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Enhancements in agricultural forecasting in bundelkhand facilitated by the use of artificial intelligence

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Abstract:

The Bundelkhand region comprises more than fifty percent of Uttar Pradesh's total pulse farming area, although its output is inferior to the state average. This requires the execution of many technical interventions, alongside the establishment of infrastructure as well as marketing tactics. Developing sophisticated predictive models is crucial for properly forecasting crop yields, as changes in the climate and rising unpredictability intensify the worldwide food safety dilemma. A sophisticated prediction model for projecting crop yields was created to tackle these difficulties. The model aimed to address concerns about global food security in light of the increasing population. The study focuses on eleven widely farmed crops in Bundelkhand. The Bundelkhand area produces crops like cassava, maize, potatoes, rice (paddy), soybeans, and wheat. Groundnut, cotton, mustard, and cotton. The integration of Artificial Neural Networks, or ANN, alongside the Optimization Algorithm resulted in the development of an artificial intelligence system designed to accomplish this goal. The model integrates meteorological conditions, pesticide use, and historical yield data.After training the ANN with an improved model using 70 percent of the data that was accessible, we assessed its performance with the final thirty percent. A comparison was performed between the model's accuracy and that of ANN models, using statistical benchmarks. The suggested model surpassed other models, attaining superior measurements with an RMSE of 14.83, MAE of 88.53, MAPE of 0.07, and a R^2 of 0.98 overall agricultural production prediction. The results demonstrate an improvement in the accuracy and reliability of agricultural output forecasts compared to the currently used methods. A comprehensive system aimed at augmenting agricultural production forecasting via enhanced predictive skills, hence possibly improving the effectiveness of resources and optimizing crop management, is shown by the proposed model. This study illustrates the capacity of machine learning to tackle global agricultural issues and improve food security measures, holding substantial importance for agricultural strategy and formulation of policies.

INTRODUCTION:

To ensure global food security, accurate forecasting of agricultural[1] production is crucial. It provides assistance to firms in formulating efficient planning and aids governmental choices about trade in goods. Moreover, however harvest forecasting is essential for agricultural decision-making, it is a challenging[2] endeavor owing to the many variables that might affect it. Moreover, it aids in the formulation of policies and emphasizes critical factors that augment production. Farmers adjust their crop yields according to changing environmental[3] circumstances, whereas conventional forecasting relied on farmers' intuition.Nevertheless, contemporary forecasting aids in bridging information gaps that arise from this diversity.A multitude of factors may influence agricultural productivity. These elements include environmental circumstances[4], agricultural techniques, and characteristics specific to each crop variety. The development of a reliable and interpretable model for predicting harvest results has many substantial obstacles. This is due to the aforementioned circumstances.

Forecasting agricultural output is a complex task, but it has the ability to drastically decrease the uncertainty around food production. In contrast, precise forecasting is difficult owing to the many variables influencing agricultural output. These risks include unexpected disease epidemics and devastating[5] natural calamities. To tackle this pressing problem, it is critical to devise techniques that are both inventive and flexible to adeptly maneuver through the dynamic agricultural landscape. Artificial intelligence (AI) provides several effective solutions by using vast datasets and discerning intricate, nonlinear correlations among significant variables. The use of sophisticated artificial intelligence techniques in agricultural production forecasting facilitates the discovery and modeling of intricate, nonlinear interactions among many parameters, resulting[6] in more accurate forecasts. Common practices include the use of ensemble algorithms for machine learning, regression analyses, statistical approaches, adapting neural-fuzzy inference engines [7], including neural networks, among other models developed using deep learning.

Recently, the agricultural industry has seen a notable increase in the use of machine learning (ML) techniques, especially since the turning point of the twenty-first century. Artificial neural networks (ANNs) are a useful tool for addressing agronomic difficulties [8]. Artificial Neural Networks (ANNs) demonstrated significant efficacy in the detection and categorization of crop protection measures. Advanced algorithms have been important in automating harvesting procedures [9] and improving the precision of product quality categorization .

