Shahid Bahonar University of Kerman
Agricultural Biotechnology Journal
Iranian Biotechnology Society
Print ISSN: 2228-6705 Online ISSN: 2228-6500

Using agricultural big data analytics in plant breeding and genetics to increase food yield

Ashu Nayak

*Corresponding Author. Assistant Professor, Department of CS & IT, Kalinga University, Raipur, India. E-mail address: ku.ashunayak@kalingauniversity.ac.in

Kapesh Subhash Raghatate

Research Scholar, Department of CS & IT, Kalinga University, Raipur, India. E-mail address: kapesh.kumar.nayak@kalingauniversity.ac.in

Abstract

Objective

When it comes to a healthy economy and population, the agriculture sector is essential. Smart Agriculture (SA) is a game-changing strategy that optimizes agricultural techniques with the use of cutting-edge technology like Big Data Analytics and the Internet of Things (IoT), in response to the rising need for food on a worldwide scale. The Internet of Things (IoT) gathers massive quantities of data from farms, allowing for more accurate disease control, irrigation methods, and crop output predictions. The goal of this research is to predict and improve grape plant production using an N-stage Convolutional Neural Network (CNN) trained using data from the SA database.

Materials and Methods

Optimal irrigation scheduling and amount prediction methods are also implemented in the research via the use of Machine Learning approaches. One useful method for early detection and treatment of plant illnesses is being investigated in this research: a Double Generative Adversarial Network (DGAN). This network might be used by farmers.

Results

The primary goal of this study is to develop a multi-stage convolutional neural network (CNN) model that can considerably boost agricultural output, with a focus on grape production.

Conclusions

A comprehensive strategy for grape plant development management is offered by the model via the integration of critical characteristics such as irrigation scheduling and disease diagnosis. Farmers are able to maximize their resources and output with the aid of this method, which also enhances the accuracy of yield predictions and facilitates better management decisions. In order to increase food production on a worldwide scale and promote sustainable agricultural techniques, this study's findings may lead to the wider use of Smart Agriculture methods.

Keywords: Agriculture, big data analytics, food yield, genetics, plant breeding

Paper Type: Research Paper.

Citation: Nayak A, Raghatate KS (2024) Using agricultural big data analytics in plant breeding and genetics to increase food yield. *Agricultural Biotechnology Journal* 16 (4), 335-348.

Agricultural Biotechnology Journal 16 (4), 335-348. DOI: 10.22103/jab.2025.24002.1610

Received: September 26, 2024. Received in revised form: December 08, 2024.

Accepted: December 09, 2024. Published online: December 30, 2024.

Publisher: Faculty of Agriculture and Technology Institute of Plant Production, Shahid Bahonar University of Kerman-Iranian Biotechnology Society.

Introduction

Big data is typically characterized by three key factors: volume, velocity, and diversity (Hancock & Khoshgoftaar 2020). Volume pertains to the rapid increase in the data gathered, such as the abundance of high-resolution and high-frequency satellite and aerial pictures. Velocity relates to the rate at which data is collected, such as the use of real-time in-field cameras to monitor the development of plants. Variety encompasses various sources of information and forms, such as standard survey information and social media postings about foods and food-borne diseases. Within the agricultural sector, big data is commonly perceived as integrating analytics and technology to gather and organize fresh information and analyze it more practically and timely to support decision-making (Li et al. 2022). This perspective takes into account both the information itself and the techniques employed to get value from the information.

Given the expected world population of over 9 billion by 2050, it is imperative to enhance agricultural productivity and improve Food Supply Chains (FSC) to effectively fulfill the increasing demand for nourishment, fiber, and energy (Perdana et al. 2022). The effects of global warming and urbanization also hinder this objective. Agricultural Big Data (Ag-BD) will be a crucial element of the subsequent green revolution, which is necessary to fulfill these requirements (Cravero et al. 2022).

Several governments and commodities markets are now using Ag-BD sets to promptly identify disturbances in FSC for commodity crops, including wheat, maize, rice, and soybeans. The field of SA has evolved due to advancements in data collection from remote sensors. These advancements include enhancements in time and space decisions, spectral decisions, and the availability of various sensor technologies like satellites, aerial vehicles, and ground-based systems.

