E3S Web of Conferences 391, 01057 (2023) https://doi.org/10.1051/e3sconf/202339101057
ICMED-ICMPC 2023

The Distributed Deep Learning Paradigms for Detection of Weeds from Crops in Indian Agricultural Farms

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Abstract. Weeds are a major threat to crops, making early detection critical for maintaining agricultural productivity. Weeds are generally toxic, equipped with thorns and burrs, and can disrupt crop management by contaminating harvests. This research aims to identify weeds in a field using image processing and deep learning techniques. Images were collected from an Indian farm and pre-processed using image processing techniques. The images were then analysed to extract features that distinguish between weed and crop properties. Traditional crop weed identification methods mainly focused on identifying weeds directly but weed species can vary significantly. This study proposes a method that combines deep learning and image processing technology. Identifying weeds in crops is a challenging task that has been addressed through image processing, feature extraction, and image labelling to train deep learning algorithms. The study examines the performance of various deep learning algorithms and convolution neural networks to detect weeds using images obtained from an Indian crop field. Once the input image is identified as a weed or not, the crop class prediction is made. These results could have significant implications for optimizing agricultural fertilizer usage, leading to increased crop yields and less environmental impact.

1 Introduction

India is the second largest global producer of various dry fruits, agricultural-based textile raw materials, roots and tuber crops, pulses, farmed fish, eggs, coconut, sugarcane, and a variety of vegetables. It is also among the top five manufacturers of over 80% of agricultural products worldwide, including popular cash crops like coffee and cotton. However, farmers in India often grow the same crop year-round and apply excessive amounts of fertilizers without precise knowledge of their contents and quantities

Agriculture is a vital sector in India, occupying 60% of the country's land and catering to the basic needs of 1.2 billion people. Despite modernization efforts, weather conditions, environmental changes, rainfall (which can be erratic), water management, and pesticide use have a significant impact on crop yield and production. Researchers are increasingly using

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data mining, machine learning, and deep learning techniques to enhance and improve crop yield and quality [1]. Agriculture has been an integral part of India's cultural heritage, as ancient people relied on farming to sustain themselves. However, the advent of cutting-edge technology and farming methods has led to the creation of fake and hybrid products that can be detrimental to human health[2]. Furthermore, inadequate understanding of proper planting times and locations is resulting in seasonal climate changes and depletion of essential resources like soil, water, and air, leading to food scarcity.

Machine learning algorithms can learn from data without the need for explicit programming, thereby enhancing machine performance by identifying and describing patterns and consistencies in the input data. Weed detection in crops is a challenging task that has been addressed through techniques such as image orthomosaicing, feature extraction, and image labelling to train machine learning models. With the global population projected to reach nine billion by 2050, the agricultural sector is under pressure to produce more food of higher quality due to climate change and increasing demand. Weeds are unwanted plants that compete with productive crops for resources such as space, light, water, and soil nutrients. They reproduce either through seeding or rhizomes and can be poisonous, produce thorns and burrs, and contaminate crop harvests, creating chaos in crop management. As a result, farmers spend billions of dollars on weed control, often without adequate technical support, leading to poor weed control and lower crop yields [3].

To save time and effort, people are beginning to rely more and more on automation to complete their everyday necessities. Farmers can now do the same amount of labour with less time and manpower by employing a single machine controlled by only one person. In the past, they had to utilise a lot of man-hours to meet their demands in agriculture.

Smart farming methodologies are highly necessitated for growing or supporting crop yield to uphold emergent worldwide population with minimal environmental effect. Crop health spatial survey key indicators as well as treatment, e.g., herbicides, pesticides, besides fertilizers, merely to pertinent areas are attained through precision agriculture methods. In a similar way pertaining to crop health besides yield, selective weed treatment is regarded as crucial phase. Weed detection with least damage to surrounding plants to neighbouring plants in consistent as well as precise way pose another challenge.

