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TOWARDS BUILDING AN INTELLIGENT MOBILE APP FOR RAINFALL PREDICTION USING WEIGHTED AVERAGE ENSEMBLE DEEP SUPERVISED LEARNING

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Abstract:

Predicting rainfall accurately and on time is essential for a variety of tasks, including electricity generation, building, flood warnings, aviation operations, and the sustainable use of water resources. Traditionally, rainfall forecasts were based on physical models of the atmosphere, which are imprecise over extended periods of time due to their instability to perturbations and thus, are inaccurate for large periods. Artificial Intelligence (AI) techniques as a means of predicting rainfall have been applied in most developed countries, these have been found to offer many possibilities. AI techniques are more robust to perturbations. Over the past 20 years, rainfall forecasting using AI approaches has demonstrated astounding precision. Rainfall forecasting accuracy could be increased by AI algorithms that use historical weather data elements to reveal hidden trends. This study thereafter proposed the development of an AI mobile app for predicting rainfall that is based on weighted average ensemble deep supervised learning that combines three machine learning algorithms namely; Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and Gated Recurrent Unit (GRU). . In order to prevent future outbreaks of rainfall hazards, the proposed AI mobile app for rainfall prediction will aid in raising awareness among the public, government officials, planning agencies, disaster management agencies, and related organizations.

Keywords: Rainfall Prediction, Artificial Intelligence, Deep Supervised Learning, Mobile App

I. INTRODUCTION

A branch of climate change research called weather forecasting makes predictions about the state of the atmosphere at a future date and place (Mann and Gleick, 2015). Predicting the amount of rain is a crucial component of weather forecasting. Predicting rainfall with precision has been one of the most crucial problems in hydrological study, despite the advances in science and technology in recent decades. Predicting when it will rain is important for many different kinds of human endeavors. Preparing ahead of time for unexpected and potentially fatal rainfall can greatly mitigate its consequences by implementing adequate security measures. (Dada *et al.*, 2021).

However, because rainfall forecasting modeling is extremely complex and nonlinear, researchers still face difficulties in designing an efficient prediction system. Rainfall forecasting demands the employment of progressive computer modeling and simulation techniques in order to achieve accurate predictions (Ganachari and Kumari, 2021). Traditionally, rainfall forecasting has relied on statistical methods and numerical weather prediction models. While these approaches have yielded valuable insights, they often struggle to capture the complex and non-linear patterns inherent in rainfall data. The fields of artificial intelligence and machine learning have shown great promise in recent years as methods for forecasting problems. The goal of artificial intelligence (AI) is to create and implement intelligent systems that use human knowledge, reasoning, self-learning, and problem-solving to make decisions that are effective and efficient. (Ojokoh *et al.*, 2020). With the availability of large amounts of historical meteorological data and increases in computing power, machine learning algorithms can potentially reveal hidden patterns and relationships within rainfall data.

In the field of weather prediction, artificial intelligence techniques have already shown to be a viable substitute for conventional deterministic methods (Smola and Vishwanathan, 2008). AI's primary subfields of deep learning and machine learning have significantly improved rainfall prediction accuracy. Numerous machine learning techniques have been researched for rainfall forecasting in different places, including China, South Africa, and other nations (Stephan *et al.*, 2017; Klutse, *et al.*, 2016; Sittichok *et al.*, 2016; and Wu *et al.*, 2015).

Nonetheless, researchers and scholars are working to improve the modeling systems' precision and dependability. In reality, the next phase of applying these cutting-edge techniques involves minimizing the forecast errors offered by solutions including convolutional neural networks, fuzzy logic, long short-term memory, neural networks, gated recurrent neural network decision trees, and numerous other techniques inspired by artificial intelligence (Chen *et al.*, 2021; Coulibaly *et al.*, 2020). However, the accuracy of rainfall prediction relies on both the applied classifiers and the training data (Chen *et al.*, 2018).

