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Development A Web-Based System for Real Time Prediction of Drought in Northern Nigeria Using Markov Chain Technique

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Abstract— Drought is caused by a continuous decrease in rainfall over a long period of time, generally a season or longer, however, other climatic variables (such as high temperatures and low relative moistness) are strongly linked to it in many regions of the world and can exacerbate the severity of drought occurrence. Droughts also spread out more slowly and last far longer than other natural catastrophes (though the precise duration is unknown), making it hard to anticipate when they will start and stop. Because of its erratic rainfall pattern and short rainy season, the effects of drought in Northern Nigeria (North-east and North-west) are extremely severe. Approximately 300,000 animals perished in the North-Eastern portion of Nigeria during the drought of 1972-1973, accounting for roughly 13% of the total cattle population. However, research has shown that if individuals are aware of the approaching drought ahead of time, these impacts can be reduced. This research aims to develop a system that will help with early warning by monitoring and forecasting droughts. In this Project, Droughts are forecasted using a Markov chain algorithm based on data from sensors placed in strategic places, with warnings provided via a web interface. The Markov chain algorithm creates a transition matrix of stochastic processes using prior data, and then forecasts the next state using a dot product of the current state and the transition matrix. For the Markov chain prediction approach, the Mean Absolute Error (MAE) and Root Mean Absolute Error (RMSE) were about 21.48 percent and 21.01 which indicates that the model isn't totally accurate.

Keywords—*drought, web based, real-time, Markov chain.*

I. BACKGROUND OF STUDY

Studies and inquiries have proven that climate shows the behavioral patterns of the atmosphere over relatively long period of time all over the globe. The summation of the atmospheric elements and their variations over a short period of time constitutes weather. Elements such as atmospheric pressure, wind, temperature, humidity and precipitation. Climatic variability and change caused by either human activities (such as burning of fusil fuel, deforestation, industrial production) or processes within the climate environment have brought about climate hazards, loss of life and properties, damages to economies and ruin to the ecosystem as a whole. Through research and survey analysis, Africa is said to be one of the major continents facing challenges of chaotic atmospheric and climate change that has resulted to drastic natural disaster namely drought (Justin et al, 2014). It is only essential to observe, monitor, understand and come up with adaptative measures and mitigation processes for risk and damage reduction.

Drought is one amongst the disastrous natural hazards and a recurring event that has taken a great toll on man and his environment. Drought is as a result of prolonged deficit or insufficiency of precipitation or rain.[1][2] Drought is said to be a creeping disaster as its entrance comes unannounced and is sometimes mistaken for a bit of desiccation and its impacts builds over time.[3][4]

II. STATEMENT OF PROBLEM

Nigeria as a country is still battling with innovative technology. The number of workstations, observatory and analytical systems and models put in place for confronting the dangers, risks and devastating impacts of natural disasters, one such as Droughts are still upcoming. Over the years, many developments of analytical indexes, frameworks and models have been considerably propagated but systems that could provide the necessary and timely information to individuals and communities threatened by Drought to be prepared and ready to act towards reducing its impact and render a better chance to avoid the risks are but a few to mention.[5][6]

III. MARKOV CHAIN ALGORITHM

Over a century ago, a Russian mathematician named Andrey Markov discovered a new form of probability theory by applying mathematics to a music genre; poetry [3] Markov Chain Algorithm is a stochastic model which describes a state transition process in one or more random variables. It is important to note that all Markov chains must satisfy the Markov property (commonly known as "memoryless property").

A Markov Chain is a succession of random variables: $\mathrm{X}^0, \mathrm{X}^1, \mathrm{X}^2 \ldots \mathrm{X}^{\mathrm{n}}$ in which the impacts of the estimates of X^0, …, X^{n} on the spread of $\mathrm{X}^{\mathrm{n}+1}$ is adjudicated by the entire value of X^{n} (Raddouane et al, 2018). The following equation 1 below, depicts a mathematical representation.

$$P\left(x^{(n+1)} | x^{(n)}, \{x^{(t)}: t \in \varepsilon\}\right) = P\left(x^{(n+1)} | x^{(n)}\right) \quad (1)$$

where ε is any of the subsets of $\{0, \ldots, \mathrm{n}-1\}$.

