IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

CROP DETECTION USING MACHINE LEARNING

[1]R. Abinaya, [2]Dr.M. Caroline Viola Stella Mary

[1]PG Student, [2]Professor IT
[1,2]Department of Information Technology
[1,2]Francis Xavier Engineering College, Tirunelveli, India.

Abstract : Applications of machine learning are changing how decisions are made and how data is processed, which is having a significant impact on the world economy. Considering the global food supply crisis, one of the industries where the influence is substantial is agriculture. This project's primary objective is to develop a trustworthy crop detection system through the application of machine learning techniques. Our goal is to use state-of-the-art algorithms and image processing techniques to accurately recognize and classify various crops within agricultural landscapes. Through providing farmers and the public with relevant data regarding the health, growth stages, and distribution of their crops, this system aims to enable farmers to make data-driven decisions that optimize agricultural productivity, manage pests, and allocate resources. Our objective is to integrate machine learning models trained on massive datasets to provide a scalable and efficient solution that can be used to different farming practices and geographical areas. In the end, this will promote food security and sustainable agriculture.

***IndexTerms* - Innovative algorithm, image processing, crop classification, support vector machine (SVM), convolutional neural network (CNN), crop detection, and feature extraction.**

I.INTRODUCTION

The rapid evolution of machine learning technology has enabled significant breakthroughs in numerous industries, including agriculture. Crop identification, a crucial aspect of agricultural management, expects to gain significantly from these technological advancements. Because traditional crop identification methods usually rely on satellite imagery and human observation, they are labor-intensive, time-consuming, and error-prone. Machine learning offers a workable alternative for identifying and monitoring crop kinds and health by utilizing massive amounts of data to increase precision and productivity. In recent years, crop detection has become more effective when machine learning is combined with remote sensing technologies like Unmanned Aerial Vehicles (UAVs) and satellite sensors. These technologies provide high-resolution, real-time data that enables detailed analysis of agricultural conditions over large areas. Large-scale dataset processing and analysis, pattern recognition, and accurate prediction-making have all been demonstrated to be very well-suited to machine learning algorithms. This is particularly true for algorithms that rely on deep learning.

This study's primary goal is to examine crop identification using machine learning techniques and evaluate their effectiveness and potential to increase agricultural productivity. We will analyze and discuss the benefits and drawbacks of the newest cutting-edge methods, including convolutional neural networks (CNNs), support vector machines (SVMs), and ensemble learning. Furthermore, the challenges of implementing these techniques in practical agricultural settings will be examined, encompassing the need for substantial annotated datasets, processing power, crop diversity, and environmental unpredictability. This work aims to provide a comprehensive review of how machine learning could alter crop identification methods to increase the sustainability and efficiency of agricultural systems. By utilizing machine learning, making educated decisions, and optimizing resource use, agricultural stakeholders and farmers may enhance food security.

II.LITETRATURE REVIEW

The research of kumar et.al is about the integration of Sentinel-1 SAR and Sentinel-2 optical data for crop type mapping was the main focus of the investigation. Data fusion, geometric rectification, and radiometric calibration were among the preprocessing procedures. The capacity to differentiate between various crop kinds was improved by the integration of SAR and optical data, especially in hazy areas

In this paper Lee et al featured that Sentinel-2 time-series data were used in this investigation for crop classification and monitoring. Co-registration, atmospheric correction, and Savitzky-Golay filter smoothing of NDVI time series were important preprocessing methods. Time-series data greatly increased crop classification accuracy, as the study showed.

The study proposed by Garcia used UAV-based multispectral data and machine learning techniques to recognize different crop types. Segmentation, noise reduction, and radiometric correction were preprocessing processes. The study demonstrated how well UAV photography can provide precise and in-depth crop classification.

Chen et al examined the use of hyperspectral imaging for crop type detection, with a focus on preprocessing methods such spectrum normalization, noise reduction, and dimensionality reduction using ICA. The hyperspectral data's rich spectral information improved the capacity to distinguish between various crop types.

