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Deep Learning: A Climate Smart Agriculture Tool for Groundnut Farmers

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Abstract

Groundnut is an oil seed crop, which is grown widely in the country, and approximately 80% of groundnut is produced in the rainfed condition. Unlike weather factors even the prices of agriculture commodities are volatile in nature and the groundnut prices also behaves in an unusual pattern. A traditional farmer faces recurrent challenges. Deep learning methods and the accessibility of satellite imagery have, however, created new opportunities for more accurate and effective agricultural yield estimates. Large-scale yield estimation and understanding the impact of the variability of agricultural growing circumstances are critical due to the increased frequency of extreme climate occurrences. Crop growth condition models can be utilized with time series of spatially explicit information from satellite remote sensing (RS). For efficient agricultural management, guaranteeing food security, and making wise decisions about resource allocation and market forecasting, accurate and timely estimation of crop yields is essential. Crop yield estimation has historically depended on time-consuming field surveys and statistical models. Machine Learning (ML) is an exciting application of Artificial Intelligence. It provides the ability to learn by experiences without any explicit. The proposed model is based on simple\and cost-effective hardware that can be used by agriculture officers and farmers to get good productivity of crops. SCS model is trained by classifying dataset and tested subsequently. The accuracy and performance of an ML classifier depend only on the type and size of the dataset. Crop selection by real-time sensing data and soil analysis attributes is a big contribution in research of smart agriculture. A model was proposed basing on three modules: crop selection, crop management, and crop maturity. It used parameters soil moisture, temperature, humidity, air pressure, and air quality with weather conditions for better crop selection and health monitoring. A real-time sensory data was used for analysis on Thing Speak application with KNN algorithm. Some data mining techniques are applied for data preprocessing and comparing real-time data with trained data for crop prediction. It also considered crop prices for crop prediction, listed on National Commodity and Derivative Exchange. The KNN classifier is applied for data analysis has focused on IoT-oriented agricultural methods for weather monitoring. The prediction methods are investigated for commercial and scientific perspectives, cost of IoT components, Think Speak application is used for data analysis. An Android application is also designed to intimate the farmers about required water level of fields. IoT framework best use of land to improve farming methods and increase crop production with profit maximization. A wireless sensor network was deployed in the field to sense data for different parameters and for proper monitoring of field. It proposed a crop prediction method for crop yield maximization and quality of crops by considering real-time data of metrological factors using ML algorithms: precipitation, temperature, humidity, and solar light. Soft computing techniques can be employed to estimate the yield of various crops. As a result of rapid advancements in technology, crop models and decision tools have emerged as vital components of precision agriculture worldwide. These models and tools utilize linear regression techniques, non-linear simulations, expert systems, Adaptive Neuro-Fuzzy Interference Systems, Support Vector Machines, Data Mining, Genetic Programming, and Artificial Neural Network (ANN) to predict harvest outcomes particularly under the influence of climate change. These prediction methods play a significant role in improving the accuracy and reliability of yield estimation in agricultural systems. ANNs successfully address identification, classification, and regression challenges in crop disease identification, harvest mechanization and product quality sorting. Multiple linear regression and discriminant function analysis were employed to construct a groundnut yield forecasting model, utilizing weather indices including maximum temperature, minimum temperature, total rainfall, morning relative humidity, and evening relative humidity. Employing techniques such as stepwise multiple linear regression, principal component analysis was combined with stepwise multiple linear regression, ANN, and penalized regressions like least absolute shrinkage and selection operator and elastic net. The models, particularly least absolute shrinkage and selection operator and elastic net, demonstrated remarkable accuracy, boasting a normalized root mean square error of under 10% across most test locations. Farmers using traditional methods in agriculture face problems such as low crop yield due to unpredicted weather, wrong amount of water and nutrients, and wrong selection of crop. In previous research work, limited parameters were used that are insufficient for high yield of crops. Our research is aimed at maximizing the crop yield by selecting suitable crop. We tackle this issue by applying technology methodically and evidence-based analysis. For instance, adding required amount of nutrients gives improved yields. Our work is based on selection of the influential parameters. Deep learning techniques used to give improved accuracy with less computational cost as compared to previous research.

