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Artificial Neural Network (ANN) for Predicting Crop Yield Based on Remotely Detected Crop Metrics

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Abstract: It is becoming increasingly well-known to use remote sensing for regional crop research. One of the hardest things for researchers utilizing remote sensing to do is anticipate and map crop yield at scales other than the field scale. In this project, the effective creation of a scientific model utilizing neural network to forecast crop productivity on a regional level utilizing well-known feed forward and techniques for back-propagation use crop parameters that are received by remote sensing. The Meals In order to design and calibrate the Forward Back Propagating Neural Network (FFBPNN) model, Ground truth data and parameters were acquired by remote sensing in a Mat lab setting. The instance provided reliable and precise outcomes.
The performance of the suggested model was statistically tested using the coefficient of determination, root mean squared error; mean absolute error, average ratio of anticipated yield to goal crop production and relative error. This project also looked at how the amount of buried neurons affected the model's functionality. Statistical investigation confirmed the applicability of the developed ANN model to parameters for paddy yield estimation based on remote sensing.
Keywords: Forward Back Propagating Neural Network (FFBPNN), artificial neural network, crop yield.

I. INTRODUCTION

Agriculture contributes significantly to GDP (gross domestic product) in practically all developing economies. When planning for the population's food security, crop yield prediction at the regional level is essential. This activity holds higher significance for a variety of applications, such as crop planning, water use efficiency, crop losses, and economic calculations, among others. Conventional techniques for estimating crop production that rely on ground observation, such visual inspection and sampling surveys, call for on-going crop parameter monitoring and documentation. Because of their widespread and repeating coverage, remotely sensed pictures have a lot of potential for assessing agricultural output and extent over wide areas Remote sensing imagery's spectral data provides extremely exact characteristics of the crop.

Agronomic models, which are based on experimental or computational methods, can be used to estimate crop yields at the regional level. Mechanical simulations are complicated mathematical procedures that require a large number of input parameters. However, empirical approaches can only be used within the data range for which they were designed, meaning that they are simpler and require less data to be used. Found an empirical correlation between the harvest of crops in-situ and a vegetation index. This discovered association frequently holds solely for the specific crop type and seasonally acquired RS data.

1) Machine learning techniques have shown to be an effective empirical model and self-adaptive method of estimating agricultural yield, and they are also significantly simpler than mechanistic models when compared to conventional linear and nonlinear statistical modelling. For calculating agricultural yield from remote sensing photos, machine learning algorithms-especially Artificial Neural Networks (ANN)-are helpful. Using a feed-forward back-propagating neural network (FFBPNN), models for predicting paddy yield were created in the current study. Artificial Neural Network (ANN) models that are feed forward networks typically operate quickly and require little memory.

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The primary benefit of neural networks is their capacity to leverage previously unanticipated knowledge that hides inside data. "Neural network learning" or "neural network training" refers to the process of "capturing" unknown information. The back propagation (BP) algorithm, a type of supervised training that utilizes the derivatives of the error function to minimize the network's error, is used to train feed-forward networks. The network processes the inputs, compares the final output to the targeted outputs (set as the target), and simultaneously creates the weight coefficients. Calculating errors involves comparing expected and desired outputs The primary crop grown in the research region is the paddy.

Unfortunately, no precise model has been created to forecast paddy yield; instead, conventional approaches are used. In light of the previous explanation, the current study's goal was to create streamlined models for predicting paddy yield using historical yield data and remote sensing factors. The following are some of the specific goals: Examine how well artificial neural network (ANN) models predict yield using crop parameters that are acquired by remote sensing and historical yield data at the regional level. Tracking how model performance varies as model parameters change. Statistical testing of the model's performance