The study investigated by Thomas uses the multisource data fusion, which combines information from ground-based, satellite, and unmanned aerial vehicle sources, for crop classification. Preprocessing included radiometric and atmospheric corrections as well as feature extraction from many data sources. The integrated technique significantly increased the categorization accuracy. Menon, R., Thomas, S., and Ramachandran, S. (2022) are cited. Multisource Data Fusion for Enhanced Crop Type Classification. Remote Sensing and the Environment, 268-112748.

The featured study which was published in 2023 by Li et al seeks to determine the application of convolutional neural networks (CNNs) to high-resolution picture crop type categorization was investigated. Preprocessing included applying edge detection filters, standardizing data, and augmenting it. In tests involving crop classification, the CNN model demonstrated a high degree of accuracy and resilience.

The study investigation by Rodriguez et al used optical imaging and SAR data to provide reliable crop classification in a range of weather scenarios. Preprocessing comprised optical picture enhancing techniques and SAR-specific procedures like terrain adjustment and speckle filtering. Even in foggy areas, the combination produced trustworthy classification findings.

In 2024 Wang et al proposed that for large-scale crop type mapping, this study used machine learning algorithms on MODIS time-series data. Temporal smoothing, gap filling, and feature extraction were all part of the preprocessing. Large datasets were handled well by the machine learning method, which also increased classification accuracy.

The research made by Zhao et al was about the study concentrated on using hyperspectral data and deep learning algorithms to detect crop types. Spectral normalization, noise reduction, and data augmentation were all part of the preprocessing. For precise classification, the deep learning models outperformed other models in capturing intricate spectral characteristics.

This approach was suggested by Mohsen Shahhosseini, Guiping Hu, Rafael A. Martinez-Feria, and Sotirios V. Archontoulis. The most effective crop recommendations for farmers to consider when making decisions might come from pre-growing season crop production predictions of outputs including grain yields and nitrogen losses. It makes use of the LASSO Regression, Ridge Regression, Random Forests, and Extreme Gradient Boosting machine learning (ML) techniques. This article primarily discusses how preseason data is used by ML meta-models to estimate maize yield? To obtain reasonable predictions, what is the required amount of data to train machine learning algorithms? Which variables in the input data are frequently employed to make correct predictions? And fourth, do all machine learning meta-models enhance prediction? When the training dataset grew from 0.5 to 1.8 million data points, yield prediction error across all ML models dropped by 10%–40%, 37 but N loss prediction error did not exhibit any discernible trend.

The primary focus of this proposed study is on crop production forecast, crop cost prediction, and the algorithms employed in these processes. These elements allow for the achievement of smart farming. After completing the feature extraction procedure, the data or columns to be processed using algorithms are taken, their accuracy is determined, and a graph pertaining to the data is plotted. The classification technique has been used to determine the algorithm's accuracy. The statistical analysis of the attribute in the provided dataset is then produced using the Bayesian network. The patterns with the nonlinear effect and underlying concept are then compared using the ANN. This study was get proposed by S.R. Rajeshwari in 2019.

This work was proposed by Anand M. Ambekar, Vijay S. Rajpurohit, and Ramesh A. Medar. In this study, long-term time series (LTTS), weather and soil variables, the Normalized Vegetation Index (NDVI), and supervised machine learning (SML) methods are suggested for sugarcane production forecasting in the Karnataka (India) region. Three steps make up their yield forecasting process: i) soil-and-climate attributes are projected for the duration of the SCLC; ii) NDVI is projected using Support Vector Machine Regression (SVR) computation by considering soil-and-climate credits as information; iii) sugarcane crop is projected using SVR by considering NDVI as information. Here, temperature, precipitation, soil moisture, and soil temperature are the characteristics that are used. These procedures are repeated for various sets of data.