Keywords: RNNs; CNN; ANN; LSTM Network; ML Classifier; KNN Classifier; ML Algorithms; loT

Abbreviations: ANN: Artificial Neural Networks; DNN: Deep Neural Networks; ML: Machine Learning; RF: Random Forests; SVM: Support Vector Machines; fAPAR: fraction of Absorbed Photosynthetically Active Radiation; NDVI: Normalized Difference Vegetation Index; LM: Levenberg–Marquardt, BR: Bayesian Regularization; SCG: Scaled Conjugate Gradient; MSE: Mean Squared Error; SPAD: soil and plant analyzer development; NDVI: Normalized Difference Vegetation Index; BPNN: Back Propagation Neural Network; ELM: Extreme Learning Machine. MRBVI: Modified Red-Blue Vegetation Index; HM: Harvest Maturity; FF: first flower; MAPE: Mean Absolute Percentage Error.

Introduction and Review

Deep learning methods and the accessibility of satellite imagery have, however, created new opportunities for more accurate and effective agricultural yield estimates. Large-scale yield estimation and understanding the impact of the variability of agricultural growing circumstances are critical [1-3] due to the increased frequency of extreme climate occurrences. Crop growth condition models can be utilized with time series of spatially explicit information from satellite remote sensing (RS) [4,5]. For efficient agricultural management, guaranteeing food security, and making wise decisions about resource allocation and market forecasting, accurate and timely estimation of crop yields is essential. Crop yield estimation has historically depended on time-consuming field surveys and statistical models [6]. Estimating agricultural yield prior to harvest is an Estimating agricultural yield prior to harvest is an important issue in agriculture, as the changes in crop yield from year to year influence international business, food supply, and global market prices. Also, early prediction of crop yield provides useful information to policy planners. Appropriate prediction of crop productivity is required for efficient planning of land usage and economic policy. In recent times, forecasting of crop productivity at the within-field level has increased. The most influencing factor for crop productivity is weather conditions. If the weather based prediction is made more precise, then farmers can be alerted well in advance so that the major loss can be mitigated and would be helpful for economic growth. The prediction will also aid the farmers to make decisions such as the choice of alternative crops or to discard a crop at an early stage in case of critical situations. Further, predicting crop yield can facilitate the farmers to have a better vision on cultivation of seasonal crop and its scheduling. Thus, it is necessary to simulate & predict the crop yield before cultivation for efficient crop management and expected outcome. As there exists a non-linear relationship between crop yield and the factors influencing crop, machine learning techniques might be efficient for yield predictions. Due to its capacity to automatically uncover patterns and representations from enormous datasets, deep learning, a branch of machine learning, has attracted considerable interest in a number of fields [7]. Deep learning algorithms can analyze enormous volumes of spatial and temporal data when paired with satellite imagery to produce valuable insights about crop development and yield potential. The development of crops is influenced by a variety of climatic conditions, including temperature, precipitation, and vegetation indices, which are all depicted in satellite imagery. The appropriateness of several neural network models, such as artificial neural networks (ANN) and deep neural networks (DNN), and machine learning (ML) models, such as random forests (RF), support vector machines (SVM), has been examined in a number of studies for yield estimation [8]. Further it lessens the need for labor-intensive field surveys, which decreases the time and expense of data collecting [9,10].

Prediction of agricultural phenomenon has proved to be helpful for farmers and decision makers across the world. It has further helped to understand prevailing market situation, production [11-14] price behavior [15,16] and possible pests and disease attack if meteorological variables are changed suddenly. Moreover, Indian agriculture has massive land holding over wide variety of climate and potential to produce sufficient agricultural produce. As a result, many researchers have tried to predict and forecast many agricultural phenomenon [17] like prediction of rainfall, prices [18] of different agriculture produce across markets and area, production of different crops over the years using sophisticated statistical methodology. In most of the cases, authenticity of the data is a big question and the data obtained must be analyzed properly. On many instances, obtaining the auxiliary variables is difficult, therefore, time series models have become popular in the prediction process.