The indexes $t = 0, 1, 2, \ldots$ are often referred to as successful "times". [8][9][10]

A. Data Presentation

Under the data presentation, where information concerning alertness and preparedness obtained from the drought prediction system to the end user, it comprises of two major tools namely; the Web Application and the Prediction Model, see Fig. 1.

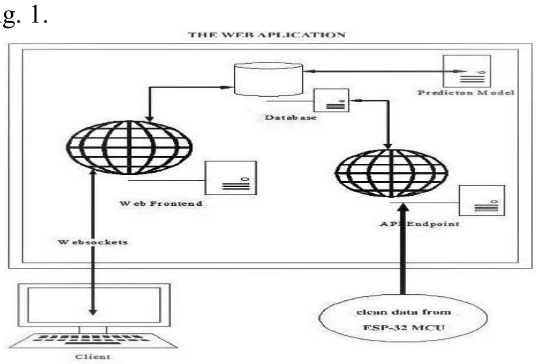

Fig. 1, Web Application Model

B. Web Application

This was achieved or built using Django and was hosted on a web-server. The Web Application is solely tasked with the responsibility of displaying the predicted real time charts, soil moisture sate value, sending notifications to intended personnel through the Web-Application and also the incorporation of the Web Application with the prediction model which renders the computing and recomputing of Transition Matrix (for forecasting purpose) over a period of time. [11][12].

C. Prediction Model

A Prediction Model is a type of technique that utilizes a Machine Learning algorithm and Data Mining processes to predict and forecast potential future outcomes. In this project where the development of a Drought Early Warning (DEWS) is made feasible, Markov Model is used as the Prediction Model. [13][14][15]

A Markov Model is a stochastic or probabilistic model which that uses stochastic processes to describe sequence of possible events. The stochastic processes utilized in the model is referred to as Markov Chain. In Markov Model, the probability of a possible event occurring is only dependent on the present and not on the series of events before. This entails that the probability of transiting from a state to another is totally dependent on the current state and not on the former preceding states (Markov Property). [16][17][18]

In the Statistical phase, the Markov Chain is completed by specifying probabilities to the transitions in the chain.

The equation below describes and shows the model's dependencies on present states alone and not on the past states:

$$Pr(X_{n+1} = x \mid X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n) = Pr(X_{n+1} = x \mid X_n = x_n)$$

if both dependent probabilities are appropriately defined, that is if: $Pr(X_1 = x_1, \ldots, X_n = x_n) > 0$.

The Markov Chain Algorithm is the prediction model utilizing the states shown in the Markov Chain in the figure, the Model can give predictions on the soil's state. [19][20]

D. Generating Transition Matrix

Transition matrix is also referred to as a probability or stochastic matrix. It mostly consists of a square type of matrix (n x n) responsible for illustrating the transition of a stochastic model such as the Markov model. The Transition Matrix describes the probabilities of state(s) moving to another or back to itself and this is created and fed into the Markov Prediction Model. Considering the three states (Normal, Almost Drought and Drought) used for prediction, the Transition Matrix will be a 3x3 matrix as shown in the equation 5. The Transition Matrix determines the likelihood of the states changing or moving from 'Normal' to either 'Almost Drought or Drought' or maintaining the same state in regards to the agreed-upon dependent probabilities for transition from one state to another.

$$P(X_{n+1}) = \begin{bmatrix} P(N|N) & P(N|AD) & P(N|D) \\ P(N|AD) & P(AD|AD) & P(D|AD) \\ P(N|D) & P(AD|D) & P(D|D) \end{bmatrix} \quad (5)$$

$$\begin{bmatrix} \text{Next} \\ \text{State} \end{bmatrix} = \begin{bmatrix} \text{Matrix of Transition} \\ \text{Probabilities} \end{bmatrix} \begin{bmatrix} \text{Current} \\ \text{State} \end{bmatrix}$$

$$S1 = PS0 \quad (6)$$

$$\text{Initial State, } S0 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

$$\text{Matrix of Transition Probabilities, } P = \begin{bmatrix} 0.55 & 0.25 & 0.30 \\ 0.25 & 0.45 & 0.45 \\ 0.20 & 0.30 & 0.25 \end{bmatrix}$$