According to a recent congressional acceptance, Smart Agriculture (SA) has demonstrated the potential to enhance on-farm yields (Friha et al. 2021). A recent article in Fortune magazine highlighted the possibility of boosting farm profits by nearly $100 per acre by implementing prescriptive agriculture (Camgözlü & Kutlu 2023). This approach utilizes forecasting modeling and Ag-BD to optimize various farm operations, such as adjusting seed planting volume and applying fertilizer according to local soil features and long-term weather predictions. Ag-BD and predictive computing are crucial in monitoring and managing infectious illnesses in farm animals. Moreover, data generation in agriculture and biotechnology has greatly increased in recent years due to the very rapid development of high-performance technologies (Mohammadabadi et al. 2024). These data are obtained from studying products, foods, and biological molecules to understand the role of different aspects of agriculture in determining the structure, function, and dynamics of living systems (Pour Hamidi et al. 2017). Artificial neural networks have been proposed to alleviate limitation of traditional methods and can be used to handle nonlinear and complex data, even when the data is imprecise and noisy (Pour Hamidi et al. 2017). Agricultural data can be too large and complex to handle through visual analysis or statistical correlations. This has encouraged the use of machine intelligence or artificial intelligence (Ghotbaldini et al. 2019). Thus, the main goal of this study was to predict and improve grape plant production using an N-stage Convolutional Neural Network (CNN) trained using data from the SA database.

History of AG-BD: The U.S. Department of Agriculture (USDA) remains the primary source for maintaining and disseminating agricultural information, including surveys and economic and scientific information (Massa et al. 2024). The USDA responded to the G8 international meeting on Open Information for Agriculture by launching the Global Open Data for Agriculture and Nutrition (GODAN) Project (Shonhe 2021). This initiative aims to facilitate open data exchange to contribute to the worldwide food supply.

The U.S. Bureau of Employment Statistics, the National Oceanographic and Atmospheric Agency (NOAA), and the National Aeronautics and Space Agency (NASA) also consistently offer a substantial amount of satellite imagery, progressively improving in quality and frequency. Several open imagery databases, including Amazon's Web Services (AWS), Google Earth Engines, and NASA Earth Interchange, are accessed through systems (Kharel et al. 2020). Imaging datasets are crucial as Ag-BD assets in several agricultural uses, such as SA and yield predictions (Veerasamy & Fredrik 2023). As online social media becomes increasingly popular, more individuals share Ag-BD, such as information on food consumption and food-borne diseases. Data from social media sites such as Twitter and Google Search is obtained and analyzed (Zoran et al. 2022).

Enhancing crop quality is crucial for achieving higher production levels, necessitating accurate yield forecasting (Liu et al. 2021). Observing plants and identifying diseases is essential to determine plant development and, consequently, the overall yield (Srinivasa Rao et al. 2023). All essential plant growth features will be thoroughly examined, including identifying illnesses as contributing variables. Prior studies have focused solely on a limited number of growth indicators, while others have exclusively developed techniques for disease identification (Hassan & Maji 2022). This article examines growth characteristics and illness detection. In modern times, farmers are not enthusiastically pursuing farming owing to many challenges like pest infestations, illnesses, unpredictable weather patterns, climatic fluctuations, and erratic rainfall (Angin et al. 2020). Technological innovations are necessary to enhance the efficiency, profitability, and SA (Surendar et al. 2024). SA offers abundant prospects for exploration and advancement. The research has conducted thorough surveys, employing highly efficient methodologies for optimal production.

Materials and methods

Proposed Ag-BD-based Plant Breeding Model-Dataset and study area: Machine Learning (ML) algorithms need a substantial amount of data to be handled with optimal efficiency. Flexible data facilitates recognizing patterns by removing extraneous elements not essential for learning. Creating a deep-reinforcement learning approach for the farming system is highly challenging due to its complex and predictable behavior. This section provides a comprehensive overview of the database for predicting irrigation and agricultural productivity. This study investigates the expected productivity of grape cultivation areas in the southern region of India. The information includes specific climate, soil, and soil properties, as well as the amount of fertilizers used by grape crops in the study area, based on normal climatic and soil parameters.

Agricultural Biotechnology Journal; Print ISSN: 2228-6705, Electronic ISSN: 2228-6500

The data gathered during the irrigation phase encompassed the measurements of temperature, moisture, rainfall, and pH levels of the grape plant variety. Data sets of grape leaf pictures were acquired to identify plant diseases and forecast agricultural yields. A dataset spanning 15 years has been gathered. Information on common climatic factors has been utilized, including temperatures, rainfall, plant evapotranspiration guidance, prospective evapotranspiration, moisture, and distinctive features such as ground frost incidence and diurnal and wind velocity. The Indian Meteorological Agency provides climatic data and photographs of grape plants through their metadata toolkit online. The soil parameters encompass the maximum soil volume, pH, and quantity of soil macronutrients (nitrate, phosphate, and potash). This section demonstrates the use of the suggested approach on specific databases.

