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INTELLIGENT BASED CROP PREDICTION FOR AGRICULTURE APPLICATION

M.PANDILAKSHMI 1 and DR.S.SUGANTHI 2

1 Final Year PG Student, 2 Assistant Professor.

Department Of Computer Science,

G.Venkataswamy Naidu College,

Kovilpatti,

Tamil Nadu, India.

ABSTRACT:

Agriculture is one amongst the substantial area of interest to society since a large portion of food is produced by them. Agriculture is the most important sector that influences the economy of India. Predicting crop yield based on the environmental, soil, water and crop parameters has been a potential research topic. Agriculture for years but the results are never satisfying due to various factors that affect the crop yield. Deep-learning-based models are broadly used to extract significant crop features for prediction. Though these methods could resolve the yield prediction problem there exist the following inadequacies: Unable to create a direct non-linear or linear mapping between the raw data and crop yield values; and the performance of those models highly relies on the quality of the extracted features. Finally, the agent receives an aggregate score for the actions performed by minimizing the error and maximizing the forecast accuracy. The input is taken from the dataset repository. The system is developed with the KNN and Logistic regression for predicting the crop .Finally, the experimental results shows that the accuracy, precision, recall, and f1-score.

INTRODUCTION:

Agriculture is one of the substantial area of interest to society since a large portion of food is produced by them. Currently, many countries still experience hunger because of the shortfall or absence of food with a growing population. Expanding food production is a compelling process to annihilate famine. Developing food security and declining hunger by 2030 are beneficial critical objectives for the United Nations. Hence crop protection; land assessment and crop yield prediction are of more considerable significance to global food production.

Further, machine learning resembles an umbrella that holds various significant strategies and methodologies. On observing the most prominent models in agriculture, we can see the utilization of artificial and deep neural networks. Deep learning is a subgroup of machine learning that can determine outcomes from varying arrangements of raw data. Deep learning algorithms, for example, can develop a probability model by taking a decade of field data and providing insights about crop performance under various climatic conditions.

Data scientists utilize various machine learning algorithms to derive actionable insights from the available information. Another intriguing area of artificial intelligence is reinforcement learning. These can be examined as an essential class of algorithms that can be utilized for streamlining logic for dynamic programming. Reinforcement learning is the preparation of machine learning models to make decision sequences. The agent learns to accomplish an objective in an ambiguous, potentially complex environment. Based on the agent's action, the environment rewards it. This scenario depicts the machine as the agent and its surroundings as the environment.

As a coastal state, Tamil Nadu faces uncertainty in agriculture which decreases its production. With more population and area, more productivity should be achieved but it cannot be reached. Farmers have had word-of-mouth in past decades but now it cannot be used due to climatic factors. Agricultural factors and parameters make the data to get insights about the Agri-facts.

The growth of the IT world drives some highlights in Agriculture Sciences to help farmers with good agricultural information. The intelligence of applying modern technological methods in the field of agriculture is desirable in this current scenario. Machine Learning Techniques develop a well-defined model with the data and help us to attain predictions. Agricultural issues like crop prediction, rotation, water requirement, fertilizer requirement, and protection can be solved. Due to the variable climatic factors of the environment, there is a necessity to have an efficient technique to facilitate crop cultivation and to lend a hand to the farmers in their production and management.

This may help upcoming agriculturalists to have better agriculture. A system of recommendations can be provided to a farmer to help them in crop cultivation with the help of data mining. To implement such an approach, crops are recommended based on climatic factors and quantity. Data Analytics paves the way to evolve useful extraction from the agriculture database. Crop Dataset has been analyzed and recommendation for crops is done based on productivity and season.

Tamil Nadu is the 7th largest location in India the has sixth largest populace. it's miles the main producer of agriculture merchandise. Agriculture is the main career of Tamil Nadu people. Agriculture has a valid tone in is aggressive world. Cauvery is the main supply of water. Cauvery delta regions are called as the bowl Tamil Nadu. Rice is the essential crop grown in Tamil Nadu. different vegetation like Paddy, Sugarcane, Cotton, Coconut and groundnut is grown. Bio-fertilizers are produced effectively. Many areas Farming acts as major source of occupation.