Traditional machine learning methods struggle to identify characteristics and analyze intricate agricultural data. Deep learning and machine learning models are used to forecast crop yields; yet, problems include converge to local optima, restricted parameter adjustment, and high-dimensional farming datasets remain prevalent [10].

Studies demonstrate that swarm-based optimization enhances the design and parameter calibration of neural network algorithms [11]. Bio-inspired algorithms intelligently construct network topologies and improve connection weights as well as prejudice factors more efficiently than gradient-based approaches. Estimating agricultural production using neural network parameters requires the use of advanced optimization methods [12-13].Advantages of swarm intelligence.

BACKGROUND STUDY:

A select few of the many studies that have been conducted by a variety of authors for the purpose of crop forecasting using AI are described below.

B. Patidar et al. [15] evaluated agricultural productivity with machine learning methodologies. The research highlighted the significance of precise output forecasts in agriculture, especially in India. It examined temperature, precipitation, fertilizer use, historical yield, and economic variables including the minimum support price. The effects of gradient boosters, Support Vector Machines, Decision Trees, Random Forests (RF), as well as Linear Regression were examined. We concluded that Linear Regression accurately predicted agricultural production. Dhaliwal and Williams [17]. The random forest model performed best using 3.29 Mt/ha RMSE value and 0.77 correlation. The study found that year, location, seed supplier, and meteorological were most important. Advanced analytics may enhance commercial sweet corn farming, according to this study.

Recent research on predictive accuracy underscores the importance of hybrid modeling methodologies. In a comprehensive public soybeans dataset, Oikonomidis et al. [18] shown that the CNN-DNN hybrid model surpassed all other models, including traditional methods. Hybrid deep learning systems can assess production from intricate, non-linear agricultural information. Gaso et al. [19] examined 700,000 soybean production data points obtained from Sentinel-2 imaging, meteorological conditions, and geographic data across 310 farms from 2020 to 2022. All of the deep learning models (1D-CNN, LSTM, while Transformers) exceed the baseline in geographical prediction, with the 1D-CNN exhibiting superior performance concerning topography.

Machine learning-based agricultural production forecasting has been ineffectual.

Despite certain limitations, Decision Trees, Support Vector Machines, K-Nearest Neighbors, and Random Forest algorithms demonstrate effective performance in agricultural data management.

Overfitting, computational time, and scalability represent substantial obstacles.Recent investigations suggest that metaheuristic optimization alongside deep learning methodologies may enhance the precision of agricultural production forecasts. This integrated approach mitigates forecasting limitations, thereby improving agricultural productivity [19-20]. The utilization of Artificial Neural Network (ANN)-Levy models enhanced the accuracy of Crop Outcome Assessment (COA) agricultural projections. The global search capability of the Levy flight-enhanced COA improves the efficacy of artificial neural networks when applied to large, nonlinear agricultural datasets.

PROPOSED METHODS AND DATSET

The Organization for Food and Agriculture maintains a comprehensive database relevant to food and agricultural systems in the Bundelkhand area. This institution manages the management of the comprehensive database. The information includes essential elements such as the particular farming product, crop yield, rainfall levels, pesticide use, and temperature readings, including 10 unique types. Moreover, the file includes information on atmospheric conditions. The provided information encompasses yearly statistics on nations, agricultural products, and associated yields. The data covers the timeframe from 2010 to 2024.

Precipitation and temperature constitute two elements that profoundly affect agricultural production. Climatic factors significantly impact agriculture production. Moreover, environmental influences, including pesticide use, affect the comprehensive growth of crops. The pesticide data for each agricultural item was obtained from the repository managed by the FAO.

DATA PROCESSING:

The first step comprises the cleansing of data collected from public sources. This phase begins immediately after the acquisition of the specified data. Upon concluding this procedure, categorical variables, including particular agricultural kinds, are converted into numerical values using label encoding. This converts category variables into quantitative representations.A variety of crucial attributes are anticipated to be included into the produced information. These features include encoded identities for crops and nations, production year, yield statistics, average precipitation, pesticide use, and mean temperature.