Techniques: The planned effort is categorized into three phases: Agriculture, plant disease identification, and plant production. The output of the irrigation stage is compared utilizing the ML techniques. The plant illness is detected using the DGAN technique, and the ultimate crop production is forecasted by combining the irrigation stage, plant disease identification, and crop yield predictions (Figure 1).

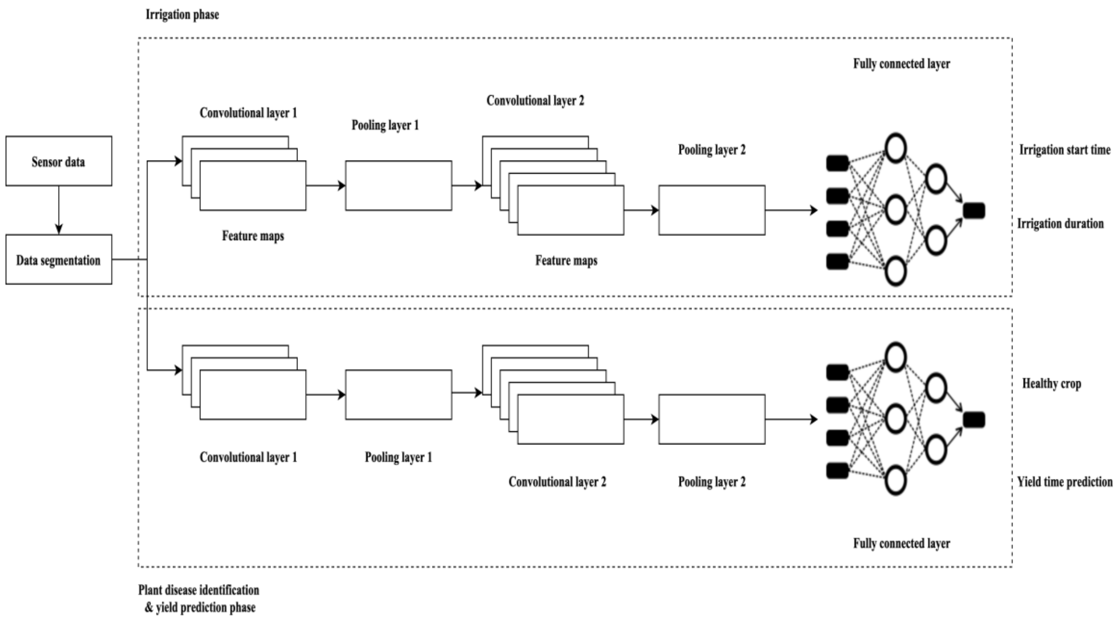

Figure 1. Workflow of the DGAN architecture

The diagram illustrates the segmentation of sensor information using an n-stage Convolutional Neural Network (CNN). The process consisted of two distinct steps. The first stage included irrigating the input through a convoluted level, followed by a reduction in size by pooling. This procedure persisted until the system achieved the ultimately linked layer. Two results are generated from this process and transmitted to the second step, the illness detection stage. In the second step, the identical process occurred again, resulting in two outcomes: the flourishing plant and yield forecast, which serve as our ultimate output. The methodology of the suggested study is outlined below.

Irrigation: The irrigation stage represents the initial stage of the CNN system. Many datasets were gathered during this stage, including temperature, moisture, precipitation, pH levels, and crop characteristics. The n-stage CNN segments the datasets. After this stage, two outcomes were generated: the initiation time of watering and its duration. The watering start period and length in this scenario remain constant while the irrigation information and plant photos are forwarded to the subsequent step, plant disease identification. This general approach was used throughout the initial stage. Three methods were employed to carry out the watering phase in grape crops.

Disease Identification: Initially, the picture datasets are gathered. Now, the research examines the sequential procedures required for deploying CNN in the illness identification stage. The output, which includes the initial stage's irrigation data and plant leaf photos, served as the input for this step. Initially, the input data was fed into the convolutional level and subsequently sent to the pooling level, resulting in a half reduction of its dimensions. The identical procedure persisted until it achieved the ultimately linked level. Two results were generated from this stage: the forecast of plant well-being and crop production estimates, which serve as our final result. The DGAN technique serves as an enrichment tool for processing images.