Agriculture makes a dramatic impact on the economy o f a country. Due to the change of natural factors, Agriculture farming is degrading now-a-days. Agriculture directly depends on the environmental factors such as sunlight, humidity, soil type, rainfall, Maximum and Minimum Temperature, climate, fertilizers, pesticides etc. Knowledge of proper harvesting of crops is in need to bloom in Agriculture. India has seasons of

1. Winter which occurs from December to March

2. Summer season from April to June

3. Monsoon or rainy season lasting from July to September and

4. Post-monsoon or autumn season occurring from October to November.

Due to the diversity of season and rainfall, assessment of suitable crops to cultivate is necessary. Farmers face major problems such as crop management, expected crop yield and productive yield from the crops. Farmers or cultivators need proper assistant regarding crop cultivation as now-a-days many fresh youngsters are interested in agriculture.

Machine learning is an important choice guide tool for crop yield prediction, consisting of helping selections on what plants to grow and what to do all through the developing season of the crops. several machine gaining knowledge of algorithms had been applied to assist crop yield prediction studies.

In this study, we completed a scientific Literature assessment (SLR) to extract and synthesize the algorithms and capabilities which have been utilized in crop yield prediction studies. based on our search criteria, we retrieved 567 relevant studies from six digital databases, of which we have decided on 50 studies for further evaluation the use of inclusion and exclusion criteria. We investigated those decided on research carefully, analyzed the techniques and functions used, and furnished suggestions for similarly studies. in line with our evaluation, the most used functions are temperature, rainfall, and soil type, and the most applied set of rules is synthetic Neural Networks in these fashions.

After this observation based on the analysis of machine learning-based 50 papers, we performed an additional search in electronic databases to identify deep learning-based studies, reached 30 deep learning-based papers, and extracted the applied deep learning algorithms.

According to this additional analysis, Convolutional Neural Networks (CNN) is the most widely used deep learning algorithm in these studies, and the other widely used deep learning algorithms are Long-Short Term Memory (LSTM) and Deep Neural Networks (DNN).

Crop yield forecasting is of main concern for market participants from farmers to commercial trading companies, such as large agricultural companies, and non-commercial trading companies, such as hedge funds. Early season production forecast is key to price discovery mechanism for those billion dollar crops. Yield forecast has major impact on positions taken in the market according to what is the anticipated supply of crops and the given demand.

Not many studies have truly forecasted yield out of sample and compared to a benchmark forecast such as the one provided by the USDA World Agricultural Supply and Demand Estimates (WASDE). Furthermore, crop condition ratings are the most widely used indicator of yield potential by market participants throughout the growing season of crops, however, little research has been done using the ratings. Lehecka (2014) investigated the informational value of the crop condition ratings during report release days and non-report release days finding significant differences in return variabilities between the two proving the impact of the weekly release of crop condition ratings has on market participants.

Only two previous studies, Kruse & Smith and Fackler & Norwood, have analyzed crop condition ratings as a forecasting tool but at the time of their research there was not enough observations to make an out-of-sample forecast. The estimates in both papers were in-sample, therefore, not aligned with the USDA WASDE, which is a true forecast. This thesis aims to fill the gap in the literature of using crop condition ratings to make out of sample yield forecast of the main commodities grown in the United States.

Other lines of research have mainly focused on agronomy simulation models that incorporate complex mathematical equations and demand difficult inputs for calibration of the 2 model. Furthermore, these models are usually not made to be applicable at a large regional scale making it problematic to obtain a forecast of yield on the national or state level. Remote sensing imagery of crops is another method that has been applied to forecast yield but the technique needs improvement in its spatial resolution and cost-effectiveness since the technique is not widely available to a wide range of market participants.