Note: the sum of each column must be one (1)

$$\text{From (7); Hence, } S1 = \begin{bmatrix} 0.55 \\ 0.25 \\ 0.20 \end{bmatrix}$$

$$S2 = PS1 \quad (8)$$

$$S2 = \begin{bmatrix} 0.55 & 0.25 & 0.30 \\ 0.25 & 0.45 & 0.45 \\ 0.20 & 0.30 & 0.25 \end{bmatrix} \begin{bmatrix} 0.55 \\ 0.25 \\ 0.20 \end{bmatrix}$$

$$S2 = \begin{bmatrix} 0.425 \\ 0.340 \\ 0.235 \end{bmatrix}$$

$$S3 = P(S2 = P(S1 = PS0))$$

Therefore:

$$S^n = P^n S_0 \quad (5)$$

IV. IMPLEMENTATION

The Python Programming Language was utilized to fully develop and design the prediction model. Due to the fact that the task of training and prediction may be both space and time consuming, it is conducted as a background activity in the web application. Using Celery, a Python module that allows web applications to run background activities without interfering with requests, when the moment arrives, the Markov chain algorithm is run. A Predicted probabilities for the next state may be created using the equations, which is a dot matrix multiplication of the vector of the current state probability and the transition matrix. The state with the highest chance of occurrence is chosen as the next state based on the projected probability. Using a time step of five seconds or for every fifth seconds, the predictions of the next state are obtained.

A. Simulation Design

A simulation utilizing the dataset obtained from NIMET was used to assess the accuracy of the Markov Chain Algorithm. The data set was divided into 75 percent train data and 25 percent test data for the simulation. The simulation was then run using the anaconda program and Jupyter Lab (a python library for data analytics).

B. Design Considerations

In order to achieve the intended goal of the project, careful thoughts and consideration of the system design were anticipated. The consideration of the system is classified into hardware and software.

C. Hardware Position Design Consideration

The consideration of the hardware design is the integral aspect of the system design since the hardware design consist of the data collection unit necessary for drought prediction. It comprises of components that provide quality and accurate data at affordable price and small size. The system is placed on the ground with the soil moisture inserted into the soil and rain sensor and LCD placed on top of the enclosure of the hardware system in order to achieve the intended function.

V. PERFORMANCE EVALUATION

The system's performance will be assessed based on the system's output (prediction accuracy), the accuracy of soil moisture level estimate, power consumption, and the time it takes to deliver alerts to the user following the forecast (response time). The Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) will be generated and used to evaluate the system's performance to estimate the accuracy of the forecast.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |(P_i - G_i)| \tag{9}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - G_i)^2} \tag{VI.6}$$

Where

P_i shows the perceived condition of the ground. G_i represents the predicted condition ground. N represents the number of observations or predictions. This measure is also used to calculate the accuracy of the soil moisture estimation, as well as to compare data with and without temperature and humidity adjustment. To determine the response time, the time at which the forecast was made will be compared to the time at which the notice was received by the user.

VI. RESULT AND DISCUSSION

The goal of the project is to create a Warning System. The observation system is built with ESP-32 and sensors, as stated in the previous section. The Markov Chain model is applied in Python and integrated with the Web application to create the prediction system. The program's output was analyzed using the criteria given in section, and the findings are reported in this section.