II. LITERATURE SURVEY

1) Forecasting crop yields prior to harvest is essential for developing, implementing, and improving food safety policies as well as for marketing and storing agricultural products. The weather affects crop development and growth. Consequently, weather variable models can offer trustworthy crop yield forecasts. Choosing the optimal crop production forecasting model might be challenging. In order to determine the best model for rice yield prediction, five alternative models were compared in this study: ridge regression, stepwise multiple linear regressions (SMLR), an artificial neural network (ANN), the least absolute shrinkage and selection operator (LASSO), and an elastic net (ELNET).
2) Using machine learning (ML) in conjunction with remote sensing and meteorological data, this study created a tailored yield prediction model and a fast methodology for estimating rice production. Building a crop yield estimation model requires addressing a number of challenges, such as data processing and quality difficulties, choosing an appropriate machine learning model that can learn from limited time-series data that are currently available and comprehending the non-linear relationship between past crop yield, meteorological variables, and remote sensing. This research used several data processing methodologies and a specially created machine learning model to raise the accuracy of crop yield estimation in Nepal at the district level.
3) One of the most important fields that contribute to the development of every country is agriculture. It affects not just the country's economy but also the global food grain statistics. It's never easy for farmers to produce crops in a sustainable manner. Due to constantly shifting environmental circumstances, farmers have always faced challenges in achieving optimal agricultural yields. The primary causes of crop yield unpredictability include variations in weather patterns, resource availability, and types of land. Therefore, scientists everywhere are attempting to develop methods that can effectively and precisely predict crop production well in advance, enabling farmers to make the necessary preparations for upcoming challenges.
4) Accurate yield forecasts help with the application of precision agriculture technologies and improve crop management choices. Recently, unmanned aerial vehicle (UAV)-based remote sensing research has employed convolutional neural networks (CNNs) to estimate crop yields; however, the modelling has not taken weather data into account. This work used UAV multispectral photos at the heading stage and meteorological data to investigate the possibility of multimodal deep learning on rice yield forecast accuracy. On the prediction accuracy, the effects of layer thicknesses, CNN topologies, and weather data integration techniques were assessed. Overall, it was possible to provide more accurate rice yield projections using the multimodal deep learning model that integrated weather data and multispectral imaging captured by unmanned aerial vehicles.
5) Focuses on predicting rice yields in Chhattisgarh, India, using weather data and various modeling techniques, including stepwise multiple linear regression (SMLR), artificial neural networks (ANN), LASSO, elastic net (ELNET), and ridge regression. ANN performed best in Raipur and Surguja, while ELNET and LASSO excelled in Bastar. Ensemble models, particularly random forest (RF), improved accuracy across all regions. The research highlights the importance of advanced modeling techniques for better crop yield predictions, which are crucial for agricultural planning and food security. Weather conditions were found to significantly affect rice yields across different districts.
6) Author developed models to predict rice yields, focusing on the impact of extreme weather like typhoons and droughts. They compared artificial neural networks (ANN) with traditional multiple linear regression models. The study found that ANN models were more accurate, with better R^2 values and lower RMSE scores. Fine-tuning ANN parameters, such as learning rates and hidden nodes, improved predictions, especially with smaller datasets. While ANN models take longer to develop, their higher accuracy makes them valuable for managing agriculture in Fujian's difficult climate conditions.

7) Author improved paddy yield predictions in Tamil Nadu's Cauvery Delta Zone using advanced machine learning methods like support vector machines (SVM) and general regression neural networks (GRNN). Traditional methods struggled with the complexity of crop yield factors, but GRNN provided the most accurate predictions, achieving an R^2 value of 0.9863 and a low RMSE of 0.2295. The model analyzed key variables like soil pH, temperature, and rainfall from historical data to predict yields. GRNN outperformed other models due to its high accuracy and fast prediction time, making it a valuable tool for agricultural decision-making and reducing risks for farmers.
8) The research used crop yield data from Rajasthan between 1997 and 2019, including crops like wheat, rapeseed, and barley. Some crops and regions were excluded due to missing data, which impacted prediction accuracy. Data was processed by encoding, standardizing, and handling missing values to prepare it for modeling. Machine learning models, particularly Random Forest and SVM, performed better than deep learning models like LSTM, likely due to the smaller dataset. The study suggests that combining machine learning with expert knowledge can improve crop yield predictions. Future research should focus on refining the dataset with more detailed environmental data.
9) The study focuses on using machine learning techniques, such as deep learning models like RNNs and CNNs, to predict crop yields, including soybean, by analyzing data on weather, soil, and past yields. These methods offer more accurate predictions with less data compared to traditional approaches. Additionally, techniques like transfer learning help improve predictions in areas with limited data. Future research aims to explore advanced models like LSTM and fuzzy logic to further enhance crop yield prediction and support agricultural sustainability.
10) This paper examines the use of machine learning in predicting crop yields, emphasizing its importance for agricultural decision-making. While models like Neural Networks, Random Forest, and Support Vector Machines are commonly used, improvements in accuracy are needed. Researchers suggest integrating more diverse data and developing tools to help farmers make better decisions. The study also highlights the growing role of deep learning, particularly models like CNN, LSTM, and DNN, but challenges like data availability and system implementation persist.
11) In Thailand, traditional open air drying of rice is being replaced with more advanced systems like fluidized-bed dryers (FBD), which enhance drying by mixing rice with air for better heat and moisture transfer. A study found that using a nozzle in the FBD significantly reduced drying times by 38–67% compared to conventional methods. Artificial neural networks (ANNs) were used to predict moisture content changes with high accuracy, helping optimize the drying process. Future research could focus on using renewable energy sources and improving nozzle designs to reduce energy consumption further.
12) The study used an Artificial Neural Network (ANN) to predict rice yield in Maharashtra, India, based on weather data from 27 districts between 1998 and 2002. The model achieved a high accuracy of 97.5%, with strong sensitivity (96.3%) and specificity (98.1%). It was trained using a three-layer neural network and outperformed traditional methods like linear regression. The results, visualized using ROC curves, highlight ANN's potential in helping farmers make informed decisions based on predicted yields.
13) Rice is crucial for feeding over half the world's population, especially in Asia, and it supports many jobs in farming and processing. Predicting rice yields accurately helps farmers make better decisions and improve their production. Traditional methods for predicting yields were often slow and unreliable. However, new technologies using satellites with optical and radar sensors have made it easier to monitor plant health and soil conditions, even in bad weather. This study, conducted in Uttarakhand, India, used data from two satellites to collect information on rice crops at different growth stages. Researchers combined this data with machine learning models to improve yield predictions, finding that the XGB model performed the best overall.