A branch of machine learning (ML) called "deep learning" (DL) is motivated by the ways in which the human brain processes information. Unlike traditional ML techniques, for a variety of purposes, DL can automate the learning of feature sets (Shrestha and Mahmood, 2019). In machine learning, deep learning (DL) has progressively taken the lead as the most used computational method. Three main categories can be used to categorize DL techniques: semi-supervised, supervised, and unsupervised. The method known as deep supervised learning (DSL) works with labeled data. The environment is made up of a variety of inputs and outputs. Among

the deep supervised learning techniques are deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs). The RNN category also includes gated recurrent units (GRUs) and long short-term memory (LSTM) approaches. The main advantage of DSL is its ability to collect data and generate output from prior information. This approach to learning with exceptional performance is generally simpler to apply than alternative approaches.

CNN is one of the algorithms that is frequently used in the field of DSL (Zhou, 2020). CNN's primary advantage over its predecessors is its ability to autonomously identify pertinent features without supervision by humans (Gu *et al.*, 2018). Numerous fields, including speech processing (Palaz *et al.*, 2019), computer vision (Fang *et al.*, 2020), face recognition (Li *et al.*, 2020), and others, have made extensive use of CNNs. CNNs were constructed using neurons present in the brains of humans and other animals, much like a conventional neural network. More accurately, the CNN mimics the complex arrangement of cells that constitutes the visual cortex in the brain of a cat (Hubel and Wiesel, 1962). Goodfellow *et al.* (2016) identified three key benefits of the CNN: equivalent representations, sparse interactions, and parameter sharing. Long short-term memory (LSTM) is an enhanced form of recurrent neural networks (RNN) deals with the problem of storing long-term dependencies. Another RNN architecture variation that solves the LSTM problem and has a simpler structure than LSTM is the Gated Recurrent Unit (GRU).

This study thereafter proposed the development of an AI mobile app for predicting rainfall that is driven by weighted average ensemble deep supervised learning that combines three algorithms namely, Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and Gated Recurrent Unit (GRU). The proposed AI mobile app for rainfall prediction will help in creating awareness to the people, government officials, planning agencies, disaster management agencies, and related institutions in taking an effective decision in forestalling future outbreaks of rainfall hazards in Nigeria.

II. RELATED WORKS

Many researchers investigated into machine learning and deep learning techniques for rainfall forecasting. Haidar and Verma's (2018) uses a deep convolutional neural network (CNN) to estimate monthly rainfall for a selected area in eastern Australia. The researchers compared the Australian Community Climate and Earth-System Simulator-Seasonal Prediction System (ACCESS) with CNN. Likewise, the CNN was compared with a conventional multi-layered perceptron (MLP). Greater values of mean absolute error, root mean square error, Pearson correlation, and Nash Sutcliff coefficient of efficiency values were obtained for the CNN. The study concluded that CNN fared better in months with larger annual averages. In this study, the researchers solely took into account monthly data. The researchers came to the conclusion that ensemble approaches should be used in subsequent studies to merge the model diversities. Furthermore, they suggested that more datasets be used.

A Rainfall Forecasting Performance Enhancement Model using an Integrated Wavelet-Convolutional Neural Network (WCNN) was developed by Chong *et al.* in 2020. The paper's aims to improve rainfall forecasting performance with the proposed model. The study investigates the WCNN model's potential for enhancing rainfall forecasting performance. The study doesn't specify the amount of computing power needed.

A CNN-based Differential Image Processing Approach for Rainfall Classification was presented by Roberta and Francesco in 2020. In this paper, convolutional neural networks (CNN) was employed to categorize rainfall based on image processing and video matching process by automatically extracting time series feature based on meta learning idea. The model is built using a Convolution Neural Network (CNN) named SqueezeNet. It is a reduced complexity, fully convolutional network with dropout layers. The paper introduces a new approach to rainfall classification that includes seven classification classes, ranging from "No rain" to "Cloudburst", which is more comprehensive compared to previous studies that only considered two classes. The data used in this research does not capture most rainfall parameters like wind speed, pressure, temperature etc.