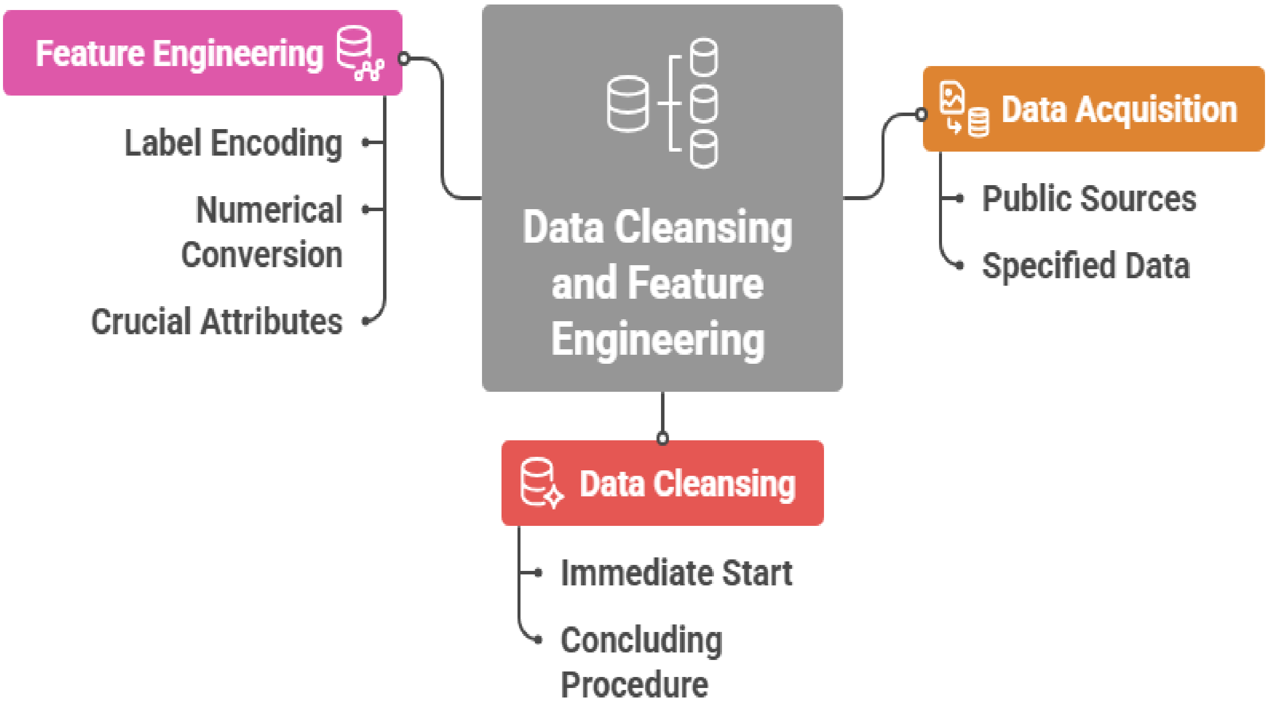

Figure 1: Show the data preprocessing

All subsequent characteristics are included in the ultimate dataset: Crop Type, Cultivation Year, Yield per Hectare, Average Annual Rainfall (mm), Pesticide Usage (tons), and Mean Temperature