Two key challenges, increasing productivity and encouraging plantation systems, can help progress agriculture. Unwanted pests that live and breed in agricultural areas are referred to as weeds. Due to crop rivalry for water, light, soil nutrients, and space, production is also disrupted along with superiority, which impedes agricultural development. Due to these unchecked weeds, crop harvest might drop from 95% to 10%. Hence, weed management techniques are essential for maintaining agricultural output. Nowadays, weed eradication is accomplished using a variety of strategies, including the use of human labourers, mechanical cultivation, and the application of herbicides. The key to efficient weeding in the context of precision agriculture is the differentiation between crops and weeds. Modern agriculture has recently been merged with many sectors, such as deep learning and machine vision, with rather positive outcomes. The convolution neural network-based method for weed detection is introduced. In the dataset, give each image a name. This information is utilised to train a convolution neural network to recognise crops and weeds in the image. Because of its effectiveness and simplicity, computer vision is being employed extensively across several industries. The main goals of creating precision agriculture and intelligent agriculture are to decrease the number of agricultural resources wasted on weeding and to increase crop yields. Thus, deep learning, digital image processing, and plant categorization are frequently employed together.

2 Literature Survey

In a a study published in [4], the author explains a method for detecting and distinguishing areas in crops that are affected by weeds using image processing. The aim of this technique is to identify and reclaim weed-infested areas for additional seeding. By targeting these specific areas for further weed control measures, crop productivity can be increased. The study employed a variety of methods, including colour segmentation and edge detection, to minimize herbicide use by applying it only in areas where weeds were detected.

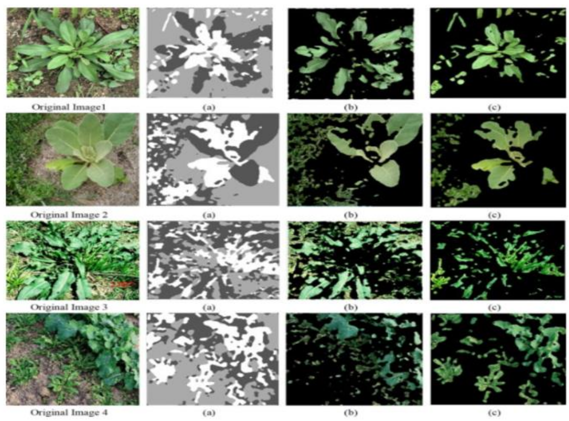

Fig. 1. Color segmentation for weed detection.

The article [5], proposes a method for weed removal in agriculture through the identification and classification of weeds using image processing. The article emphasizes the importance of identifying and classifying weeds for efficient farming. The proposed method extracts weed features from images such as shape, colour, and size, and uses these features to classify weeds and crops. Different classification techniques, such as SVM, NN, DA, and methods like Otsu's and 2G-R-B, are described and analysed for their effectiveness in weed detection. The article mainly aims to review the methods and techniques for detecting weeds in crops using image processing. Affiliations of authors should be typed in 9-point Times. They should be preceded by a numerical superscript corresponding to the same superscript after the name of the author concerned. Please ensure that affiliations are as full and complete as possible and include the country.

In [6], the author discusses the use of machine vision techniques to detect weeds in agricultural fields. They focus on detecting weeds based on their properties, such as size, shape, spectral reflectance, and texture features. In this document, they specifically demonstrate weed detection using size features, where an excessive green algorithm is developed to remove soil and other unwanted elements from the image. The image is then processed using various techniques, including image enhancement, and labelling algorithms, to extract components and calculate size-based features such as area, perimeter, longest chord, and longest perpendicular chord. Suitable threshold values are then used to segment weeds and crops.