Groundnut is an oil seed crop, which is grown widely in the country, and approximately 80% of groundnut is produced in the rainfed condition. Mainly, state includes Andhra Pradesh, Gujarat, Karnataka, Maharashtra and Tamil Nadu, were contributing nearly 90 per cent of total production of groundnut in the country. Among all the meteorological factors, rainfall plays a deciding role in the production as well as the incidence of pests and disease can cause significant damage to the production of groundnut in the country. Unlike weather factors even the prices of agriculture commodities are volatile in nature and the groundnut prices also behaves in an unusual pattern. A time series model has wide variety of application includes risk management, tourism forecasting [19] and in the medicine and pharmaceuticals sectors [20-22]. In agriculture and allied sciences, time series models are used for forecasting milk production, milk yield of certain breeds of cows, yield of a crop, prices, production, and productivity [23,24]. These models can play a significant role in stock market decision-making [25] its application in financial aspects like credit and banking sectors is also crucial [26]. The agricultural sector cannot be the exception in starting to adopt the best practices and tools that help the farmer in making decisions and encourage the agricultural investment and the growth of the economy in the sector. Having said the above and having taking into account that different public and private entities have been collecting different types of structured, semi-structured and unstructured data at different scales, such as, For example, meteorological stations, where they produce large volumes of hourly data, daily, monthly, among others, of various variables [27]. Reason why, they allow the possibility of start a path of data analytics in a sector that has the potential to grow and be each more profitable if tools, methodologies and best practices are incorporated in a preventive measures to mitigate financial risks, increasing the profitability of the agriculture crops.

In the agricultural sector, production agriculture depends on many biological factors, climatic, economic and human that interact in complex ways. Agricultural producers and companies in the agricultural industries must make countless decisions every day that impact on performance and supply chain operation respectively [28]. Therefore, decision making requires to be better grounded in various sources of information that are made progressively more difficult to manage outside the data paradigm. Remote sensing has great potential as a source of information for the prediction of agricultural production, both at the regional and the global scale, because it provides data at a level of consistency, repeatability, timeliness and scalability that is unmatched by any other data source. The costs of collecting the information and altering them into a reliable alternative for costly ground-based surveys are reduced markedly over the last decades due to the continuous improvements in remote sensing techniques [29]. In the agricultural production estimation field, satellite and areal images have become essential data sources rapidly as a consequence. The importance of yield estimation gain and crop monitoring includes on the scientific and the political agenda as the rapid growth of global population and a (negative) impact of \climate change on global crop production becomes probable. One of the principal determinants of crop yield is the percentage of solar irradiation intercepted by the plants' foliage. One way to assess the productivity of crops depends on the 'fraction of Absorbed Photosynthetically Active Radiation' (fAPAR) and the efficiency with which that energy is converted into new biomass [30]. The value of fAPAR is largely determined by the crop's foliage, which in turn can be related to the value of vegetation indices (VIs). VIs are numerical transformations of measured reflectance that are related to plant and canopy characteristics in a crop-specific and nonlinear way. The Normalized Difference Vegetation Index (NDVI) is improved by Deerin and it is used extensively.

According to Novelli, etal. [5], learning Supervised consists of predicting the values of a set of output data, from a set of input data. It is called supervised because according to the model predicts the outputs for test data, the error between what the algorithm predicted is calculated and the real value. The objective is to minimize the error, adjusting the density function of probability relating inputs to outputs. Priya, et al. [31] predicted the crop yield based on machine learning algorithms from existed data using Random Forest algorithm. To establish the models, real data of Tamil Nadu were utilized and the testing of models was done with samples. For getting accurate results in prediction of crop yield, Random Forest Algorithm can utilize. Balakrishnan, et al. [32] has been proposed ensemble model based on AdaSVM and AdaNaive for predicting the production of crops over a certain period of time. By using AdaNaive and AdaSVM, its implementation is accomplished. AdaBoost increases efficiency of SVM and Naive Bayes algorithm. Siju and Patel [33] were reviewed on the prediction of crop yield based on Data Mining focusing on Groundnut crop using the technique of Naïve Bayes. In horticulture, various applications of information mining has been illustrated and examined. The detection of crop yield prediction has been explored and actualization of Naïve Bayes technique has been done for different applications. The research works were demonstrated the expectation of Groundnut crop yield. By using different procedures of data mining, the model of exact groundnut crop yield expectation can be improved. Bhanumathi, et al. [34] were focused on breakdown various relevant properties like location and esteem from which the dirt alkalinity resolves in addition to the supplements level like Potassium (K), Phosphorous (P), and Nitrogen (N). By using the outsider applications like APIs, the Location has been taken for soil type, climate and temperature, estimation of supplements in the dirt, and precipitation measure in the area, and creation of soil can resolve.