III. ACKNOWLEDGMENTS

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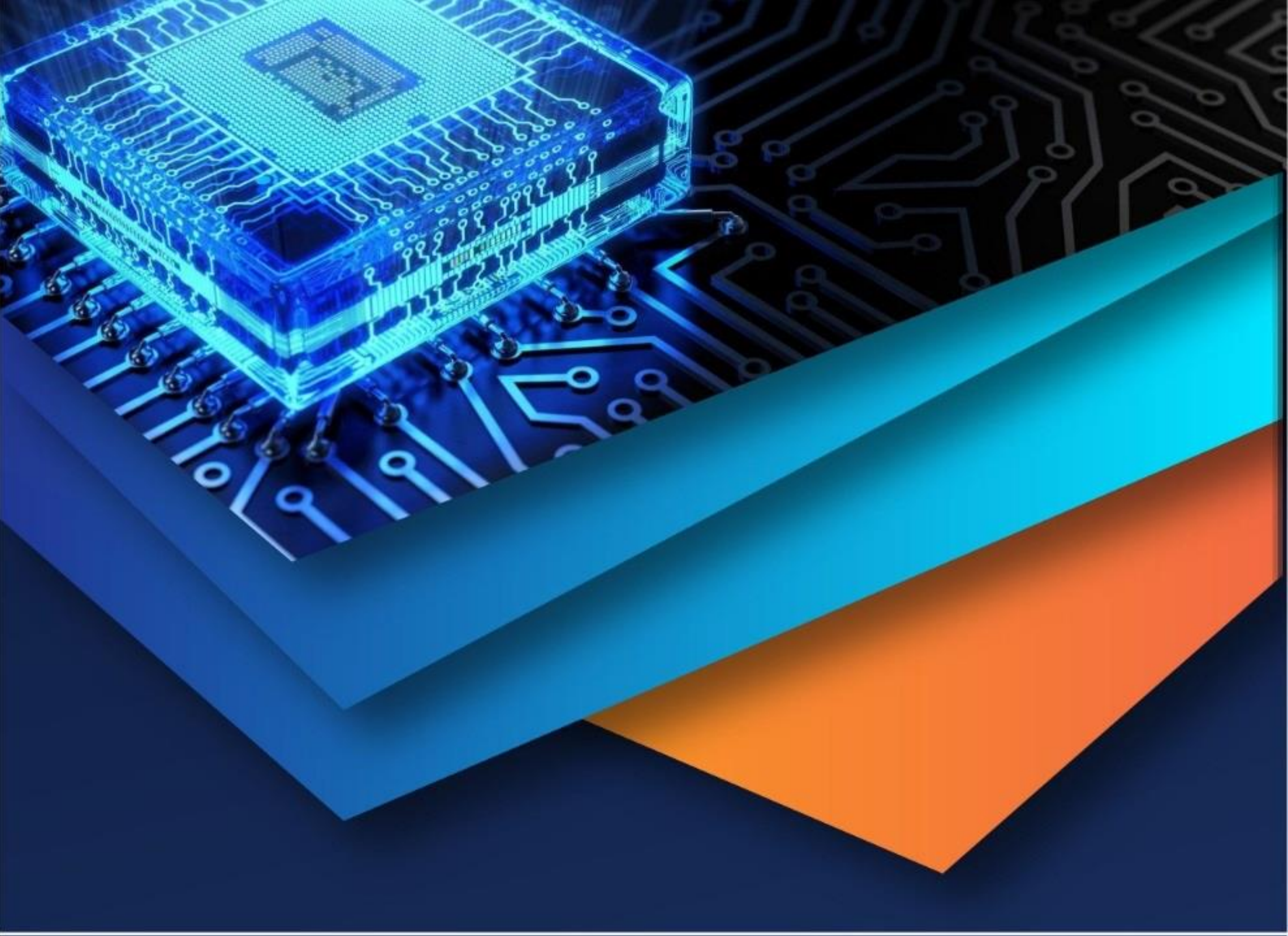

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