A. Results

The corresponding results indicating the number of false positives and negatives, as well as genuine positives and negatives, were observed when the simulation was conducted on Visual Studio Code. True positives are the number of real droughts events properly forecasted, whereas false positives are the number of drought projections that were incorrectly labeled as such (false alarms). Table 1 summarizes these figures. True negatives are the frequency of Normal/Almost-Drought predictions that were accurate, and false Negatives are the number of Almost-Drought/Normal predictions that were wrong, whereas the actual state was Drought. The results are shown in Table 2. Overall number of forecasts = 9,570

Table 1 False and True Positives

True Positives	False Positives
63	97

Table 2 False and True Negatives

True Negatives	False Negatives
7451	1959

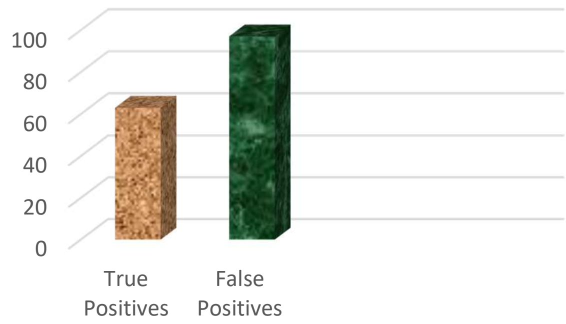

Fig. 2 Chart of true and False Positives

The algorithm's performance in forecasting drought happening is represented by: Using the True and False Positives values in Table1, the algorithm's effectiveness in forecasting drought incidence is obtained by:

$$\%\text{Positive Prediction Accuracy} = \frac{63}{63+97} = \frac{63}{160} = 0.39375$$

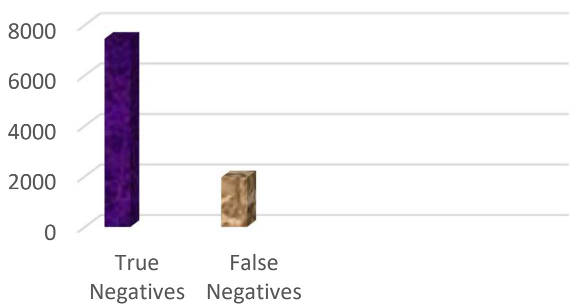

Fig. 3. Graph of True Negatives and False Negatives

The algorithm predicted 7451 true negatives and 1959 false negatives based on the True and False Negatives values in Table 2. The system's accuracy in forecasting non-flooding events is calculated as follows:

$$\%\text{Negative Prediction Accuracy} = \frac{7451}{7451\ + 1959}$$
$$= \frac{7451}{9410}$$
$$= 0.791817$$

According to the calculations, the system properly forecasted around 39.3% of drought occurrences, whereas the system correctly forecasted about 79.1% of non-drought events (Normal and Almost Drought).

It is inferred from the overall predictions produced by the system that the total successfully forecasted states are:

total correctly predicted $= 7451 + 63 = 7514$.

Total wrongly predicted $= 1959 + 97 = 2056$.

From Equation ():

$$\text{MAE} = \frac{1}{9570}\big(7514(1-1) + 2056(1-0)\big)$$
$$\frac{2056}{9570} = 0.2148$$

From Equation $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - G_i)^2}$ $(VI.)$,

$$\text{RMSE} = \sqrt{\frac{1}{9570}(7514(1-1) + 2056(1-0))^2}$$
$$= 21.01683$$

Therefore, the drought Early Warning System has an MAE OF 0.2148 and an RMSE of 0.3321. These values indicate that the model is not very accurate.

B. User Interface Results

The web application that was created provides real - time rainfall intensity rate as well as the next state of the soil moisture level (Normal, Almost Drought or Drought). As fresh data is received, it updates the graph of rainfall intensity in real time as shown in Fig. 5.