The information properties will break down and train it based on various appropriate AI calculations such as Random Forest Algorithm (RFA) and Back propagation Algorithm to design a model. In prediction of crop yield, the framework with a model to be provided the precise and exact results. Based on the soil and barometrical metrics of the land, the end client with appropriate proposals is conveyed about the required compost apportion that helps to improve the establishment of harvest yield and increment in rancher income. By considering this philosophy, the future work is extendible to build the web applications and allow the client to use this effectively for comprehending the harvest yield.

GiriBabu and Anjan Babun [35] were made a conclusion that the proposed method will provide solutions for the problems of fertilizer and water. The yield production will be more with the proposed technique. Agro algorithm is used in this paper. The accuracy in crop production didn't provide by this method properly. Ramesh and Vishnu Vardhan [36] were proposed multiple linear regression technique that can implement on existing information and assists in assessment and verification of data. It is also providing less accurate results which is the drawback of proposed method. Djodiltachoumy [37] has been focused on proposing and implementing the rule based system which should forecast the production of crop yield using the previous collected data. The utilized algorithms include clustering method and K-means algorithm. The drawback of the system is only suitable for association rule and less data is considered. Chlingaryan, et al. [38] have accomplished an audit which considered the AI techniques predominantly, estimation of yield, and nitrogen accuracy on the board. The method of back proliferation significance and harvest yield expectation precision for various lists of vegetation have been explored by the survey. Priya, et al. [31] were predicted the crop yield based on the algorithm of machine learning. By using Random Forest algorithm, the crop yield is forecasted from the existing data. Here, the real-time data of Tamil Nadu were utilized to establish the models and test them with samples. To get the crop yield prediction accurately, Random Forest Algorithm can be utilized.

Hunt, et al. [39] have been investigated on the Precision Agriculture for determining yield for crop insurance based on an Aerial Platform. Precision Agriculture (PA) is utilized for identification of field variations and dealing with them based on various strategies as it is the application of remote sensors and geospatial methodologies. Owing to irrigation practices, crop stress, and incidence of pest and disease, etc., the crop growth variability might be caused in an agricultural field. By using Ensemble Learning (EL), PA is implemented. Kamakshaih, et al. [40] has proposed objective of agriculture not only lies in enhancing the cultivation but also to satisfy the end users with high quality goods. Due to a lack of scientific knowledge about farming and no rotation of crops, fertility of lands is affected adversely. Major factors contributing to the crop quality are soil nutrients, ground water level, and type of fertilizer used. A traditional farmer facesrecurrent challenges. Soil acidity may increase due to selection of wrong crops and inadequate soil nutrient [41,42]. The unpredictable climate is the main factor for effecting crop's quality and yield. Soil fertility is an important factor for right crop selection and its health. It is aimed at overcoming few current farming issues that arise due to inefficient approaches. SCS considers metrological factors such as temperature, humidity, rainfall, CO_2 level in air, soil pH, EC, and soil type. The metrological factors directly affect the plant\growth and production [43-45]. Machine Learning (ML) is an exciting application of Artificial Intelligence. It provides the ability to learn by experiences without any explicit program [46]. The proposed model is based on simple\and cost-effective hardware that can be used by agriculture officers and farmers to get good productivity of crops. SCS model is trained by classifying dataset and tested subsequently. The accuracy and performance of an ML classifier depend only on the type and size of the dataset [47].