Virendra Panpatil, Pavan Patil, and Prof. Shrikant Kokate proposed this approach. This article explains how adding additional features to the system can improve its output and improve yields and pattern recognition. Some survey research give a brief, one-attribute summary of machine learning. The Naïve Bayes and decision tree algorithms are merged. In the given dataset, decision trees exhibit low performance and higher variances; yet, in some scenarios, naïve bayes outperforms decision trees. The combination classification approach of naïve bayes and decision tree classifier performs better than using a single classifier model. Temperature, wind, precipitation, humidity, and soil pH are among the variables.

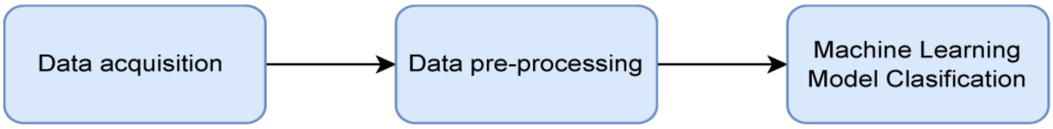
The authors of this study are M. Kalimuthu, P. Vaishnavi, and M. Kishore. They use machine learning to assist the farmer in planting appropriate crops. Here, the supervised learning algorithm Naive Bayes is employed. Here, crop seed data are gathered and used to determine temperature, humidity, and moisture content—parameters that are critical to the crops' optimal growth. The four main processes that make up the suggested system are the gathering of historical data, gathering current data, combining data, and gathering seed data. The Bayes Theorem forecasts the likelihood of an event occurring based on the likelihood of an event having already occurred. The model's accuracy in the Naïve Bayes technique is 97%.

Merin Kevin and Mary Saji This paper was suggested that by examining the agricultural region based on the characteristics of the soil, they would be able to solve the agricultural difficulties. It assists farmers in reducing losses and increasing productivity by recommending the best crop. This is a document that compares algorithms. Here, KNN, decision trees, Naïve Bayes, and KNN with cross validation SVM are the primary methods used. And it shows which algorithm works best for predicting this harvest. The testing methods that will be employed are SVM, Decision Tree, Naive Bayes, kNN, and kNN with Cross Validation. The accuracy numbers that corresponded to these were 88%, 78%, 81%, 82%, and 85%. The final system can employ KNN with cross validation since it offers the highest level of accuracy.

This paper was proposed by Nicolas F. Martinb, Naira Hovakimyana, and Alexandre Barbosaa. Here, it also makes use of the CNN architecture within the Deep Ensemble framework to redesign in order to increase efficiency. It forecasts a probability distribution of outputs rather than just one result. Here, the maps of crop inputs are found using an optimization approach based on gradients. Taking into account the risk limits, it will maximize net value. The suggested model improves on the previous version's anticipated performance while also emphasizing the significance of quantifying uncertainty. Up to 6.4% more is shown by the optimization method than is predicted by the net. Five input variables are used in this work: elevation map, prescription maps for nitrogen and seed rate, and shallow electro conductivity of the soil.

III. PROPOSED MODEL

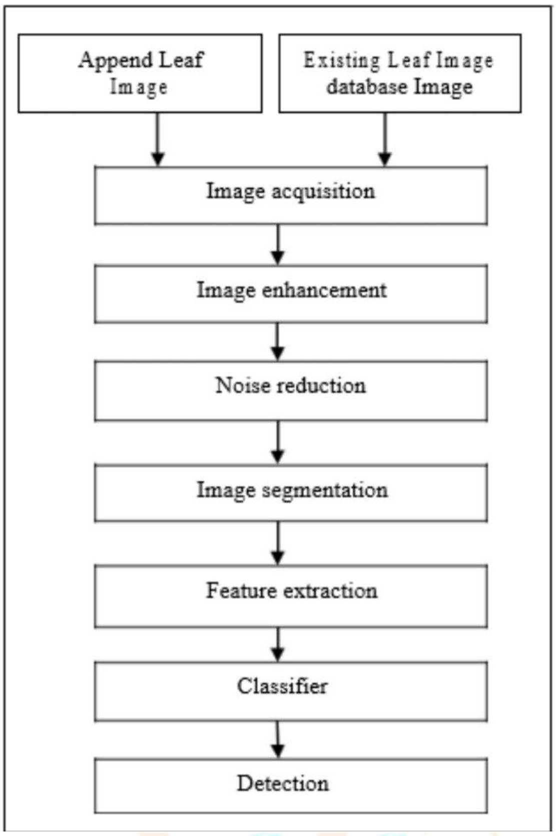
Using algorithms to identify and classify various crop kinds in agricultural fields based on image or other data inputs is known as machine learning-based crop detection. Precision agriculture software allows farmers to track crop health, spot diseases, and assess yield in order to improve practices. Machine learning-based crop detection involves using algorithms and methods to analyze drone or satellite imagery in order to identify and categorize different crops.