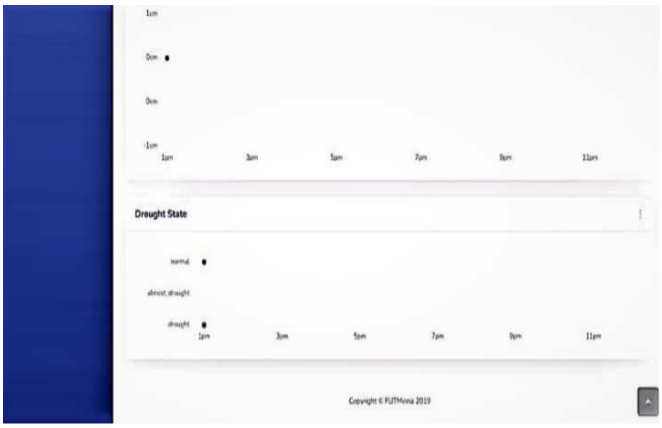

Fig. 4. Web Application User Interface showing values before testing commenced

It also includes a graph showing the current condition of the soil, as well as forecasts in red dots for the future states of the soil. Fig. 6 illustrates an image of a screenshot.

Fig. 5. Web Application User Interface showing present soil state and forecasts of the next state (depicted with red dots)

D. Web Notifications

Located at the top right corner of the Web UI interface is an Alerts Centre (represented with a Bell icon), which is responsible for informing whoever is logged on to the web UI interface about the details of the most recent forecast results. As seen in Fig.7.

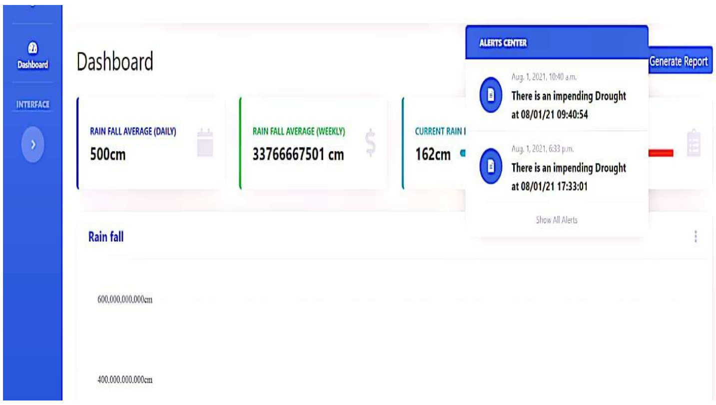

Fig. 6. Web Notifications showing forecast results

C. System Power Consumption

The battery power left over the course of 10 hours was monitored with a 1-hour interval to assess the system's power conservation. The obtained data is shown in Table 3.

Table 3. Data Obtained from Battery Unit

Hour	***Battery Reading of System (V)***
1	4.92
2	4.78
3	4.67
4	4.51
5	4.46
6	4.39
7	4.34
8	4.29
9	4.25
10	4.20

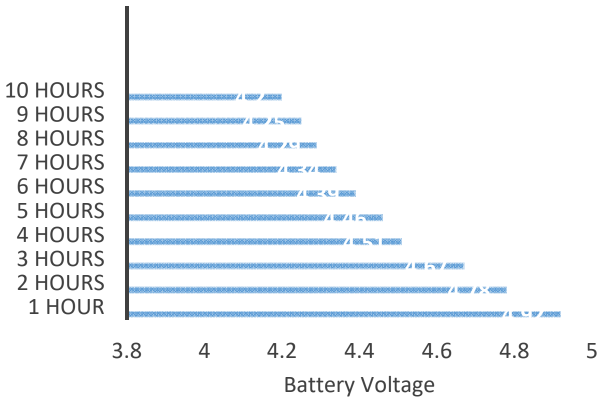

Fig. 7 Bar chart of Hourly Checks against Battery Voltage (V).

VII. CONCLUSION

Amongst all the natural hazardous occurring phenomenon, Drought is seen to be a creeping and the most reoccurring event that leaves devastating damages at its wake. Theses damages affects the lives, properties and as far as the entire community or region of a state. Hence, the call for a developed system that can monitor, forecast, and give notifications as a form of alertness on the state of drought.

The system proposed, designed, and developed utilizes wireless sensor network to perform functions such as monitoring certain physical quantities like the raindrops (Rainfall sensor), content of water level in the soil (Soil Moisture sensor), temperature and humidity (Temperature and Humidity sensor) parameters and sending the obtained data (in the form of values) gathered by the Microcontroller to the Web.

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