Plant foliage can serve as a means of detecting illness in plants. There are typically inconsistent portrayals of asymmetrical foliage extracted from various plants. Identifying diseases with an unbalanced dataset poses significant challenges. The research utilized DGAN, a dual generative adversarial system, to balance these databases. The study proposed employing DGAN to generate high-resolution images using fewer sick leave data.

The two stages of DGAN are divided. In stage 1, the research utilized both nutritious and non-nutritious leaves. The pre-trained system was initially provided with healthy pictures for conditioning the Wasserstein GAN (W-GAN). The model then utilized sick leaves to generate sick leaves with dimensions of 64*64 pixels. During the second step, 256 × 256-pixel pictures were acquired to expand imbalanced data settings by employing an adversarial network in super-resolution (SR-GAN). A comparison was made between the images generated by the Deep Convolutional GAN (DC-GAN), as shown in Figure 2.

Agricultural Biotechnology Journal; Print ISSN: 2228-6705, Electronic ISSN: 2228-6500

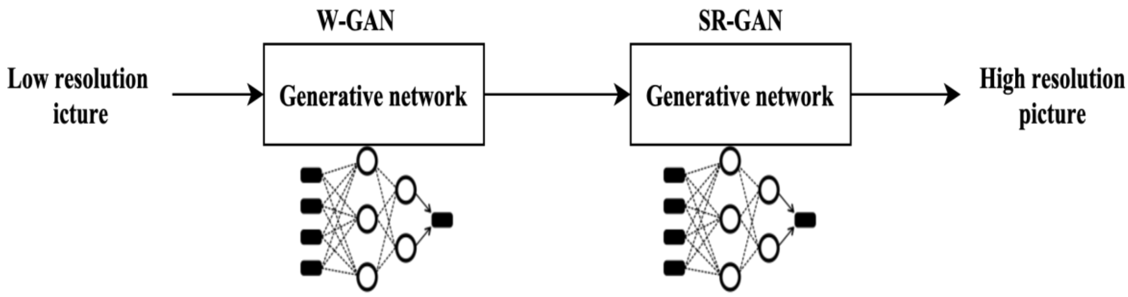

Figure 2. Workflow of the DC-GAN

Crop yield prediction: Every farmer must possess critical knowledge regarding the forecast of crop output and methods to boost yield. The pH level, soil composition, and quality determine crop productivity. Other essential factors include temperature, rainfall, precipitation levels, duration of sunshine exposure, use of fertilizers, and adherence to harvest patterns. Manual farming is considered a feedback control structure, allowing corrective actions to be implemented when an adverse impact on a crop is seen. The productivity of crop production relies on the optimal utilization of these assets. Any abnormalities that go unnoticed in the first stage might lead to unprecedented damage to agricultural productivity.

ML algorithms are employed for crop tracking and yield prediction utilizing satellite data. The challenges associated with using a time series of remote data for harvest forecasting systems might result in discrepancies among the crops of the typical vegetation changing index obtained from satellite data. This work utilized sophisticated ML techniques, including Boosting Regression Tree (BRT), Random Forest (RF), and Support Vector (SV) with Gaussian Process (GP). The values were averaged annually for every category to create a two-dimensional dataset. The ML approaches have been employed on 100 occasions, and their evaluation metrics have been deployed to gauge performance and examine stability. Each ML technique has computed the average of its results to generate returns. Comparisons across these methodologies indicate that the mean R-value of BRT through all years exceeds 0.87.

The Normalized Difference Vegetation Index (NDVI) is a straightforward graphical tool used to analyze remote sensing data, often obtained from satellites, to determine the presence of healthy greenery in a given area. This is an accepted indicator of the difference in vegetation levels. The essential capabilities of the two techniques are merged using BRT. The model being used is an RT, which is currently being trained. The RT establishes a connection between a reaction and its predictors through repeated binary divisions. The BRT is a method that intelligently combines various available models to improve the accuracy of predictions.

Results and discussion

Simulation Analysis and Outcomes: The suggested approach is assessed on grape leaves with moisture, temperature, precipitation, crops, pH, and soil irradiation measurements to determine the optimal watering schedule. Subsequently, the picture dataset is employed to identify the condition of plants and choose the quantity of crops produced. The proposed technique will be evaluated using categorization techniques, namely the Decision Tree (DT), RF, and Naïve Bayes (NB) techniques. The identification of plant diseases is conducted using the DGAN model and assessed using the ResNet and VGG methods. The estimation of agricultural production is accomplished by utilizing the BRT technique.