Typically, the process begins with the images being processed to enhance their features and eliminate noise. Next, crop-specific patterns are distinguished by machine learning models like support vector machines (SVMs) and convolutional neural networks (CNNs) that are trained on labeled data. After then, these models are applied to assess fresh images, accurately classifying and distinguishing different crop kinds depending.

Following that, these models are applied to assess fresh images, accurately classifying and distinguishing between different crop kinds according to their unique characteristics including shape, color, and texture. Using machine learning for crop identification offers practical management insights.

The first step in using machine learning for crop detection is to clearly state the project's goal, be it crop identification, crop health monitoring, or something else entirely. Next, gather pertinent data from sources like drones or satellite photos, then clean and categorize it. Select an appropriate machine learning model, such as a convolutional neural network for image data, after extracting important features from the data. Utilizing preprocessed data, train the model, assess its effectiveness, and then implement it in real-world scenarios. To ensure crop detection remains accurate and dependable over the long term, assess the model's performance on a regular basis and make necessary updates.



Some popular method includes convolution neural networks (CNN), support vector mechine(SVM) and decision tree. These system typically involves several steps:

- Data acquisition
- Data Preprocessing
- Feature extraction
- Training machine learning model
- Crop detection and classification

DATA ACQUISITION

The process of gathering information from various systems and sources is known as data acquisition. For use in machine learning techniques, data from a range of sources was gathered in earlier research. A portion of them take their own pictures by taking pictures of plants in greenhouses. Nevertheless, a lot of individuals collect image data manually, which leads to small image datasets and can hinder the development of efficient machine learning models. Rustia and Lin suggest using sensors to collect meteorological data in greenhouses. Weather stations in rural areas can provide meteorological data since they typically maintain records for an extended period of time. Search engines are the only way to obtain images. This technique can yield a vast amount of images, but domain verification is required to ensure the ground truth. This approach can yield a vast amount of photographs; however, the ground truth needs to be confirmed by subject matter experts, and data cleaning is often used to remove images that don't meet the specifications.

An further advantage of using remote sensing images from drones and satellites is the ability to retrieve image data for large agricultural areas. Crop progress can be examined using multi-temporal and hyper-spectral photography data that is frequently included in remote sensing data from satellites. Crop field growth can be effectively monitored by following the development of vegetation indices, which offer important insights. Spectral photography offers a substantial advantage over visible light spectrum data in that it can be used to compute other vegetation indexes, such as those that are predicted to be resilient to fluctuations in solar illumination. Data that is publicly accessible can also be used to construct machine learning applications.

When utilizing machine learning for crop recognition, multiple kinds of data are usually collected in order to train a model that can recognize different crops with accuracy. Here are a few typical techniques for gathering data:

1. Satellite Imagery: One of the most popular techniques for crop detection is the use of satellite photos. Crop growth, health, and changes over time can be tracked using high-resolution photography from platforms such as Sentinel, MODIS, and Landsat.

2. Aerial Photography: Crop fields can be captured in-depth photos by aerial drones fitted with cameras or other sensors. When compared to satellite imaging, these pictures might offer more recent data and a greater quality.