Haq *et al.* (2021) used the LSTM algorithm to predict the amount of rain that would fall in Sidoarjo, East Java. The study employed two methods: the first method made use of the El-Nino and Indian Ocean Dipole (IOD) characteristics, while the second method made use of the rainfall time series pattern. The prediction results using El-Nino and IOD parameters produced a more accurate result with a MAAPE value of 0.9644. This study employed 240 weekly observations.

Rainfall was predicted for Tasik Kenvir, Terengganu, by Ridwan *et al.* in 2021. The study focused on designing and evaluating several kinds of Machine Learning (ML) models, including Neural Network Regression (NNR), Boosted Decision Tree Regression (BDTR), Decision Forest Regression (DFR), and Bayesian Linear Regression (BLR), with the purpose of predicting rainfall. The two methods that are the subject of this study are utilizing the Autocorrelation Function (ACF) to forecast rainfall based on previous rainfall data and employing the Projected Error to forecast rainfall based on both historical and projected rainfall data. Both approaches find the best rainfall prediction over various time horizons utilizing several algorithms, including BDTR, DFR, BLR, and NNR. According to the results, M1 performs better when its parameter is tuned and cross-validated using BDTR. The accuracy of the model increases with the amount of input it receives. Given that BDTR has the largest coefficient of determination, it is the best regression designed for ACF. Using BDTR modeling, M1 exhibits a somewhat higher accuracy than M2. The investigation's findings showed that autonomous machine learning algorithms can reasonably forecast when it will rain. However, hybrid machine learning algorithms, which incorporate various climate change scenarios, may be able to predict rainfall with even greater accuracy.

The effect of meteorological conditions on rainfall forecast was examined by Pathan *et al.* in 2021. The researchers examine how different parameters affect rainfall. Five years' meteorological data from an American weather station was employed in this study. The gathered meteorological features were found to be correlated and interdependent. They discovered a considerable correlation between wind and rainfall, suggesting that strong winds have a significant impact on the occurrence of rainfall. They also discovered that the two most crucial factors in predicting rainfall are wind speed and lowest temperature.

Fatemeh *et al.* (2022) used CNN, LSTM, and PSO-SVR machine learning-based approaches to construct short-term rainfall forecasting that is based on statistics from the Niavaran station in Tehran, Iran. The techniques are utilized to create rainfall depth forecast models for both 5 and

15 minutes ahead. The study demonstrates that the PSO-SVR and LSTM approaches outperform the CNN approach in terms of forecast accuracy. The paper does not provide a detailed analysis of the computational requirements or computational efficiency of the different approaches, which could be important considerations for practical implementation of the forecast models.

Video-Based Convolutional Neural Networks Forecasting for Rainfall Forecasting was developed by Andrew *et al.* in 2022. The objective of the study was to enhance the present monthly regional precipitation forecasts by employing convolutional neural networks (CNNs) based on videos. Given anticipated mean sea-level pressure, 2-m air temperature videos, and benchmark rainfall data from the MetOffice GloSEA5 model. Three CNN architectures are trained for each region to predict monthly rainfall. While the overall accuracy of the individual models seems lower, they do significantly improve upon the GloSea5 model's underprediction of severe rainfall events. This analysis only took a few datasets into account.

Zhang *et al.* (2022) develop a CEEMD-WTD-GRU-based precipitation forecasting technique. The purpose of this work is to propose a new approach to precipitation forecasting that can increase the accuracy of precipitation prediction. The Wavelet Threshold Denoising (WTD) and Complete Ensemble Empirical Mode Decomposition (CEEMD) were used in the investigation. While WTD focused on IMF1–IMF3's high-frequency components to reduce noise in the original signal, CEEMD assisted in overcoming modal aliasing. To effectively handle problems with long-term memory and reflection, the GRU (Gated Recurrent Unit) model was used. The study uses the second decomposition of CEEMD-WTD-GRU to efficiently extract complicated time series information, thereby addressing the difficulties of uncertainty and unpredictability in precipitation forecasting. The research's CEEMD model lacks a noise reduction procedure.

