CROP YIELD AND WEATHER PREDICTION

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ABSTRACT: A promising study area has been predicting agricultural production based on environmental, soil, water, and crop characteristics. Deep-learning-based algorithms are widely employed in crop prediction to extract key crop traits. These technologies may solve the problem of yield prediction, but they have the following drawbacks: The effectiveness of such models is highly dependent on the quality of the derived features due to the difficulty of creating a direct non-linear or linear mapping between raw crop yield numbers and data. By providing direction and motivation, deep reinforcement learning overcomes the deficiencies mentioned earlier. Profound support realizing, which consolidates the intellectual prowess of support learning with profound learning, delivers a total system for crop yield expectation equipped for changing crude information into crop expectation values. Based on the reinforcement learning algorithm Q-Learning, the proposed work constructs a Deep Recurrent Q-Network model that is used to forecast agricultural output. The stacked layers of the recurrent neural network are fed by the data parameters. The Q-learning network creates an environment for crop production prediction based on the input parameters. The Recurrent Neural Network's output values are transformed into Q-values by a linear layer. To help predict crop yield, the reinforcement learning agent incorporates the threshold and parametric parameters. Last but not least, the agent receives a total score based on the measures taken to reduce prediction errors and improve accuracy. With an accuracy of 93.7%, the suggested model outperforms current methods in predicting crop production while keeping the original data distribution.

***Keywords** – RNN, LSTM, Deep Q Network, RF and XGBoost Classifiers.*

1. INTRODUCTION

Farming is a critical subject important to society since it creates a colossal piece of food. Numerous countries are as yet encountering hunger because of an absence of food and a rising populace. Growing food creation is a persuading strategy regarding destroying starvation. The Assembled Countries intend to achieve significant goals by 2030, including achieving food security and reducing hunger. In this way, crop assurance, land assessment, and crop yield measurement become increasingly important to global food production. In order to strengthen public food security, a nation's policymakers rely on precise gauges to make reasonable product and import assessments. Ranchers and farmers may also use yield anticipation to support financial and administrative decisions. Rural management, especially crop creation checking, is basic in deciding a district's food security. Crop creation determining, then again, is truly challenging because of various confounded factors.

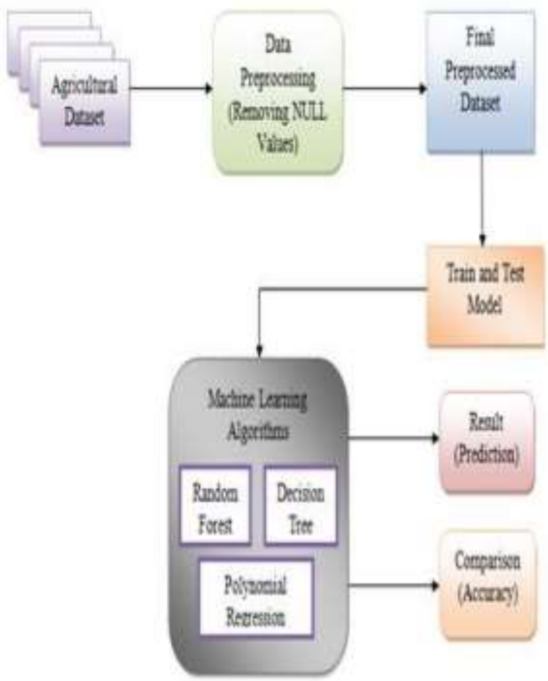

Fig.1: Example figure

Crop creation not entirely settled by meteorological conditions, soil quality, scenes, bug invasions, water quality and accessibility, genotype, collect action arranging, etc. Crop yield cycles and strategies change over time and are profoundly non-direct and complex, as evidenced by the coordination of a wide range of related parts that are characterized and affected by external causes and non-mediate runs. Managing convoluted, fragmented, confounding, and combative measurements frequently results in the inability to outline a crucial component of the horticultural structure in an essential stepwise calculation. Many exploration presently show that machine learning(ML) calculations have a higher potential than conventional measurements. ML is a part of man-made consciousness where PCs might be taught without unequivocal programming. With extraordinary anticipating power, these calculations settle non-straight or direct farming settings. ML farming systems get their procedures from the growing experience. These techniques need overtraining to finish a specific objective. The model makes assumptions to test the data after the preparation stage.