3. Ground-Based Sensors: Putting in sensors to track variables like temperature, humidity, and soil moisture might give useful information for identifying crops. These sensors can be mobile or fixed, and they can be used to track the development and health of crops in real time.

4. Weather Data: By including meteorological information into the model, such as temperature, humidity, and rainfall, crop growth and health can be predicted. A number of sources, such as satellites, internet databases, and weather stations, are available for providing weather data.

5. Crop Samples: Machine learning models can be trained by gathering physical samples of various crops and tagging them with the appropriate species. Leaves, stems, fruits, and other plant parts are all acceptable samples.

6. Crowdsourcing: Crowdsourcing platforms enable users from all around the world to contribute labeled data. This method is very useful for quickly and successfully collecting large amounts of tagged data.

7. Historical Data: Machine learning models for crop detection can be trained with historical data on crop distribution, land use, and agricultural practices. This information can be obtained from government agencies, academic institutions, or agricultural associations.

8. Field Surveys: Gathering information on crop kinds, planting schedules, and other relevant characteristics through field surveys can provide real-world data for machine learning model training.

9. Remote Sensing Techniques: LiDAR (Light Detection and Ranging) and hyperspectral photography can provide extensive data on crop properties such as height, biomass, and chemical composition.

10. Social Media and Online Platforms: Using social media platforms, agricultural forums, and online databases to collect photographs and information about crop varieties and distribution might supplement existing data sources for training machine learning models.

Researchers and practitioners can build machine learning models that effectively detect and categorize different crops by merging data from numerous sources, allowing for applications such as precision agriculture, crop monitoring, and yield prediction..

DATA PREPROCESSING

In machine learning applications, data is pre-processed before being input into the model. Images are typically pre-processed with computer vision algorithms to remove noise, improve image contrast, extract regions of interest, extract image features, and so on. In general, image pre-processing techniques yield better model results. The following subsections outline the most common data pre-processing techniques.

Manual feature extraction approaches typically require pre-processing steps such as noise reduction or contrast enhancement. The researchers must decide which feature extractors are best suited for the task at hand. When using deep learning, pre-processing is frequently focused on data augmentation, which entails enriching the training data set to boost model generalization. Deep learning produces better results when directly analyzing the original photos rather than using images that have been turned to greyscale or have had their backgrounds removed.

Preprocessing methods for crop recognition using machine learning typically entail preprocessing input data in order to improve the model's performance and efficiency. Here are a few common preprocessing techniques:

1. Image Resizing: Resizing input photographs to a uniform size can minimize computational complexity while also ensuring uniformity across the dataset.

2. Normalization: Setting pixel values to a common scale (e.g., between 0 and 1) can increase convergence during training and help the model generalize to new data.

3. Data Augmentation: Adding changes to the photos, such as rotation, flipping, or cropping, can increase the diversity of the training data and strengthen the model.

4. Color Space Conversion: Converting photos to a different color space (for example, RGB to grayscale) helps reduce data dimensionality while retaining useful information for crop detection tasks.

5. Feature Extraction: Extracting relevant features from input photos, such as texture, shape, or color histograms, can minimize input dimensionality while improving the model's ability to identify between crop types.

6. Noise Reduction: Filters or approaches for reducing visual noise, such as Gaussian blurring or median filtering, can improve input data quality and model performance.

7. Data Balancing: Balancing the distribution of classes in the dataset, particularly if specific crop kinds are underrepresented, can help to keep the model from being biased toward the majority.

8. Dimensionality Reduction: Methods such as Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbour Embedding (t-SNE) can be used to reduce the dimensionality of input data while retaining relevant information.

9. Missing Data Handling: Using imputation techniques or removing incomplete samples might help prevent errors during model training.

10. Spatial Transformations: Using geometric transformations such as affine or perspective transformations can simulate changes in viewpoint and increase the model's generalizability.

Using these preprocessing methods, researchers and practitioners can properly prepare input data for crop detection tasks, resulting in more accurate and reliable machine learning models.