Crop selection by real-time sensing data and soil analysis attributes is a big contribution in research of smart agriculture. Bhojwani, et al. [48] proposed a model based on three modules: crop selection, crop management, and crop maturity. They used parameters soil moisture, temperature, humidity, air pressure, and air quality with weather conditions for better crop selection and health monitoring. A real-time sensory data was used for analysis on Thing Speak application with KNN algorithm. Some data mining techniques are applied for data preprocessing and comparing real-time data with trained data for crop prediction. They also considered crop prices for crop prediction, listed on National Commodity and Derivative Exchange. The KNN classifier is applied for data analysis [49]. Majumdar, et al. [50] have focused on IoT-oriented agricultural methods for weather monitoring. The prediction methods are investigated for commercial and scientific perspectives, cost of IoT components, security threats, and dependency of weather parameters on irrigation of crops [49]. Imran suggested a smart irrigation and crop selection system based on the parameters like temperature, humidity, light intensity, and moisture level of soils. Experiments were\ performed on five types of soils (loamy, black, laterite, alluvial, and silt soil). Experimental results show that soil's characteristics of different lands can be used for crop selection. Think Speak application is used for data analysis. An Android application is also designed to intimate the farmers about required water level of fields [50]. Rekha, et al. [51] proposed an IoT framework to improve farming methods for best use of land to increase crop production and profit maximization. A wireless sensor network was deployed in the field to sense data for different parameters and for proper monitoring of field. Mulge, et al. [53] proposed a crop prediction method for crop yield maximization and quality of crops by considering real-time data of metrological factors using ML algorithms: precipitation, temperature, humidity, and solar light.

Groundnut (Arachis hypogaea L.) is a self-pollinating allotetraploid legume crop that belongs to the Fabaceae family [54,55]. Groundnut, also known as peanut, is recognized as the third most significant oilseed crop globally [3]. It holds great significance due to its high-quality edible oil and protein content. Moreover, the crop's byproducts, namely oilcake and haulms, play a crucial role as valuable animal feed, further enhancing its economic value in the agricultural industry [56]. China is the largest groundnut producer in the world, followed by India and Nigeria. In the year 2022/2023, China produced 37% of the global groundnut output, while India accounted for 13% and Nigeria contributed 9%. The total global production for that year was 49,535 thousand metric tons (MT) [57]. Groundnuts are typically cultivated in tropical, subtropical, and warm temperate climatic zones [58]. Therefore, Sri Lanka, located in a tropical region, provides a suitable environment for growing groundnuts. In Sri Lanka, two primary seasons exist, namely Yala and Maha. The Yala season typically extends from April to the end of August, while the Maha season spans from September to the end of March of the subsequent year, following the rainfall pattern [59]. Groundnuts are primarily grown in the dry and intermediate zones of Sri Lanka, either as rain-fed crops in highland areas during the Maha season or as irrigated crops in paddy lands during the Yala season. In Sri Lanka, the main groundnut cultivation regions include Moneragala, Kurunegala, Ampara, Badulla, Puttalama, and Ratnapura districts [60,61]. In 2021, the country's groundnut production reached 36,947 metric tons, cultivated across an area spanning 18,537 hectares [62].