2. LITERATURE REVIEW

Probabilistic maize yield prediction over East Africa using dynamic ensemble seasonal climate forecasts

We looked into whether occasional climate projections could be used to predict influence in eastern Africa. We investigated whether the capacity of these occasional gauges to estimate maize yield evolved into capacity to anticipate maize yield. We constructed a 15-part team of yield expectations by utilizing the crop model from World Food Studies (WOFOST) and occasional environment forecasts from the framework 4 gathering of the European Centre for Medium-Range Weather Forecasts (ECMWF) for the period 1981-2010 at various introduction dates prior to planting. The WATCH Forcing Data ERA-Interim (WFDEI) is used to compare maize yield measurements to reference yield records, focusing on the planting dates that are most common in the northern (July), central (March-April), and southern (December) districts. When compared to actual FAO and public revealed figures, these reference yield values have significant strengths for display relationships; However, while the normal reference yield values are somewhat higher in Tanzania, they are lower in Kenya and Ethiopia. To quantify areas of powerful probabilistic forecast, we employ the outfit mean, interannual changeability, mean errors, Ranked Probability Skill Score (RPSS), and Relative Operating Curve Skill Score (ROCSS). In many locations, year-to-year yield anomalies can be anticipated two months prior to planting. The estimated yield has greater interannual variability than the reference yield, but the difference in interannual changeability between the two yields ranges from 40% to 60%. With about two months' notice, the ROCSS provide accurate probabilistic forecasts of yields that are higher than average and lower than average for the upcoming season. We discovered that unique water-restricted maize yields can be predicted using dynamical occasional environment forecasts and the cycle-based crop recreation model WOFOST, given the various planting dates that were taken into consideration.

Deep reinforcement learning with its application for lung cancer detection in medical Internet of Things

By incorporating deep learning models into support learning calculations in a variety of applications, including computer games and mechanical technology, deep reinforcement learning has recently demonstrated significant success. Consolidating profound support learning with clinical enormous information made and accumulated through the clinical Internet of Things(IoT) is exceptionally encouraging for PC helped finding and treatment. We focus on the capability of profound support learning for cellular breakdown in the lungs finding in this examination since many individuals experience the ill effects of cellular breakdown in the lungs and around 1.8 million people passed on from cellular breakdown in the lungs in 2018. Early recognizable proof and analysis of cellular breakdown in the lungs might increment treatment adequacy and expand life. In this paper, we depict different commendable profound support learning models that may be utilized to recognize cellular breakdown in the lungs. Moreover, we portray the most predominant sorts of cellular breakdown in the lungs and their fundamental elements. At long last, we feature the open hindrances and potential future exploration ways of utilizing profound support figuring out how to recognize cellular breakdown in the lungs, which is anticipated to help the improvement of shrewd medication with the clinic IoT.

Early assessment of crop yield from remotely sensed water stress and solar radiation data

Due to the high interannual variation in the production of rain-fed crops in major agrarian regions, soil moisture (SM) that is available for evapotranspiration is essential for food security. In a similar vein, approaching solar radiation (Rs) has an effect on the photosynthetic rate of vegetated surfaces, which may have an effect on efficiency. The purpose of this study is to determine whether or not data on water pressure and Rs can be used to measure regional development. The yield water pressure and soil dampness accessibility were measured using the Temperature Vegetation Dryness Index (TVDI). MODIS items were used to evaluate TVDI during harvests' crucial development phase: MODIS/Water. At one kilometer, there is an eight-day composite LST and a composite vegetation record. The Earth's Radiant Energy System and clouds were used to investigate the connection between TVDI, Rs, and yields of wheat, maize, and soybeans. High R2 values (0.55-0.82, depending on yield and region) were observed in a few agroclimatic regions of the Argentine Pampas. The model's reasonableness was demonstrated by approval findings: Absolute Error: 13-34%, RMSE: 330-1300 kg ha-1. However, the outcomes significantly improved when the most significant yield-influencing factor was taken into consideration. It has been demonstrated that in damp areas where approaching radiation may be restricting, Rs is beneficial for winter crops. Crop water pressure produced the best results in semi-dry regions, soils with limited water maintenance limits, and summer crops. In general, the findings demonstrated that the proposed method can be used to estimate crop production at the provincial scale a few weeks before harvest.