FEATURE EXTRACTION

Feature extraction is important in crop detection using machine learning because it helps capture the main aspects of input data (such as photographs) that are vital for distinguishing between different crop kinds. The following are some common feature extraction approaches used in crop detection:

1.The Histogram of Oriented Gradients (HOG) calculates the distribution of gradient orientations in small sections of a picture. It captures the shape and texture of items in the image, which can help distinguish between different types of crops.

2. Local Binary Patterns (LBP): LBP depicts local texture patterns in an image by comparing each pixel to its neighbors. It may record crop texture details such as leaf patterns, which are typically used to differentiate across crop kinds.

3. Color Histograms: Color histograms show the distribution of colors in an image. They can record crop color features, which can differ dramatically between crop kinds.

4. Texture Features: Texture features, such as Haralick texture features or Gabor filters, define how pixel intensities are distributed spatially in an image. These features can capture the distinctive textural patterns found in many types of crops.

5. Shape Descriptors: Shape descriptors, like Hu moments or Fourier descriptors, describe the shape of objects in a picture. They can capture geometric aspects of crops, such as leaf shape or fruit morphology, which are often unique to each crop species.

6. Edge Detection: Edge detection algorithms, such as the Canny edge detector or the Sobel operator, recognize the edges of objects in an image. Edge features can capture crop structural information, such as leaf or fruit outlines.

7. Convolutional Neural Network (CNN) Features: To extract high-level features from input photos, utilize pre-trained CNN models such as VGG, ResNet, or Inception. These characteristics capture hierarchical representations of the input data that the CNN model learns during large-scale training. These characteristics capture hierarchical representations of the input data learned by the CNN model while training on large-scale datasets (for example, ImageNet).

they prevent overfitting, which might make it difficult for the model to distinguish between two objects in the image that might be overlapping (a female carrying a bag and standing in front of a car, for example). Adding pooling layers 8. Principal Component Analysis (PCA): PCA can be used to minimize the dimension of feature vectors while retaining the majority of the data's variation. It can help to condense the feature space and increase computational efficiency.

Machine learning algorithms may successfully learn to distinguish between different types of crops by extracting key characteristics from input photos, resulting in reliable crop identification and classification results. The feature extraction technique used is determined by the properties of the input data as well as the crop detection task's requirements.

TRAINING MACHINE LEARNING MODEL

A machine learning model requires a series of specific procedures to optimize the model's parameters so that it performs effectively on the given job. Here is a thorough description of the training process:

STEP 1: PREPARING THE TRAINING MODEL

To train your object detection model from beginning, you'll need an image database. Many free datasets are available for download over the internet platform. Following this, you will most likely need to perform data augmentation to avoid overfitting objects during the training phase. Data augmentation enlarges the image library by adding new references. Changing the orientation of the images, converting their colors to greyscale, or blurring them. All of these options generate fresh data, allowing the system to evaluate photos more simply.

Once you've entered your data, you'll need to use a specified format. Formatting images is critical for any machine learning software since it must interpret all of them. If the quality or dimensions of the images vary significantly, the system will find it difficult and time-consuming to process them all. After you've completed the formatting, you'll need to inform your model which kind of items you want it to identify and classify. The minimum number of photos required for an effective training phase is 200.

After you've saved the classes and annotated the photographs, you must explicitly specify the locations of the items in the images. The use of boundary boxes is then mandatory. You will only need to draw rectangles around the objects you want to identify and select the appropriate classes.

STEP 2: PREPARATION AND UNDERSTANDING OF HOW CONVOLUTIONAL NEURAL NETWORK MODELS WORK

Applications utilizing Convolutional Neural Network models typically operate with image recognition. When training your app, you will need to use this.

As is well known, a machine only analyses the data that comes from an image—its pixels—rather than the image as a whole. Feature extractors are Neural Networks, which mimic the function of human neurons. Straight from the images, they will extract features and feed them into the system for analysis. Proper annotation of the data and images aids the model in identifying salient aspects for accurate categorization. Convolutional neural networks, or CNNs, play this function.