Soft computing techniques can be employed to estimate the yield of various crops. As a result of rapid advancements in technology, crop models and decision tools have emerged as vital components of precision agriculture worldwide. These models and tools utilize linear regression techniques, non-linear simulations, expert systems, Adaptive Neuro-Fuzzy Interference Systems, Support Vector Machines, Data Mining, Genetic Programming, and Artificial Neural Network (ANN)s to predict harvest outcomes [63,64], particularly under the influence of climate change. These prediction methods play a significant role in improving the accuracy and reliability of yield estimation in agricultural systems [65]. ANNs successfully address identification [66], classification, and regression challenges in crop disease identification [67], harvest mechanization [68], and product quality sorting [69]. Multiple linear regression and discriminant function analysis were employed to construct a groundnut yield forecasting model, utilizing weather indices including maximum temperature, minimum temperature, total rainfall, morning relative humidity, and evening relative humidity [70]. In this study [71], the objective was to predict sesame oilseed yield based on plant characteristics. Several machine learning models, including radial basis, multiple linear, and gaussian process, were employed. These models were complemented by the principal component analysis method to enable a comparative analysis with the original machine learning models. The aim was to assess the efficiency of the prediction process. In this study [72], minimum and maximum temperatures, rainfall, and relative humidity were also utilized as factors in the development of wheat yield prediction models. Employing techniques such as stepwise multiple linear regression, principal component analysis was combined with stepwise multiple linear regression, ANN, and penalized regressions like least absolute shrinkage and selection operator and elastic net. The models, particularly least absolute shrinkage and selection operator and elastic net, demonstrated remarkable accuracy, boasting a normalized root mean square error of under 10% across most test locations. In this study [73], a wheat yield forecasting model was developed using an ANN that considers factors like productive soil moisture, soil fertility, weather, and the presence of pests, diseases, and weeds. The model utilized input parameters like the soil's moisture content, nitrogen, phosphorus, humus, and acidity levels, as well as precipitation data, average air temperature, and the presence of diseases and pests from 13 North Kazakhstan districts from 2008 to 2017, achieving commendable prediction results. The neural network's advantage lies in its ability to handle nonlinear data relationships and its enhanced performance with abundant training data, suggesting potential adaptability for forecasting other crops and regions. Neural networks, inspired by the nonlinear parallel structure of the human brain sys-tem, constitute a large-scale, parallel distributed information processing system. Originally derived from the biological central nervous system, ANNs are composed of interconnected nonlinear computational units. These networks emulate the intricate processing capabilities of the human brain and enable complex information-processing tasks through their parallel and distributed nature. ANN's flexibility makes it a powerful alternative to linear models. A single hidden layer ANN, with enough neurons, fits any continuous mathematical function within a given interval, given ample data and computational resources [74].

When developing a neural network model, people normally employ three distinct training algorithms, namely Levenberg-Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG). These training algorithms aid in the training process of the ANN model to achieve better results. The LM algorithm excels in various problem do-mains, surpassing simple gradient descent and other conjugate gradient methods in terms of performance and effectiveness [75]. BR is a regularization method used in tandem with a gradient-based solver. It prevents over-fitting by limiting the magnitude of the synaptic weightings relative to the sum of the squared error or mean squared error (MSE) being minimized [76]. The SCG algorithm, a supervised learning method for network-based approaches, finds widespread application in addressing large-scale problems [77]. These algorithms are utilized to train the neural network model and enhance its performance through optimization techniques [78,79]. Temperature and rainfall variations significantly impact various crop types in different regions across the globe. These climatic factors have a crucial role in influencing the growth, diverse responses of crops to temperature and rainfall variations highlight the importance of considering regional climatic conditions when planning and managing agricultural activities [80,81].The adverse impact of increasing temperatures on crop yields has been acknowledged as a notable factor. Extensive research has been conducted using advanced modeling techniques to comprehensively study this phenomenon [82-84]. Maximizing crop yield by keeping the cost as low as possible is one of the main goals of many precision agriculture systems. Early identification and prediction of crop traits such as crop disease, biomass and yield are beneficial as they allow the farmer to manage crop growth and harvesting well in advance [85]. Therefore, the estimation of yield and related parameters such as biomass, disease, plant health, nitrogen status and soil conditions has been a frequent topic in the literature [86]. Early detection and management of problems associated with farming can help increase yield and subsequent profit, and better estimation of the yield offers farmers and processors numerous benefits in terms of harvest planning, storage and transportation scheduling, sale and price negotiation and other business decisions.

The traditional yield prediction models are based on ground samples, collected from the farm, and extrapolating these samples throughout the field to estimate the yield [87]. These methods are not only costly and labor-intensive but also poorly represent the spatial variability of yield over the field. An alternative approach is a non-destructive sampling method for yield estimation which uses a remote sensing platform to acquire field images and employs various vegetation indices (VIs) to establish a regression model for crop yield [88]. Recent works on UAV-based remote sensing [1] showed the efficiency of crop traits such as yield estimation using multispectral images and ML methods [89]. For instance, Guo, et al. [90] utilized the multispectral images of maize with a Mini-MCA camera embedded in the drone to estimate the soil and plant analyzer development (SPAD) values. They also implemented various ML methods such as SVM and RF where SVM outperformed the RF with an R_2 of 0.81 in estimating SPAD value. For crop yield estimation using UAVs, the VIs derived from the multispectral and RGB images were extensively utilized by various works [91]. These studies established a strong correlation between crop yield and VIs. For instance, the normalized difference vegetation index (NDVI) is linearly related to wheat yield [92].