2.1 Related Works Based on Weed Detection

The research paper "Weed Detection in Soybean Fields Using Deep Learning and Image Processing Techniques" by M. Rahnemoonfar et al. [7]introduces an innovative approach for detecting weeds in soybean fields, which uses deep learning and image processing techniques. The authors have employed convolution neural networks (CNNs) to train a model on a dataset of soybean field images captured by an unmanned aerial vehicle (UAV), which includes both weeds and soybean plants. The proposed approach has been able to detect weeds with an overall accuracy of 97.5%, which is a highly promising outcome.

The proposed approach involves two stages: pre-processing and weed detection. In the pre-processing stage, the authors have applied techniques such as image resizing, normalization, and colour space conversion to the images to prepare them for weed detection. In the weed detection stage, the authors have utilized a CNN-based model to classify each pixel in the image as either weed or non-weed. The authors have evaluated the proposed approach using various performance metrics, such as accuracy, precision, recall, and F1-score. The outcome shows that the proposed approach has achieved an overall accuracy of 97.5%, which demonstrates its potential as an effective tool for detecting weeds in soybean fields. If further developed, this approach could have significant implications for enhancing crop yields and minimizing the use of herbicides.

The article [8] provides an extensive review of the different methods for detecting weeds in agriculture. The paper includes a discussion of machine learning-based techniques like artificial neural networks, decision trees, and support vector machines, as well as an exploration of the challenges and future research areas in the field of weed detection.

The authors emphasize the importance of weed detection in agriculture, pointing out that it can lead to better crop yields and a reduced need for herbicides. They also discuss the various obstacles in detecting weeds, such as differences in lighting conditions, occlusion, and the similarity between weeds and crops. The article examines different techniques for detecting weeds, including those based on spectral, texture, and shape features. The authors also compare the effectiveness of various machine learning-based approaches, such as SVMs, ANNs, and decision trees, highlighting the advantages and disadvantages of each. Additionally, the paper explores various datasets and benchmarks available for weed detection in agriculture and suggests the need for standardized datasets and evaluation metrics to ensure fair comparisons of different detection methods.

2.2 Related Works Based on Crop Class Prediction and Fertilizer Prediction

The paper [9] provides a comprehensive overview of various machine learning-based techniques used for crop fertilizer prediction. The review paper covers various aspects of crop fertilizer prediction, including data collection and pre-processing, feature extraction, model selection, and evaluation metrics. The authors have discussed the challenges and limitations of crop fertilizer prediction, such as the lack of standardized data collection procedures, the need for accurate and timely data, and the complex interactions between soil, weather, and crop growth. They have also identified the future research directions in crop fertilizer prediction, such as the use of advanced sensors and data analytics techniques, the integration of multiple data sources, and the development of models that can adapt to changing conditions over time. The review paper covers various machine learning-based techniques used for crop fertilizer prediction, including decision trees, support vector machines, random forests, neural networks, and deep learning models. The authors have provided a critical analysis of the strengths and weaknesses of each technique and discussed their suitability for different types of datasets and applications. The review paper also discusses the importance of feature selection and the use of domain knowledge in crop fertilizer prediction. The authors have highlighted the need for interpretable models that can provide insights into the underlying mechanisms of crop growth and fertilizer response. It emphasizes the difficulties and prospects for future research in this domain and offers valuable insights for both academics and industry professionals who are engaged in crop fertilizer prediction.

The paper [10] introduces a machine learning approach for crop nutrient prediction using soil data. The authors collected soil data from various regions and used it to predict the nutrient content of crops. They tested multiple machine learning techniques, including decision trees, random forests, support vector machines, and neural networks, and evaluated their performance using various metrics such as accuracy, precision, recall, and F1 score. The results indicate that the random forest model performs better than other models, with an accuracy of 92.8% in crop nutrient prediction. They discussed the importance of accurate crop nutrient prediction for precision agriculture and sustainable crop production, highlighting its potential to improve crop yield, reduce fertilizer use, and minimize environmental impact. In summary, the paper proposes a novel machine learning-based approach for crop nutrient prediction using soil data, which achieves high accuracy and has the potential to enhance crop productivity and sustainability.