Irrigation result: The irrigation schedule is assessed using the DT, RF, and NB approaches, considering criteria such as Mean Square Errors (MSE), Mean Absolute Errors (MAE), R-squared errors, Root Mean Square Errors (RMSE), and correctness. The precise irrigation timing can only be determined with an expert's confirmation. The research considers additional factors, such as identifying plant diseases and crop yield time, to obtain accurate predictions for irrigation schedules. The subsequent section and Figure 3 present ML algorithms' diverse performance outcomes for irrigation planning grape leaves.

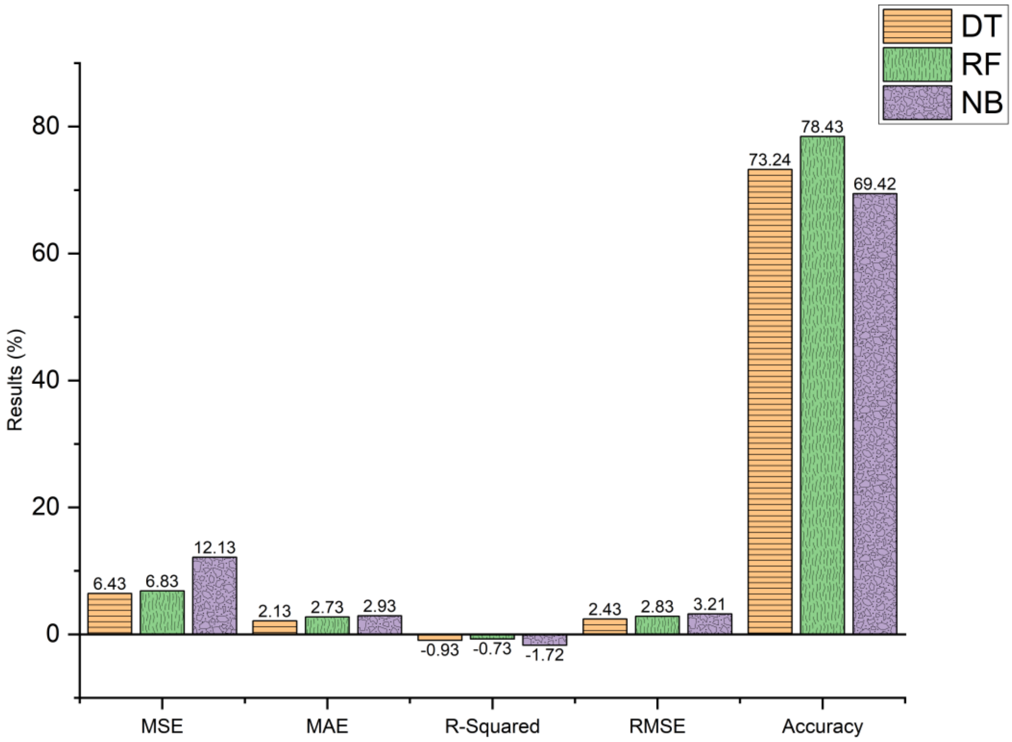

Figure 3. Irrigation planning analysis

Agricultural Biotechnology Journal; Print ISSN: 2228-6705, Electronic ISSN: 2228-6500

The results show the metric estimates for the RF, DT, and NB models. RF demonstrated the most excellent efficiency among the three methods, establishing it as the optimal implementation approach for the irrigated stage.

Plant disease identification: The DGAN is employed to enhance the quality of low-resolution photographs of grape leaves, resulting in high-quality pictures. The precision is assessed using the VGG-16 and Res-Net-50 models. The outcomes of the different algorithms are displayed in Figure 4.

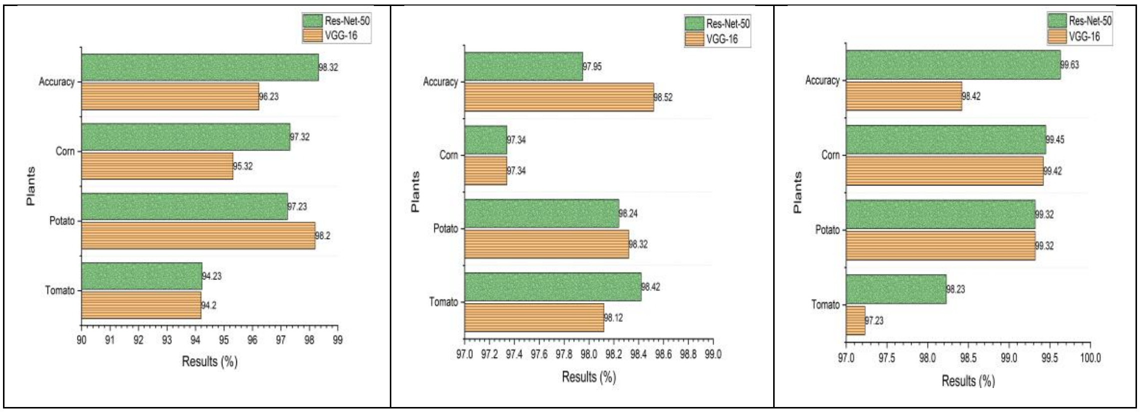

Figure 4. Plant disease identification results (a). Original, (b). Flipping & translation expansion, and (c). DGAN expansion