A comparative analysis of machine learning techniques based on LSTM, Stacked-LSTM, Bidirectional-LSTM Networks, XGBoost, and an ensemble of Gradient Boosting Regressor, Linear Support Vector Regression, and an Extra-trees Regressor was carried out by Berrera-Animas (2022) to forecast rainfall. The Bidirectional-LSTM Network and the Stacked LSTM Network with two hidden layers fared the best out of all the models. The researcher suggested that future research should concentrate on optimizing the hyperparameters and parameters of the prediction models. The researcher also suggested considering an in-depth assessment of the features' significance and the addition of new meteorological parameters in order to increase the efficacy of the rainfall forecasting models.

In order to predict rainfall, Preethi and Valayutham (2023) conducted a comparative analysis of machine learning algorithms; the wavelet methodology with Artificial Neural Network (ANN). The researcher developed a model that, after being trained on a large amount of historical weather data, could forecast the amount of rainfall in any given place. Using the relevant statistical techniques, the models' calibration and validation performance is assessed. The monthly rainfall series modeling results show that wavelet neural network models outperform ANN models in terms of effectiveness. The researchers noted that in addition to addressing the model's security issues, future work may involve the application of other deep learning techniques.

Yoga *et al.* (2023) use the LSTM algorithm to forecast weather based on time series data. The project's objective was to develop a weather forecasting model that would use the Long-Short Term Memory (LSTM) algorithm to predict future weather conditions. Various meteorological elements were combined to train the LSTM neural networks. The Root Mean Square Error (RMSE) metric was used to evaluate the developed model. The study only looks at a small number of meteorological factor, however, adding pressure and dew point will improve the model's performance even more.

III. WEIGHTED AVERAGE ENSEMBLE LEARNING

The proposed research methodology is divided into four distinct phases, they are:

- (i) Dataset acquisition and Data pre-processing phase
- (ii) Ensemble machine learning model development and implantation phase
- (iii) Model performance evaluation phase
- (iv) Model deployment on android mobile app phase

The phases are depicted in the conceptual framework given in Figure 1.