Machine learning for high-throughput stress phenotyping in plants

Robotization and high-throughput imaging advancements have brought about a surge of high-goal plant photographs and sensor information. To permit information absorption and component ID for stress phenotyping, notwithstanding, distinguishing examples and elements from this enormous corpus of information requires the utilization of machine learning (ML) advancements. Different ML strategies might be utilized at four periods of the choice cycle in plant pressure phenotyping and plant reproducing exercises: I ID, (ii) grouping, (iii) measurement, and (iv) expectation (ICQP). We give a total outline and easy to understand scientific categorization of ML devices to assist the plant local area with involving the right ML instruments and best-practice suggestions for different biotic and abiotic stress highlights.

Rainfall prediction for the Kerala state of India using artificial intelligence approaches

From 2011 to 2016, three computerized reasoning methods—K-nearest neighbor (KNN), artificial neural network (ANN), and extreme learning machine (ELM)—were used to occasionally determine the precipitation during summer storms (June to September) and post-rainstorms (October to December) in Kerala, India. Their exhibition is compared to perceptions. All of the previously mentioned techniques functioned admirably, but the ELM approach beat the KNN and ANN methodology as far as mean outright rate blunder scores throughout the mid year storm (3.075) and post-rainstorm (3.149), separately. How much secret hubs in the secret layer to a great extent affects forecast precision, and the ELM configuration gives more exact outcomes (8-15-1). This exploration exhibits that the proposed man-made consciousness frameworks have the ability to expect both the late spring storm and the post-rainstorm of Kerala, India, with low forecast blunder scores.

3. METHODOLOGY

Deep- learning-based models are broadly utilized in existing frameworks to extricate basic yield attributes for expectation. However these methodologies possibly address the yield expectation issue, they have the accompanying weaknesses: The viability of such models is strongly dependent on the nature of the extracted highlights, as it is difficult to construct a straight non-direct or direct planning between crude information and harvest yield values.

Disadvantages:

- ANN's shallow learning strategy confused non-direct connections in the yield expectation framework, and manual component extraction for yield expectation heavily relies on previous information on the data. Such issues have been addressed somewhat with the advancement of profound learning.

A Deep Repetitive Q-Organization model, which is an Intermittent Brain Organization profound learning calculation based on the Q-Learning support learning calculation, is created in the proposed work to anticipate horticultural creation. The information boundaries feed the progressively stacked layers of the Intermittent Brain organization. In light of the information boundaries, the Q-learning network establishes a yield creation expectation climate. Over the Recurrent Neural Network's upsides, a straight layer transforms into Q-values. In order to support crop creation forecast, the support learning specialist combines the limit with parametric attributes. At last, the specialist procures a general score for the means taken to limit blunder and boost expectation exactness.

Advantages:

- ❖ With an accuracy of 93.7%, the suggested model outperforms current methods in predicting crop production while keeping the original data distribution.

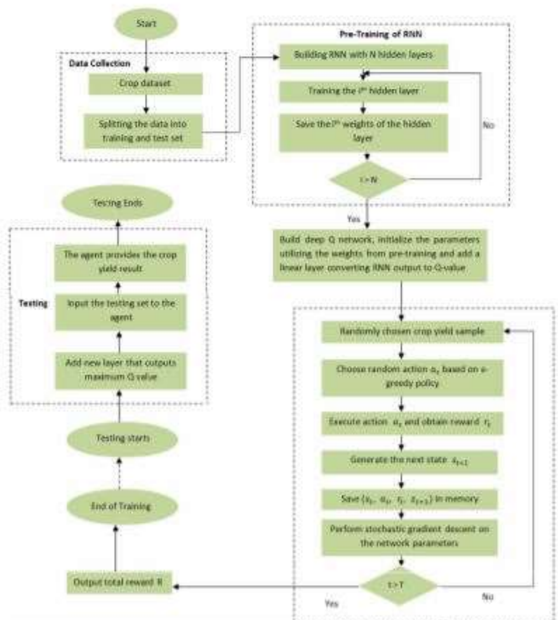

Fig.2: System architecture

MODULES:

To carry out the aforementioned project, we created the modules listed below.

- Information investigation: We will stack information into the framework utilizing this module.
- Handling: We will peruse information for handling utilizing this module.
- Splitting data into train and test: We will divide data into train and test using this module.
- Model generation: We will build RNN,LSTM,Deep Q Network,RFAnd XGBoost ClassifiersAlgorithms accuracy will be calculated.
- User input: Using this module will provide input for prediction
- Prediction: the final projected value will be presented

4. IMPLEMENTATION

The following algorithms were utilised in this research.