Similarly, a yield map for rice and wheat crops was developed using NDVI from multispectral images [93]. Since UAV has the flexibility in revisiting the field and can capture high-resolution imagery in comparison to satellite imagery, it has opened possible avenues for cheaper and more frequent image acquisition to support more accurate estimates of crop traits using predictive approaches such as ML methods [94]. For instance, Zhou, et al. [95] implemented a convolutional neural network (CNN) for soybean yield estimation with high-resolution UAV imagery. They used crop features such as plant height, canopy colour and canopy texture to train the neural network. Their model achieved an R2of 0.78 with a root mean square of391.0 kg/ha. Similarly, Guo, et al. [94] implemented four ML models, a back propagation neural network (BPNN), SVM, RF and extreme learning machine (ELM), for maize yield predictions using VIs. They showed that SVM with a modified red-blue vegetation index (MRBVI) was effective in monitoring maize yield. Besides the image feature, Guo, et al. [90] employed the combination of phenology, climate and geography data to estimate rice yield with statistical and ML methods. However, their proposal of building the yield prediction model with an individual ML method missed the cooperative nature of the ensemble approach where if one method fails to capture \the correct prediction, another ML method can pick the right prediction. Considering such limitations, this study first establishes the relationship between UAV images and peanut yield at the individual growth stage. Based on such a relationship and existing ML methods, an accurate and cooperative ensemble method for yield prediction is proposed and validated using peanuts as a study crop. Peanut is an oilseed crop grown in many countries over the world. In Australia, the peanut is mainly grown in Queensland, in the northeast of Australia. Its growth cycles include various stages: planting, emergence, emergence to first flower (FF), flowering (F), pegging, pod-filling and harvest maturity (HM). It takes around three to five months from planting to maturity [96]. Deep learning models have recently been used for crop yield prediction. You, et al. [97] used deep learning techniques such as convolutional neural networks and recurrent neural networks to predict soybean yield in the United States based on a sequence of remotely sensed images taken before the harvest. Their model outperformed traditional remote-sensing based methods\ by 15% in terms of Mean Absolute Percentage Error (MAPE). Russello [98] used convolutional neural networks for crop yield prediction based on satellite images. Their model used 3-dimensional convolution to include spatiotemporal features, and outperformed other machine learning methods. Deep learning methods have been applied for the crop yield prediction. Khaki and Wang [10] designed a deep neural network model to predict corn yield across 2,247 locations between 2008 and 2016. Their model was found to outperform other methods such as Lasso, shallow neural networks, and regression tree. You, et al. [97] applied CNNs and RNNs to predict soybean yield based on a sequence of remotely sensed images. Kim, et al. [7] developed a deep neural network model for crop yield prediction using optimized input variables from satellite products and meteorological datasets between 2006 and 2015.Wang, et al. [10] designed a deep learning framework to predict soybean crop yields in Argentina and they also achieved satisfactory results with a transfer learning approach to predict Brazil soybean harvests with a smaller amount of data. Yang, et al. [99] investigated the ability of CNN to estimate rice grain yield using remotely sensed images and found that CNN model provided robust yield forecast throughout the ripening stage. Khaki and Khalilzadeh [100] used deep CNNs to predict corn yield loss across 1,560\ locations in the United States and Canada. Accurate and efficient methods to predict the crop yield helps economists and officials in the planning process of agricultural practices according to Maya Gopal and Bhargavi [101]. Kouadio, et al. [102] analyzed that the availability of varied data has urged researchers to use data driven models to understand and produce accurate results. The prediction of the yield of any crop is not only dependent on environmental factors, such as the area, irrigation, rainfall, etc., but also the prediction algorithm, in order to expect precise results according to Sirsat, et al. [103].