You should learn more about the intricate design and operation of this specific model before implementing a CNN algorithm. The architecture of CNNs consists of multiple layers, each of which is designed to guide a distinct action. The convolutional layer is the initial filter or layer that the model applies to all of the image's pixels. The layer will extract some features from each pixel after capturing all of them. By doing this, a feature map will be produced, facilitating the initial stage of object detection and recognition. Depending on how many features you want the model to look at (the shapes, colors, textures that are visible in the image, etc.), you can apply a lot more convolutional layers.

An activation layer is applied after every piece of data has been examined and compiled into a feature map. This one is designed to make the results easier to understand so that the algorithm can process them more quickly.

During the procedure, pooling layers are used to increase the method's efficiency even further. Prior to employing further layers, these are used to collect, compress, and clean the image data. These are crucial because to a CNN model is a wonderful approach to improve its accuracy.In order to integrate all of the input features and outcomes, the images are next subjected to flattening and completely connected layers. The process of image recognition requires this stage.

There's a purpose to the training of these convolutional neural networks. Once all these layers have been trained using the training data and the results meet the desired outcomes, the application for image recognition can be launched. There is one thing, though, that you should keep in mind: the longer you train your model, the more accurate and performant your software will be.

STEP 3: EVALUATION AND VALIDATION OF THE TRANING RESULTS OF THE SYSTEM

It is crucial to go through an evaluation and validation procedure before deploying your Image Recognition model in a production setting. It will enable you to confirm that your solution meets the performance requirements for the system into which it is incorporated.

After training your model, you now wish to assess the training phase's outcomes. You must utilize a different dataset, and the trained model's evaluation will indicate the success or failure of the training process. This new dataset, known as the validation dataset, is unidentified to your algorithm.

To assess their performance and accuracy in recognizing and categorizing the photos, compare the analysis results of this new collection of photographs and pictures with the ones from the training phase.

Should you observe any discrepancies among the different outputs, you may wish to reevaluate your algorithm and start over with a fresh training phase. However, perhaps you might adjust a few of the parameters you used in the initial training session this time. Perhaps the issue stems from the fact that each image has a different format. It can be the outcome of the images' lack of variety. In this instance, you ought to attempt data augmentation in order to suggest a more expansive database. It might also be an issue with how your classes are labeled; they might not be sufficiently obvious, for instance.

Always go through one final testing phase after you're satisfied with the new training phase. This one will include presenting your algorithm with the test set, which is the third piece of data. You might have over-optimized the settings on the validation dataset, despite the fact that this final test might not seem that critical. It is imperative that you verify whether or not those changes were successful. Consequently, a final test using unidentified groups of images is required. Additionally, it's an opportunity to confirm the program's accuracy and speed of image processing.

CROP DETECTION AND CLASSIFICATION

Finally, crop recognition using machine learning is a significant tool for increasing agricultural productivity and monitoring. Machine learning algorithms can accurately detect and classify different crops.

Metrics: Use accuracy, precision, recall, F1-score, IoU, and mean average precision (mAP) to assess the model's performance.
Visual Inspection: Examine a selection of predictions visually to check that the model is making sound predictions.
Finally evaluation: Evaluate the model on the test set using relevant metrics (accuracy, precision, recall, F1-score, etc.).
Confusion Matrix: For classification tasks, a confusion matrix can reveal the types of errors that the model produces.

Export Model: Save the trained model in a deployment-ready format. Deploy the model to a cloud service, edge device, or other platform to do inference on new image algorithms using a variety of data sources, including satellite imagery, aerial images, and ground sensors.

To attain high accuracy and dependability, the technique entails precise data preparation, careful model selection, vigorous training, and thorough evaluation. Implementing these models allows farmers and agricultural stakeholders to make better decisions, enhance resource usage, and improve crop management approaches. With continuous technical breakthroughs and expanded data availability, machine learning-based crop recognition has significant potential for the future of precision agriculture.