The hybrid of those two facets of research showed improvement over the use of only one or another but still remain ineffective in conveying useful information for market participants' decision making in a timely manner. Empirical studies, on the other hand, make use of information that incorporates the determinants of crop yield in a broad sense. For instance, the USDA crop condition ratings data used in this thesis conveys information about how the crops are developing responding to a variety of events throughout the growing season such as weather, pests and diseases, and it is reported every week from April to November, as mentioned before, being the most widely used indicator of yield potential.

As mentioned before, this thesis focuses mainly on the ideas developed by Kruse and Smith (1994) and Fackler and Norwood (1999). Kruse and Smith associated a given set of yields to each of the categories Very Poor, Poor, Fair, Good and Excellent condition of crops included in the Crop Progress and Condition Report of the USDA. The authors developed a weighted maximum likelihood method to estimate the set of soybean and corn yields associated with each category. Fackler and Norwood develop a method of weighting the percentage of yields in each category. They also solved the issue that yield forecasts can increase when crop conditions worsen by eliminating the Very Poor category considering them abandoned acres. Yet, the comparisons made in both papers are not completely aligned with the USDA's 3 forecasts given that the USDA provides real forecasts while these paper's forecasts are insample. Empirical studies emphasize statistical evidence and are conveniently used given its simplicity and timeliness compared to experimental type of data obtained in agronomy studies or remote sensing imagery. However, empirical studies might overlook information such as plant physiology obtained by the other types of research.

Crop yield research and forecasting have long been of interest for several reasons. On a macroeconomic scale, understanding the determinants that affect crop yield allow societies to comprehend and manage the factors that impact the supply of basic resources, food and fuel, which in turn affect the demand side. On a microeconomic scale, crop yield is a direct determinant of commodity prices, which in turn affects farm income, investments in agriculture and companies' profitability.

Different approaches have been used to assess and forecast crop yield throughout the growing season. This thesis will review four main approaches: agronomy studies, remote sensing imagery, hybrid models, and empirical models. 2.2 Agronomy Theory Agronomy studies make use of Crop Simulation Models (CSM) that incorporate plant physiology, pests and disease, genetics, weather, management practices and environmental variables such as soil condition, planting density, and row spacing to determine crop yield.

Crop Simulation Models are defined as computerized representations of crop growth, development, and yield simulated through mathematical equations as a function of agronomic parameters. Models range from simple to complex depending on their purpose (Basso et al., 2013). In the case of yield prediction and forecasting, the use of CSM poses several challenges. A dynamic crop model is typically designed to simulate plant growth, development, and yield at a specific field, where central tendency, variances and trends of underlying agronomic parameters are certain (Jagtap and Jones 2002). Applying field scale models to large regions requires aggregation of effects and combination of all input parameters to predict and forecast 7 yield reasonably. Errors are introduced when models are used at a scale for which they were not developed.

Crop Simulation Models must be tested across broad agricultural areas to be useful for large-area yield predictions (Jagtap and Jones 2002) making the use of CSM for yield prediction and forecasting often difficult. The strength of a CSM is their ability to be extrapolated beyond a single experimental field (Basso et al., 2013). There are several types of CSM developed to integrate different Decision Support Systems (DSS) in agriculture. A widely used software is the Decision Support System for Agrotechnology Transfer1 (DSSAT) which comprises CSMs for over 42 crops. A good example of a CSM that is part of the DSSAT is the CROPGRO-Soybean model, which was used by Jagtap and Jones to predict regional yield and production in Georgia (2002).

They developed and tested a methodology to use the CROPGRO-Soybean at a regional scale instead of a field specific prediction. The study covered the state of Georgia over 1974-1995 time period. Yields were simulated for each year based on how soybean cultivars respond to soil, weather, water stress, and management. Their simulations starts at planting and ends when harvest maturity is predicted. To account for spatial variability since the model is being implemented at a regional scale, the inputs used in their model were aggregated for the region covered using different methods.