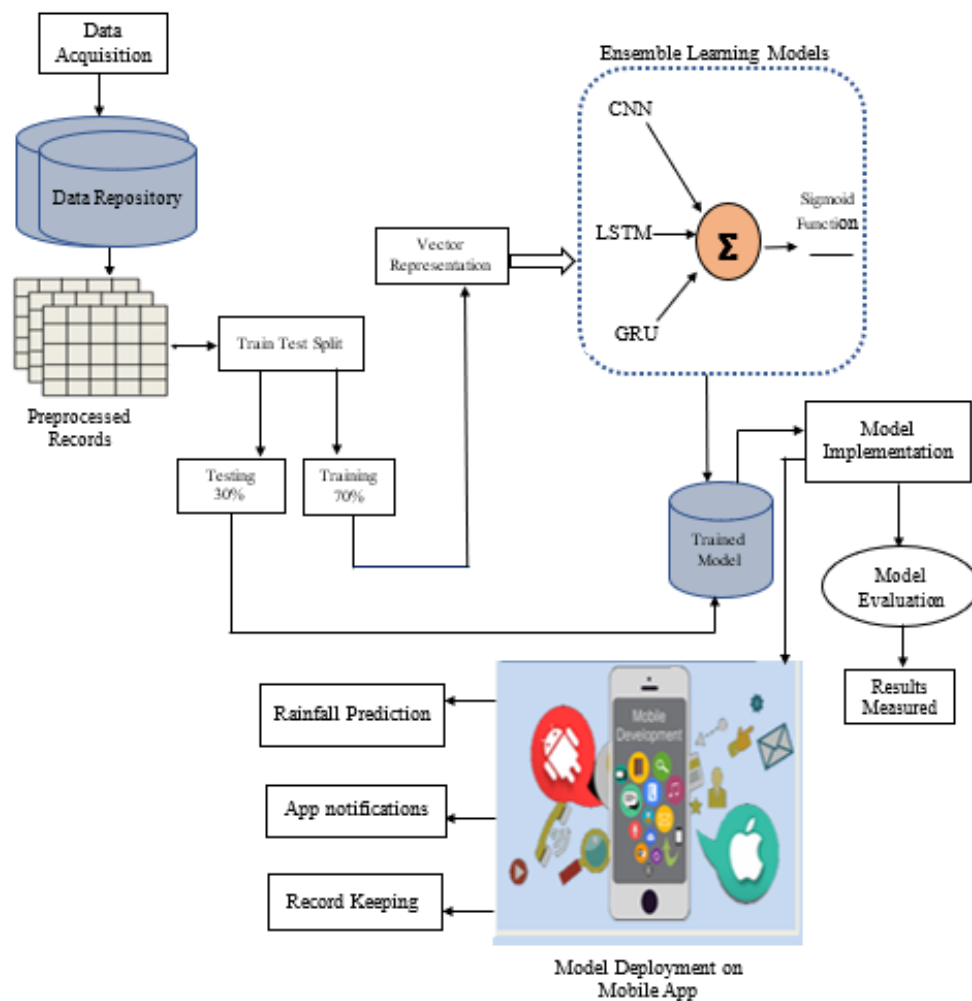


Figure 1: The Proposed Rainfall Forecasting System

The data acquisition is the first stage in this proposed study during which the sources, quantities, and other features of the data will be analyzed manually in order to identify them. Acquisition of short-term rainfall data will be done in this phase. The weather dataset of daily rainfall for six states (Ondo, Cross River, Imo, Kwara, Bauchi, and Kaduna) each representing the six geopolitical zones in Nigeria for 30 years between 1992 and 2022. Numerous real-time atmospheric surface metrics, including the amount of precipitation, relative humidity, temperature, dew point, wind speed, and surface pressure, will be included in the data.

Pre-processing of the data is necessary since noise and insufficient information often have a negative influence on raw data. Data cleansing and normalization are two typical pre-processing subtasks that will be used in this study. The missing numbers will be filled up using the mean average method. The Min-Max normalization procedure, which is outlined in Eq. 1, will be applied to an interval range of 0 to +1 in order to harmonize these values:

$$\gamma = \frac{(x-x_{min})}{x_{max}-x_{min}} \quad (1)$$

where

x is the data that requires to be normalized;

x_{min} is the minimum value for a given feature category;

x_{max} refers to the maximum value for a given feature category;

γ is the normalized data;

- (i) The second phase is the weighted average ensemble learning model development and implementation phase. The datasets will be divided into two set: training and testing. Test data will be used to evaluate the model's performance, while the training set will be used to train and fit the model. This research proposed a weighted average ensemble deep supervised learning that combines three machine learning algorithms, CNN, LSTM, and GRU. The benefit of CNN to automatically identifying key features without supervision by humans, good computational efficiency, carries out parameter sharing and unique convolution and pooling procedures. Furthermore, LSTM is quite effective at analyzing large amounts of data. The GRU algorithm's employment in this combination also has the benefit of making model training simple.

The addition of model weights will result in the weighted average ensemble-based learning. For the purpose of calculating the total prediction, each model is given a fixed weight that is multiplied by the forecast it makes. Every model in the classifier will have a different contribution depending on its model weight. Equation 2 displays the final weight output of the models from the classifier.

$$WC = w_i(CNN) + w_j(LSTM) + w_k(GRU) \quad (2)$$

where WC is the final weight of the ensemble classifier

w_i is the model weight of CNN

w_j is the model weight of LSTM

w_k is the model weight of GRU

- (ii) The third phase will involve model evaluation. The purpose of evaluating the model is to confirm and ensure that the full-scale deployment will be successful. The following standard metrics: Mean Square Error, Root-Mean-Square Error, Mean Absolute Error, Relative Error, Percentage Relative Error, and Accuracy discussed in Equations (3-8) will be used to evaluate the model.

