuracy of 92.01% for the dataset taken and it may vary from this model to another based the data that is being considered. It is crucial to remember that each model has strengths and weaknesses based on the type of data being analysed when comparing the results and discussing different models. While ARIMA is effective for analysing stationary time series data, VAR is helpful in examining the connections between a number of time series variables. On the other hand, Prophet is made specifically for time series data with seasonal patterns On the other hand, Prophet can record non-linear correlations between the variables and is built to handle seasonality and trend changes in the data. In several research, Prophet has been found to perform better than ARIMA models, particularly when the data has a significant seasonal component like the dataset that is being used in this method. Overall, the decision of which model to apply is based on the particular requirements of the study as well as the type of data being examined. In order to choose the model that best meets the needs of the analysis, it is crucial to evaluate and contrast the outcomes of each model. Table I shows the comparative analysis of the ARIMA, VAR and PROPHET models.

TABLE I. COMPARATIVE ANALYSIS OF RESULTS.

ARIMA	VAR	PROPHET
The ARIMA calculates future values of a variable based on its previous time lags. It is applicable only to assess stationary time series data. Fig 2 represents forecasted result of ARIMA model with the accuracy of about 65%.	The VAR model calculates the future values of a variable based on the previous time lags and the previous lags of some other dependent variable. Result of var model is in textual table format where each of the dependent parameters which are responsible for the final drought score has been forecasted with the accuracy of about 80%	Prophet model that is intended primarily for time series data with seasonal patterns. Prophet can handle missing data and outliers. Fig 3 represents forecasted results of PROPHET model with the accuracy of about 92.01%.

V. CONTRIBUTIONS

The prediction of drought using time series forecasting models has several practical applications and uses. Here are some common examples:

- Water resource management: Drought prediction helps water resource managers make informed decisions regarding water allocation, reservoir management, and water conservation measures.
- Agricultural planning: These models assist farmers in planning their planting schedules, selecting appropriate crops, and adjusting irrigation practices based on anticipated drought conditions.
- Disaster preparedness and response [22]: Governments and relief agencies can anticipate the severity and duration of droughts, prepare relief supplies, and allocate resources for drought-affected regions.
- Environmental management: Time series models aid in predicting drought-related stress on ecosystems, enabling conservationists and environmental managers to develop mitigation plans, protect sensitive areas, and implement measures to preserve biodiversity and ecological resilience.

VI. CONCLUSION

In conclusion, employing a mix of ARIMA, VAR, and prophet models can be useful in delivering a more precise and thorough prediction when predicting drought [23] in a specific location. For the future scope one can try to implement the hybrid model and get the more accurate result. We can gain a more thorough knowledge of the many and interconnected elements that affect drought in the area by combining these models. This could aid in the creation of efficient drought management and mitigation solutions, such as water conservation techniques, early warning systems, and drought-tolerant agricultural varieties.

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