The authors also used a yield bias correction factor to account for stress not covered by the model. They found that the yield correction factor reduced bias in the model from 57 to 11%. The calibrated model also predicted relative yield trends with more than 70% precision. On the corn side, Hodges et al. used the CERES-Maize model, also part of the DSSAT, to estimate production for the U.S Corn Belt during 1982-1985 time period (1987). The model was 1 dssat.net 8 implemented to estimate variation in production in response to yearly variation to weather. They used data from 51 weather stations available throughout the growing season in 14 Corn Belt states.

The model simulates plant growth processes and yield using soil conditions and daily weather data. As the growing season progresses, they substitute actual weather data instead of predicted weather. The calibration of the model for the locations studied is given by supplying five genetics coefficients for the hybrid grown in that location. They find that production estimates were 92, 97, 98 and 101%, for each year respectively, of the figures reported by NASS. They concluded the model is reasonably accurate for large area production forecasting where adequate weather data is available.

The authors also suggest that forecasting would be improved if soil profile data were available for each station among other parameters. Other softwares have also being used to predict and forecast yields on regional scale. Moen et al. used the General- Purpose Atmosphere-Plant-Soil Simulator (GAPS)2 to simulate corn yields in the Eastern crop reporting district of Illinois for the 30-year period 1960-1989 (1994). The maize model used in GAPS simulates both growth and partitioning.

The inputs used to run the model were weather data, soil series, crop varieties, and planting times adjusted for nitrogen use, pests and disease, and harvest losses. The simulated yield for each year was compared to the historical yield obtained by farmers in the region. They considered four different scenarios incorporating different combinations of soil and planting data information. They found that one soil and seven different planting dates, and three soils and seven different planting dates provided the most accurate estimates of corn yield with a fit of 63 and 61%, respectively.

The accurate prediction of yield variability is as important, or more important than, accurate prediction of absolute yield. In terms of wheat, Supit used the WOFOST model developed into the Crop Growth Simulation Model (CGSM)3 , another software currently used for prediction of national yield per area for various crops in the European Union. The study predicted national wheat yield for twelve European countries during a 10-year period. The research encompasses four prediction models evaluated in terms of the Relative Root Mean Square Error (RRMSE) and the Root Mean Square Error (RMSE) against published national yield. These models used as inputs crop growth simulation results, planted area, and a trend function.

The author tests a linear trend function and a nitrogen fertilizer application trend function finding that prediction results depends on the selection of trend function for a given country. He concludes that the use of CGMS in combination with a trend function holds a promise for further improvement. Other successful examples of a CSM application is the Yield Prophet4 which matches crop inputs with potential yield in a given season. The Yield Prophet is operated as a web interface for the Agricultural Production Systems Simulator (APSIM) another DSS for agriculture that incorporates several CSM. The SALUS Model5 (System Approach to Land Use Sustainability) is similar in detail to the DSSAT models.

As another example of a DSS, SALUS is targeted at farmers or extension specialists who can simulate the impact of different management strategies on yield (Basso et al. 2013). 3 http://www.supit.net/ 4 www.yieldprophet.com.au/5http://salusmodel.glg. msu.edu/ 10 As mentioned before, difficulties in using CSM for yield prediction have usually been associated with intensive data for models' parametrization, the need for calibration and mainly, the "point-based" nature of CSM, which makes models inadequate for regional or national scale predictions (Basso et al. 2013).

Current research has been focusing in correcting this problem by implementing Geographic Information Systems (GIS) into crop models and remote sensing (RS) making hybrid models more robust than the ones which only use CSM. Finally, agronomy studies have many facets to approaching yield variability and forecasting. Some other studies have focused on yield variability under climate change and weather phenomena, and yield gap studies, which investigate the difference between observed yields and potential yield6 for a given region.

SYSTEM PROPOSAL

2.1 EXISTING SYSTEM:

In existing, it constructs a Deep Recurrent Q-Network model which is a Recurrent Neural Network deep learning algorithm over the Q-Learning reinforcement learning algorithm to forecast the crop yield. The sequentially stacked layers of Recurrent Neural network is fed by the data parameters. The Q- learning network constructs a crop yield prediction environment based on the input parameters. Finally, the agent receives an aggregate score for the actions performed by minimizing the error and maximizing the forecast accuracy.