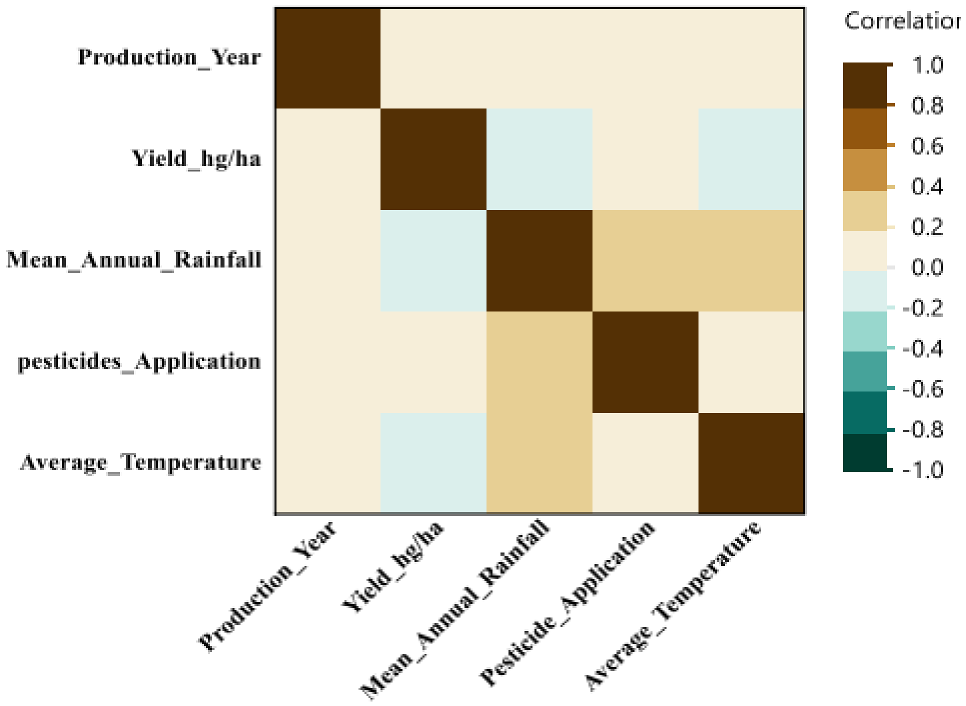

Figure 2: In this heat map, the correlation matrix with the yield variable is shown.

The dataset has two columns containing categorical data. The columns are labeled as Crop_Type as well as Nation. It is crucial to acknowledge that these category variables intrinsically lack any correlation with other aspects. In contrast, a significant percentage of machine learning techniques need that every one of the output and input variables be represented numerically. This is because these methods are not explicitly intended to handle labeled data directly. Therefore, it is essential to transform this classified data into numerical information to enable further analysis.