The results indicate that the categorization improves as the data set is expanded using DGAN. VGG-16 and Res-Net-50 exhibit high similarity in their classification of data sets, resulting in DGAN pictures that closely resemble the previously generated ones. The DGAN can generate numerous pictures by utilizing random noise, which helps address the limited diversity issue in the extended data set due to spinning and transformation enlargement. Plant disease identifications directly impact the forecasts of watering and the timing of crop output.

Crop yield prediction: This study utilized advanced machine learning techniques, including BRT, RF, SV, and GP, to analyze grape plants. The ML approaches are evaluated by comparing their error metrics, namely MAE, RMSE, and R. Figure 5 demonstrates that the BRT technique exhibits lower error rates than RFR, SVR, and GPR. The outcome can be refined by considering the various outputs of this application, such as irrigation planning, plant disease identification, and yield time forecasting. Predicting irrigation planning can be enhanced by utilizing the output from identifying plant diseases and crop yield time estimation.

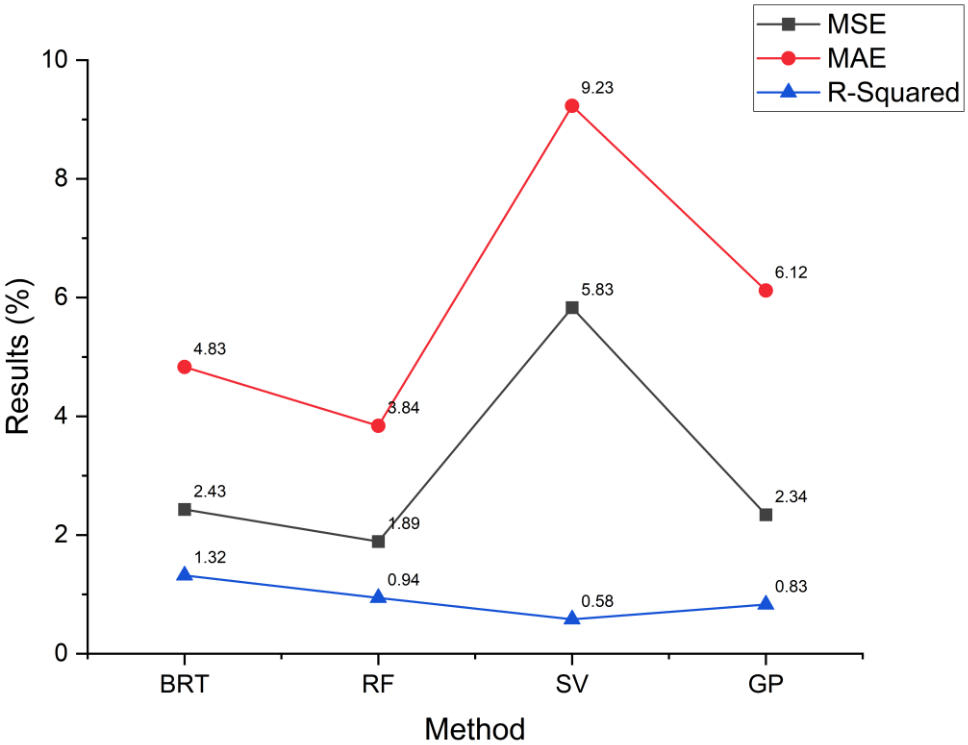

Figure 5. Crop yield prediction results

The proposed methodology will be evaluated utilizing classification techniques, including the DT, RF, and NB approaches. The RF produced the best results out of these three ML models. The research achieves superior accuracy rates by utilizing the DGAN picture dataset alongside Res-Net and VGG scenarios compared to the original dataset photos and traditional enhanced pictures. The error rate for predicting agricultural production is determined using several ML methods, such as BRT, RF, SV, and GP. SV method has much-reduced error rates compared to alternative methodologies.