RNN:

Recurrent neural networks(RNN) are artificial neural networks that are broadly used in voice acknowledgment and regular language handling. RNN notice designs in information and use them to estimate the following likely result.

LSTM:

LSTM is a contraction for long short-term memory organizations, which are used in Profound Learning. It is a sort of recurrent neural networks (RNNs) that might learn long haul conditions, especially in succession forecast undertakings.

Deep Q Network:

Reinforcement There are two sorts of learning calculations: model free and display based RL calculations. To conjecture future states and rewards, model free RL calculations don't prepare a model of their current circumstance's change capability. Without model calculations incorporate Q-Learning, Profound Q-Organizations, and Strategy Inclination since they don't produce a model of the climate's change capability.

RF:

Random Forest is a managed ML procedure that creates and consolidates a few choice trees to shape a "woods." It could be utilized in R and Python for order and relapse undertakings.

XGBoost Classifiers:

XGBoost is a conveyed gradient boosting tool compartment that has been created to be exceptionally effective, versatile, and compact. It utilizes the gradient boosting system to build ML calculations.

5. EXPERIMENTAL RESULTS

Fig.3: Home screen

Fig.4:User Input for crop

Fig.5: Prediction result

Fig.6: User input for temperature

Fig.7: Prediction result for temperature

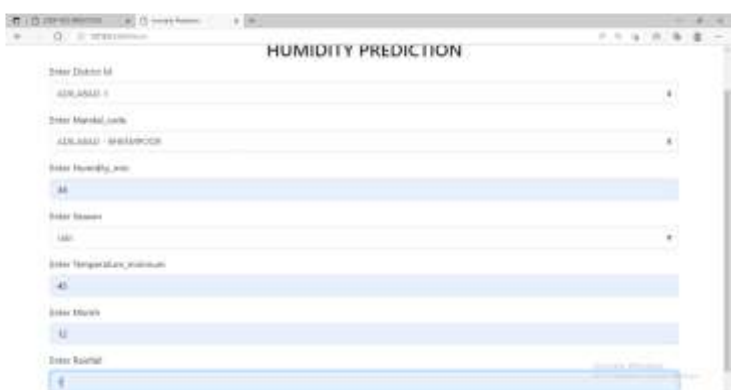

Fig.8: User input for humidity

Fig.9:Prediction result

6. CONCLUSION

A one-of-a-kind agricultural output prediction system was developed as a result of DRL research, boosting the independence and intelligence of AI algorithms. The suggested Deep Recurrent Q-Network is useful and adaptable for yield prediction, as demonstrated by the efficiency and accuracy testing results. By creating a yield prediction environment, the suggested strategy enables the agent to self-explore, experience repeat crop yield prediction detection, and learn. The results of the dataset prediction show that the yield prediction agent is in charge of the process, indicating that the suggested method can accurately define the characteristics of crop yield. The primary objective is to combine RNN-based feature processing with DQN-based self experimental analysis. The DRQN-based method offers a comprehensive solution that isolates the non-linear mapping between crop yield and climate, soil, and groundwater properties, in contrast to the supervised learning-based crop yield prediction approach. When developing agricultural production prediction models, this advantage may significantly reduce the amount of expert reliance on previous information. As a result, the suggested method recommends using a more extensive model for yield prediction. However, the RNN-based DRL may cause the gradients to burst or evaporate if the time series is too long. It is essential to comprehend the statistical uncertainty associated with these predictions, even though experimenting with data prediction using a variety of machine learning predictive algorithms may serve as a basis for decision-making. Consequently, it is necessary to construct a framework that predicts their prediction's purpose and uncertainty. Probabilistic predictive modeling strategies like information theory, probabilistic bias-variance decomposition, composite prediction strategies, probabilistic boosting and bagging approaches, and so on can be taken into consideration to deal with the uncertainty in statistical predictions that can be observed as a future extension of the existing model. Utilizing a DRL based on an LSTM is yet another method of research.

7. FUTURE SCOPE

In order to construct a functional model that is more extensive, new agricultural production prediction factors related to pests and infestations, as well as crop damage, may be incorporated into the existing framework in the future. An exciting alternative that ought to be pursued is enhancing the training process's computational efficiency.

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