Mean Square Error (MSE): At high output levels, the MSE value shows how well the model fits the data. The model fit is better when the MSE is less. This evaluation is calculated as shown in Eq. 3.

$$MSE = \frac{\sum_{i=1}^n (X_i - \bar{X}_i)^2}{n} \tag{3}$$

where X_i are observed values and \bar{X}_i are modeled outputs for rainfall and n is number of observations.

Root-Mean-Square Error (RMSE): The RMSE is a good measure of prediction accuracy. An RMSE value of 0 would represent a perfect fit to the data because it is always non-negative. Generally speaking, a smaller RMSE is preferable to a greater one.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_i - \bar{X}_i)^2}{n}} \tag{4}$$

where X_i are observed values and \bar{X}_i are modeled outputs for rainfall and n is number of observations.

Mean Absolute Error (MAE): It determines the average by taking the absolute difference between the predicted and actual values. The model fit is better when the MAE is less.

$$MAE = \frac{\sum_{i=1}^n |X_i - \bar{X}_i|}{n} \tag{5}$$

where X_i are observed values and \bar{X}_i are modeled outputs for rainfall and n is number of observations.

Relative Prediction Error (E): If the relative prediction error is small enough, or nearly zero, it is considered good.

$$E = \frac{\langle |(\bar{X}_i - X_i)| \rangle}{\langle X_i \rangle} \tag{6}$$

where $\langle \rangle$ implies the average over the whole test set.

Percentage Relative Prediction Error (PE) is computed in Eqn. (7)

$$PE = \frac{|(\bar{X}_i - X_i)|}{X_i} \times 100 \tag{7}$$

Relative Accuracy (A): The calculation of Relative Accuracy involves deducting accuracy from 100. $A = 100 \text{ percent} - PE$ (8)

(iii) The fourth phase is the model deployment on the android mobile app and testing phase. Results will be in a graphical chart for easy understanding. In this phase, a mobile app will be developed that embeds the ensemble model developed. Also in this phase, pilot test will be conducted on a sampled population in the case studies areas. The mobile app will be installed on volunteer's mobile devices for full scale deployment.

The android mobile app will have the following key features:

- (i) **Rainfall Predictions:** This rainfall forecast app feature will forecast daily rainfall
- (ii) **App notifications:** This will notify the various app users on daily rainfall prediction as well as degree of the rainfall indicating 'cloudy', 'partly cloudy', and 'very cloudy' to provide accurate information.
- (iii) **Record Keeping:** This feature will keep records of previous prediction for easy reference.

IV. CONCLUSION AND FUTURE WORKS

Rainfall prediction is still a major global concern that has caught the interest of businesses, governments, risk management organizations, and scientific communities. Predicting rainfall accurately and on time can be highly beneficial in taking preventative precautions against flooding, construction projects, transportation, agriculture, flying operations, and other potential threats. Prediction of rainfall has inspired diverse approaches from numerical weather prediction, regression analysis, computational and artificial intelligence techniques. However, there is the need to obtain quicker and accurate rainfall prediction over period of time because of the influence exacted across various fields of human endeavour. This study proposed an intelligent mobile app for rainfall prediction using weighted average ensemble deep supervised learning. The next stage of this research is to completely implement the proposed model with real-life datasets. Also the proposed model will be deployed on the android mobile app and pilot test will be conducted on a sampled population in the case studies areas. The proposed AI mobile app will help in creating awareness to the people, government officials, planning agencies, disaster management agencies, and related institutions in taking an effective decision in forestalling future outbreaks of rainfall hazards.

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