Conclusions: The prediction of agricultural yield is crucial for increasing production efficiency. The declining number of experienced farmers highlights the need to understand the most effective ways for cultivating crops in areas with scarce assets, especially for inexperienced agricultural practitioners. Although other studies have been conducted in this field, the results of this research suggest that using the most excellent rendering techniques can lead to beneficial outcomes for several reasons, such as optimizing times for watering and aiding in identifying plant diseases. A practical approach for SA has been developed using N-stage CNN and ML algorithms. The experimental results illustrate that this technique yields a valuable and precise output by taking into account irrigation planning, illness identification, and crop production forecast. This work offers future development possibilities by utilizing more GAN methodologies that create a greater volume of images. By doing this, the precision of disease diagnosis and the ability to estimate crop yield may significantly improve.

Acknowledgement: The author declares that no financial support, grants, or other resources were received during the preparation of this manuscript.

Conflict of Interest: There is no conflict of interest.

References

Angin P, Anisi MH, Göksel F, et al. (2020). Agrilora: a digital twin framework for smart agriculture. J Wireless Mobile Netw Ubiquit Comput Depend Appl 11(4), 77-96.

Camgözlü Y, Kutlu Y (2023) Leaf Image Classification Based on Pre-trained Convolutional Neural Network Models. Nat Eng Sci 8(3), 214-232.

Cravero A, Pardo S, Sepúlveda S, Muñoz L (2022) Challenges to use machine learning in agricultural big data: a systematic literature review. Agron J 12(3), 748.

Friha O, Ferrag MA, Shu L, et al. (2021) Internet of Things for the future of smart agriculture: A comprehensive survey of emerging technologies. IEEE/CAA J Autom Sinica 8(4), 718-752.

Ghotbaldini H, Mohammadabadi MR, Nezamabadi-pour H, et al. (2019) Predicting breeding value of body weight at 6-month age using Artificial Neural Networks in Kermani sheep breed. Acta Scientiarum Anim Sci 41, e45282.

Hancock JT, Khoshgoftaar TM (2020) CatBoost for big data: an interdisciplinary review. J Big Data 7(1), e94.

Hassan SM, Maji AK (2022) Plant disease identification using a novel convolutional neural network. IEEE Access 10, 5390-5401.

Kharel TP, Ashworth AJ, Owens PR, Buser M (2020) Spatially and temporally disparate data in systems agriculture: Issues and prospective solutions. Agron J 112(5), 4498-4510.

Li C, Chen Y, Shang Y (2022) A review of industrial big data for decision making in intelligent manufacturing. Engin Sci Technol Int J 29, e101021.

Liu Q, Yang F, Zhang J, et al. (2021) Application of CRISPR/Cas9 in crop quality improvement. Int J Mol Sci 22(8), e4206.

Massa OI, Karali B, Irwin SH (2024) What do we know about the value and market impact of the US Department of Agriculture reports? Appl Econ Perspect Policy 46(2), 698-736.

Mohammadabadi M, Kheyrodin H, Afanasenko V, et al. (2024) The role of artificial intelligence in genomics. Agric Biotechnol J 16 (2), 195-279.

Perdana T, Onggo BS, Sadeli AH, et al. (2022) Food supply chain management in disaster events: A systematic literature review. Int J Disaster Risk Reduct 79, e103183.

Pour Hamidi S, Mohammadabadi MR, Asadi Foozi M, Nezamabadi-pour H (2017) Prediction of breeding values for the milk production trait in Iranian Holstein cows applying artificial neural networks. J Livestock Sci Technol 5 (2), 53-61.

Shonhe L (2021) Sharing Open Data in Agriculture: A Learning Curve for Developing Countries. Open Access Implic Sustain Soc Pol Econ Dev 244-266. IGI Global.

Srinivasa Rao M, Praveen Kumar S, Srinivasa Rao K (2023) Classification of Medical Plants Based on Hybridization of Machine Learning Algorithms. Indian J Inf Sour Serv 13(2), 14-21.

Surendar A, Saravanakumar V, Sindhu S, Arvinth N (2024) A Bibliometric study of publication-citations in a range of journal articles. Indian J Inf Sour Serv 14(2), 97-103.

Veerasamy K, Fredrik ET (2023) Intelligent Farming based on Uncertainty Expert System with Butterfly Optimization Algorithm for Crop Recommendation. J Internet Serv Inf Secur 13(3), 158-169.

Zoran G, Nemanja A, Srđan B (2022) Comparative Analysis of Old-Growth Stands Janj and Lom Using Vegetation Indices. Arch Tech Sci 2(27), 57-62.