DISADVANTAGES:

- Low accuracy
- Doesn't Efficient for handling large volume of data.
- Theoretical Limits
- Incorrect Classification Results.
- Less Prediction Accuracy.

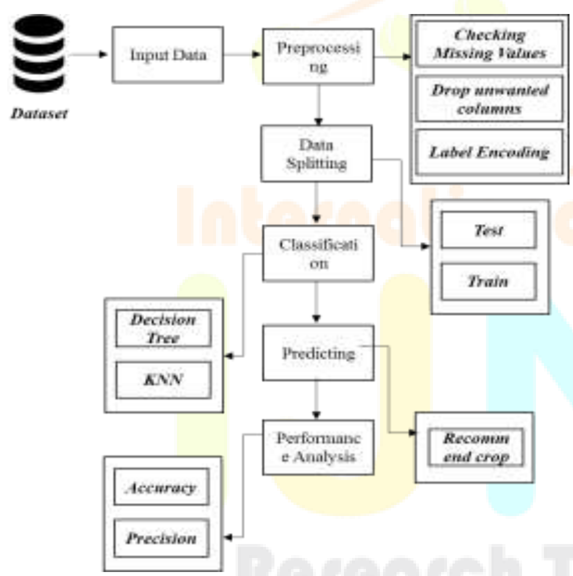
1. PROPOSED SYSTEM:

In this system, the crop yield dataset was taken as input from the dataset repository. Then, we have to implement the data pre-processing step. In this step, we have to handle the missing values for avoid the wrong prediction. Then, we have to split the data into test and train. In this step, test is used to predicting the model a and train is used for evaluate the model.we have to implement deep learning algorithms such as KNN and Logistic regression .Finally, the experimental resultsshows that the performance metrics such as accuracy, precision, recall, and confusion matrix.

2.2.1 ADVANTAGES:

- Implement the deep learning algorithm
- High performance.
- Provide accurate prediction results.
- It avoids sparsity problems.

SYSTEM ARCHITECTURE:



MODULES:

- Data selection
- Data preprocessing
- Data splitting
- Classification
- Performance Analysis

OUTPUT TESTING:

After performing the validation testing, the next step is output asking the user about the format requiredfor test of the proposed system, since no system could be useful if it does not produce the required output in the specific format. The output displayed or generated by the system under consideration. Here the output format is considered in two ways. One is a screen and the other is printed format. The output format on the screen is found to be correct as the format was designed in the system phase according to the user needs. For the hard copy also output comes out as the specified requirements by the user. Hence the output testing does not result in any connection in the system.

RESULT GENERATION:

The Final Result will get generated based on the overall classification and prediction.

The performance of this proposed approach is evaluated using some measures like,

Accuracy:

Accuracy of classifier refers to the ability of classifier. It predicts the class label correctly and the accuracy of the predictor refers to how well a given predictor can guess the value of predicted attribute for a new data.

AC= (TP+TN)/ (TP+TN+FP+FN)

Precision:

Precision is defined as the number of true positives divided by the number of true positives plus the number of false positives.

Precision=TP/ (TP+FP)

Recall:

Recall is the number of correct results divided by the number of results that should have been returned. In binary classification, recall is called sensitivity. It can be viewed as the probability that a relevant document is retrieved by the query.

CONCLUSION

This system was proposed for efficient crop yield detection using deep learning algorithms such as KNN and LR. Experimental results analysis showed that our proposed method is efficient and can achieve better performance results on average when compared with Refinement algorithm. Hence the proposed approach provides a perception of implementing a more generalized model for yield prediction.

FUTURE ENHANCEMENT

In future we can use real time weather and soil datasets which will be gathered personally by equipment's or the datasets can be acquired from trusted websites. To further modify the model we can combine different classifiers to build one single model which is called Ensemble. By doing this we can achieve a level of performance which could not be achieved by single algorithm. Also, the nature of the Dataset affects the analysis therefore, more cleaned and pre-processed can be used for better results.

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