IV. Abbreviations

SVM	Support Vector Machine
ML	Machine Learning
CNN	Convolutional Neural Network
SGD	Stochastic Gradient Descent
UAV	Unmanned Aerial Vechicle
ICA	International cooperative Alliance
SAR	Specific Absorption Rate
LASSO	Least Absolute Shrinkage and Selection Operator
ANN	Artificial neural networks
ISSN	International Standard Serial Number
ITTS	International Tax and Transaction Services
SVR	Systemic Vascular Resistance
NDVI	Normalized Difference Vegetation Index
IRJET	International Research Journal of Engineering and Technology
KNN	k-nearest neighbor
LiDAR	Light Detection and Ranging
PCA	Principal Component Analysis
HOG	Histogram of Oriented Gradients
LBP	Local Binary Patterns
VGG	Visual Geometry Group
ResNet	Residual Network
IoU	Intersection over Union
MAP	Mean Average Precision

V. REFERENCE

[1] Gehlot, A.; Sidana, N.; Jawale, D.; Jain, N.; Singh, B.P.; Singh, B. Technical analysis of crop production prediction using Machine Learning and Deep Learning Algorithms. In Proceedings of the International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), Chennai, India, 24–25 September 2022; pp. 1–5.

[2] Google. Bard Chatbox. Google. Available online: https://bard.google.com (accessed on 2 April 2023).

[3] Kuradusenge, M.; Hitimana, E.; Hanyurwimfura, D.; Rukundo, P.; Mtonga, K.; Mukasine, A.; Uwitonze, C.; Ngabonziza, J.; Uwamahoro, A. Crop Yield Prediction Using Machine Learning Models: Case of Irish Potato and Maize. Agriculture 2023, 13, 225. [CrossRef]

[4] Li, L.; Wang, B.; Feng, P.; Liu, D.L.; He, Q.; Zhang, Y.; Wang, Y.; Li, S.; Lu, X.; Yue, C.; et al. Developing machine learning models with multi-source environmental data to predict wheat yield in China. Comput. Electron. Agric. 2022, 194, 106790. [CrossRef]

[5] Moysiadis, V.; Tsakos, K.; Sarigiannidis, P.; Petrakis, E.G.M.; Boursianis, A.D.; Goudos, S.K. A Cloud Computing web-based application for Smart Farming based on microservices architecture. In Proceedings of the 11th International Conference on Modern Circuits and Systems Technologies (MOCAST), Bremen, Germany, 8–10 June 2022; pp. 1–5.

[6] OpenAI. New and Improved Content Moderation Tooling. OpenAI. 2022. Available online: https://openai.com/blog/new-and-improved-content-moderation-tooling/ (accessed on 1 April 2023).

[7] Oré, G.; Alcântara, M.S.; Góes, J.A.; Oliveira, L.P.; Yepes, J.; Teruel, B.; Castro, V. Crop Growth Monitoring with Drone-Borne DInSAR. Remote Sens. 2020, 12, 615. [CrossRe]

[8]Ranjan, P.; Garg, R.; Rai, J.K. Artificial Intelligence Applications in Soil & Crop Management. In Proceedings of the IEEE Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), Gwalior, India, 21–23 December 2022; pp. 1–5.

[9] van Klompenburg, T.; Kassahun, A.; Catal, C. Crop yield prediction using machine learning: A systematic literature review. Comput. Electron. Agric. 2020, 177, 105709. [CrossRef]

[10] Vashisht, S.; Kumar, P.; Trivedi, M.C. Improvised Extreme Learning Machine for Crop Yield Prediction. In Proceedings of the 3rd International Conference on Intelligent Engineering and Management (ICIEM), London, UK, 27–29 April 2022; pp. 754–757.

[11] Xu, W.; Kaili, Z.; Tianlei, W. Smart Farm Based on Six-Domain Model. In Proceedings of the IEEE 4th International Conference on Electronics Technology (ICET), Chengdu, China, 7–10 May 2021; pp. 417–421.