مجله بیوتکنولوژی کشاورزی
دانشگاه شهید باهنر کرمان
انجمن بیوتکنولوژی ایران
شاپا چاپی: ۶۷۰۵-۲۲۲۸ شاپا الکترونیکی: ۶۵۰۰-۲۲۲۸

استفاده از تجزیه و تحلیل داده‌های بزرگ کشاورزی در اصلاح نباتات و ژنتیک برای افزایش عملکرد غذا

اشو نایاک

*نویسنده مسئول: استادیار، گروه علوم کامپیوتر و فناوری اطلاعات، دانشگاه کالینگا، رایپور، هند. آدرس پست الکترونیکی: ku.ashunayak@kalingauniversity.ac.in

کاپش سابهاش راغاته

پژوهشگر، گروه علوم کامپیوتر و فناوری اطلاعات، دانشگاه کالینگا، رایپور، هند. آدرس پست الکترونیکی: kapesh.kumar.nayak@kalingauniversity.ac.in

تاریخ دریافت: ۱۴۰۳/۰۷/۰۵ تاریخ دریافت فایل اصلاح شده نهایی: ۱۴۰۳/۰۹/۱۸ تاریخ پذیرش: ۱۴۰۳/۰۹/۱۹

چکیده

هدف: وقتی صحبت از اقتصاد و جمعیت سالم می‌شود، بخش کشاورزی ضروری است. کشاورزی هوشمند (SA) یک استراتژی تغییردهنده بازی است که تکنیک‌های کشاورزی را با استفاده از فناوری‌های پیشرفته مانند تجزیه و تحلیل داده‌های بزرگ و اینترنت اشیا (IoT) در پاسخ به نیاز روزافزون به غذا در مقیاس جهانی بهینه می‌کند. اینترنت اشیا (IoT) مقادیر انبوهی از داده‌ها را از مزارع جمع‌آوری می‌کند و امکان کنترل دقیق‌تر بیماری، روش‌های آبیاری و پیش‌بینی محصول را فراهم می‌کند. هدف از این تحقیق، پیش‌بینی و بهبود تولید گیاه انگور با استفاده از شبکه عصبی کانولوشنال (CNN) مرحله N آموزش دیده با استفاده از داده‌های پایگاه داده SA بود.

مواد و روش‌ها: روش‌های برنامه‌ریزی بهینه آبیاری و پیش‌بینی مقدار نیز با استفاده از روش‌های یادگیری ماشینی در تحقیق اجرا می‌شوند. یکی از روش‌های مفید برای تشخیص و درمان زودهنگام بیماری‌های گیاهی در این تحقیق مورد بررسی قرار می‌گیرد: شبکه متخاصم دوگانه (DGAN). این شبکه ممکن است توسط کشاورزان استفاده شود.

نتایج: هدف اصلی این مطالعه توسعه یک مدل شبکه عصبی کانولوشنال چند مرحله‌ای (CNN) بود که می‌تواند به طور قابل‌توجهی بازده کشاورزی را با تمرکز بر تولید انگور افزایش دهد.

نتیجه‌گیری: یک استراتژی جامع برای مدیریت توسعه گیاه انگور توسط این مدل از طریق ادغام ویژگی‌های حیاتی مانند برنامه‌ریزی آبیاری و تشخیص بیماری ارائه شده است. کشاورزان با کمک این روش می‌توانند منابع و بازده خود را به حداکثر برسانند، که همچنین دقت پیش‌بینی عملکرد را افزایش می‌دهد و تصمیمات مدیریتی بهتر را تسهیل می‌کند. به منظور افزایش تولید مواد غذایی در مقیاس جهانی و ترویج تکنیک‌های کشاورزی پایدار، یافته‌های این مطالعه ممکن است منجر به استفاده گسترده‌تر از روش‌های کشاورزی هوشمند شود.

واژه‌های کلیدی: اصلاح نباتات، تجزیه و تحلیل داده های بزرگ، ژنتیک، عملکرد مواد غذایی، کشاورزی

نوع مقاله: پژوهشی.

استناد: نایاک اشو، راغاته کاپش سابهاش (۱۴۰۳) استفاده از تجزیه و تحلیل داده‌های بزرگ کشاورزی در اصلاح نباتات و ژنتیک برای افزایش عملکرد غذا. *مجله بیوتکنولوژی کشاورزی*، ۱۶(۴)، ۳۳۵–۳۴۸.

Publisher: Faculty of Agriculture and Technology Institute of Plant Production, Shahid Bahonar University of Kerman-Iranian Biotechnology Society.