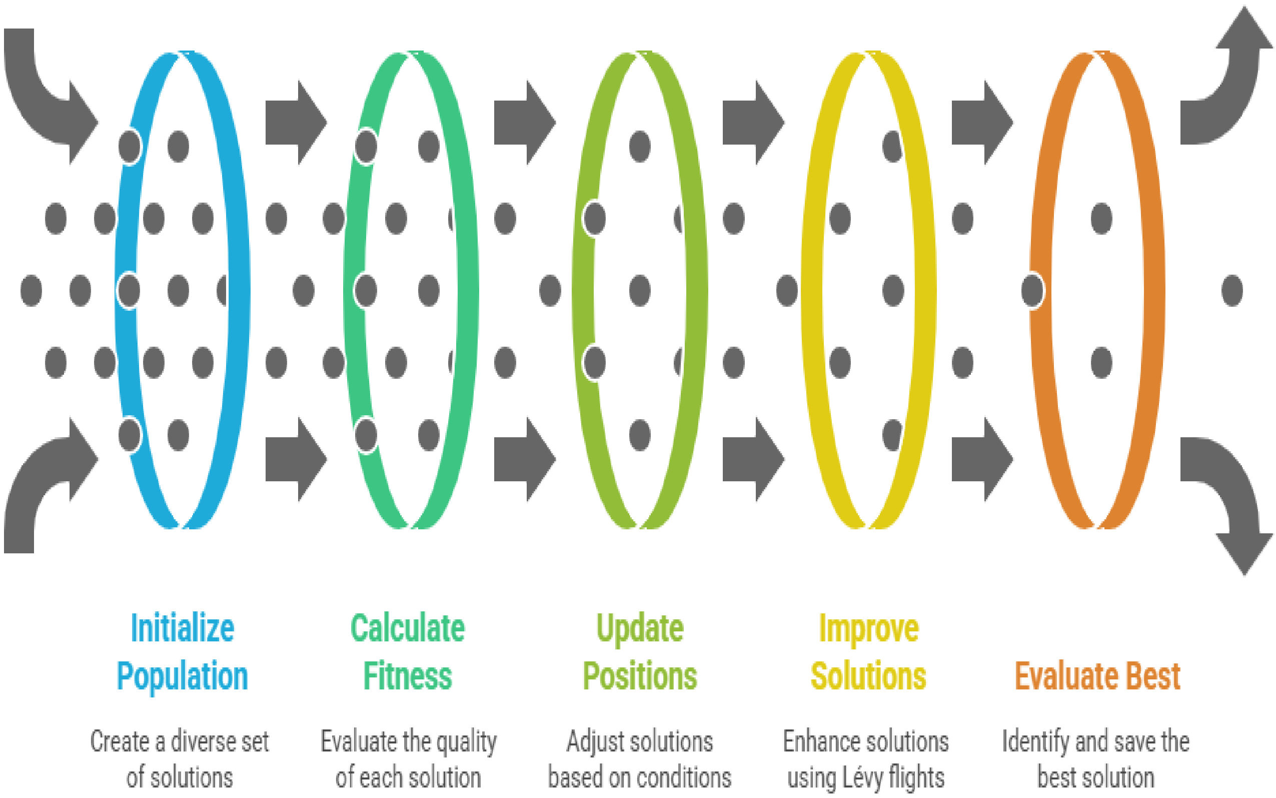

Figure 3:Optimization Process Funnel

Following are the steps of process funnel

1. Input data and adjust parameters (specify the population size and the iteration count).
2. Assess the population's fitness level and initialize it.
3. Modify the positions according to the criteria (you may use either updating rules or random positions based on a and n).
4. Improve current solutions with the use of Lévy flights
5. Suggest and document the most effective treatment.
6. Continue iterating until the maximum iteration limit is reached.
7. Generate the most optimal response

This section is dedicated to the methodology of forecasting agricultural production, considering various input factors. These variables encompass the nation, crop type, year, average precipitation, pesticide application, and mean temperature levels. Artificial neural networks (ANN) along with meta-heuristic optimization techniques are also incorporated into this methodology. To assess the potential advantages of this proposed approach, four key statistical metrics were employed.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - \widetilde{Y}_i)^2}$$	(1)
$$MAE = \frac{1}{N}\sum_{i=1}^{N}\lvert Y_i - \widetilde{Y}_i\rvert$$	(2)
$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{Y_i - \widetilde{Y}_i}{Y_i}\right\rvert$$	(3)

The performance of the proposed model as determined by variable exclusion analysis, displaying absolute error metrics in hg/ha.

Parameters	R^2	RMSE	MAE
Mean_Annual_Rainfall & Average_Temperature	0.717	88,332	67,170
Crop_Type	0.190	85,332	66,622
Mean_Annual_Rainfall	0.591	66,150	45,641
Average_Temperature	0.721	49,007.09	29,570
Pesticide_Application	0.791	42,013	27,652

CONCLUSION:

This study introduces decision support instruments for global policymakers and producers. These instruments are intended to forecast the output of ten major commodities globally from 2010 to 2024. This extensive examination examines cassava, maize, potatoes, rice (paddy), legumes, & wheat. Cotton, mustard, groundnut, and cotton are the principal necessities. The research used data from the Food and Agriculture Organization, examining many criteria such as agricultural production, pesticide usage, temperature, cultivated area, crop type. A distinctive hybrid model integrating artificial neural networks (ANN) as well as optimization was developed to enhance prediction accuracy. The optimization process was enhanced by using strategies that augment exploration capabilities and inhibit the emergence of local optimum solutions. The artificial neural network (ANN) paradigm was assessed by comparing its effectiveness with that of other hybrid models, including the optimization technique and the traditional ANN approach. Various statistical criteria were employed in the conducted performance assessments.The feasibility study indicates that the model is successful across many agricultural systems, crop kinds, and growth circumstances, thereby confirming its appropriateness for actual agricultural decision-making. Future ambitions include the incorporation of supplementary datasets and the exploration of meteorology through remote sensing. We want to examine diverse and cross-sectional agricultural data using ANN-Optimization and Transformer models. Our objective is to improve the model and support farmers and agricultural authorities in making educated choices on crop management.

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