However, when such models are to be applied on a large scale regions (like districts and states), the availability and collection of data for creating models is highly problematic according to Kaul, et al. [104]. Basso, et al. [105] analyzed that the precision of results in the prediction of the yield for any crop can be achieved by providing appropriate inputs and selecting proper models without changing the traditional agricultural practices and their systems. Basically, the most popular annual productivity seed or grain is groundnut (Arachis hypogaea L). The groundnut is a well-known source of nutritious food that contains healthy ingredients such as fat, vitamins, dietary fibers, minerals and protein [106]. The main seed oil crop in India is groundnut, which has taken the productivity area of 208,149 ha and it yields 0.45 million tons of groundnut. Hence, the controlling procedure of pests and diseases can enhance the productivity of groundnut [107]. The report of India has shown; there may 40–60% of losses yield in groundnut production. Sometimes the ranges may increase to 93% based on the different diseases in groundnuts like collar rot, stem rot, leaf spot, etc [108]. The enlarger number of diseases can affect the groundnut. Moreover, the oil obtained from the groundnut is used for cooking and soap production [109]. After the oil extraction, the remaining products are used in poultry feed. However, the raw, boiled and roasted groundnut seeds are used for eating. Mostly, the groundnut plants are caused\ by fungal, viral, rust and leaf spot diseases [110]. These made the losses in economic and productivity. The fungal disease, such as leaf blight, leaf scorch, pepper spot, Alternaria, Phomopsis, Phoma, Phyllosticta, Drech-slera leaf blight, anthracnose and Cylindrocladium leaf spot, affects the groundnut plant. Nowadays, the process of identifying groundnut disease is a major challenging prob-lem [111]. The various image processing, artificial intelligence [40,112-116] and graphical processing units are widely used to detect the plant diseases

[40]. Particularly, many of the researchers suggested various research techniques and pesticides to control and manage groundnut diseases. Few of the existing research mechanisms are formulated as follows. Bakker, et al. [117] proposed a method of plant growth-promoting rhizobacteria (PGPR) for controlling pests. It is a latent defense method and set in motion systematically based on the pathogen's infection exposure of plants. El Houby [108] introduced the K-nearest neighbor (K-NN) method for the\ detection of plant diseases. The method is used to extract the features, and it classifies the data based on their measures. But it does not predict the diseases correctly. Yang, et al. [118] proposed a powerful and flexible method of machine learning mechanism to make the amalgamation of well suitable system knowledge. The main advantage is few of the learning algorithms are used in agricultural fields. The process of classification models with high spectral agricultural image decisions making is used in the regression of logistic and decision trees. Therefore, a rural area in America initiates the application-oriented smart-phone to analyze the groundnut and plant diseases [119]. The process of automatic feature extraction is a key point of deep learning. The required problem features are elected automatically, and there is no need for any fixed or handcrafted features. The explicit features are selected, and it reduces the specialist works (i.e. traditional pattern\ recognition). Therefore, the different kinds of supervised,\ semi-supervised and unsupervised problems were recovered. The hidden layers consist of many layers, but a minimum amount of three hidden layers are applicable. The nonlinear feature transformation of one phase is presented in deep learning [120]. Significantly, the single sets of features are trained by using the group of\ neurons in every hidden layer and it depends upon the previous layer output. The amount of hidden layer is raised as well as the data generalization and complexity also get\ increased. The trainable classifier with a hidden layer carried out low-level, mid-level and high levels of the\ feature extraction process [120-123].

Conclusion

Farmers using traditional methods in agriculture face problems such as low crop yield due to unpredicted weather, wrong amount of water and nutrients, and wrong selection of crop. In previous research work, limited parameters were used that are insufficient for high yield of crops. Our research is aimed at maximizing the crop yield by selecting suitable crop. We tackle this issue by applying technology methodically and evidence-based analysis. For instance, adding required amount of nutrients gives improved yields. Our work is based on selection of the influential parameters. The ML algorithms used in our proposed research give improved accuracy with less computational cost as compared to previous research. To facilitate farmers, an Android app is developed. The cost of our system is very low, and all the used sensors are easily available and easy to use. In future, more parameters and crops can be added to this system. The more accurate and efficient ML algorithms like CNN and LSTM can also be studied. SCS model can be\ integrated with security to protect crop data. For crop monitoring, drone cameras can also be used. Fertilizer recommendation system can also be developed on the basis of real-time sensory data of soil nutrients.

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