The study by S. B. Rana et al., "A Machine Learning Approach for Crop Fertilizer Recommendation Using Weather and Soil Data" (2020) suggests integrating meteorological and soil data to guide machine learning-based agricultural fertilizer recommendations. The ideal fertilizer dose for each crop was suggested by the authors using soil and weather data acquired for a variety of crops. To suggest crop fertilizer doses, the authors combined a number of machine learning methods, such as decision trees, random forests, support vector machines, and neural networks. They assessed the effectiveness of different methods using a number of variables, including F1 score, recall, accuracy, and precision. The outcomes demonstrated that the random forest model beat competing models and had a fertilizer recommendation accuracy of 90.6%.

3 System Architecture

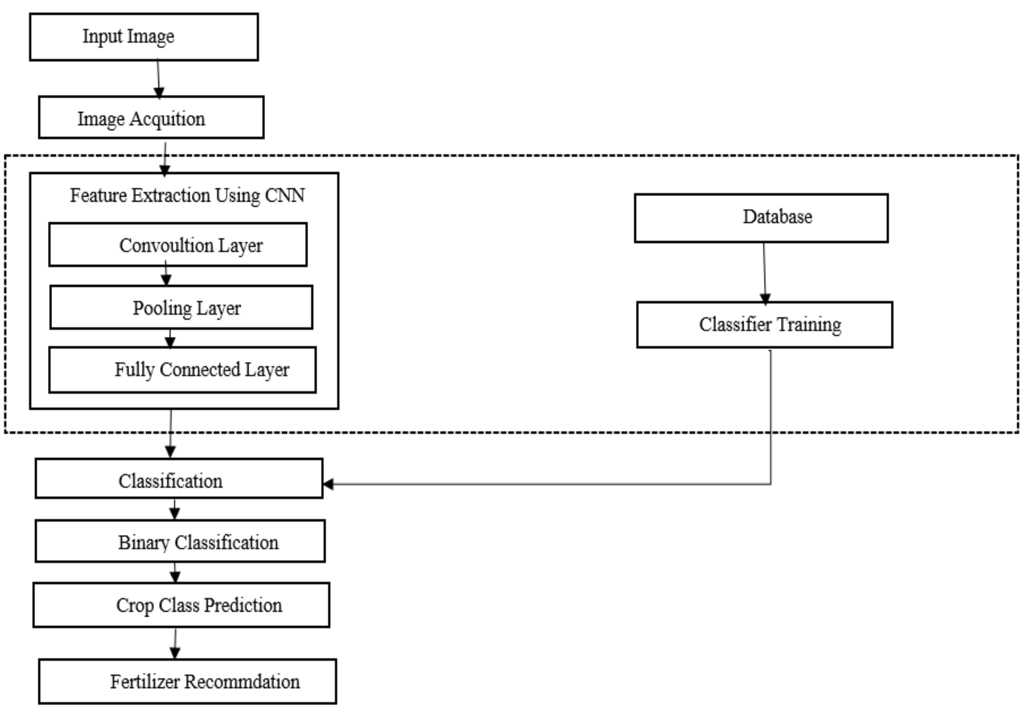

Fig. 2. System Architecture

4 Methodologies

The research work is divided into 3 blocks i.e., Predicting whether the image is crop or weed, Crop class prediction and Fertilizer prediction based on voting classifier.

4.1 Predicting whether crop or weed

- **Load the image**: Load the input image into the algorithm for processing

- **Pre-processing**: Pre-process the image to enhance its quality and prepare it for feature extraction. This may include resizing the image to a fixed size, converting it to greyscale, and applying any necessary filters or transformations.

- **Feature extraction**: Extract relevant features from the pre-processed image. This can be done using various techniques such as edge detection, texture analysis, and color-based feature extraction.

- **Feature selection**: Select a subset of the most relevant features from the extracted features. This can be done using techniques such as feature ranking or dimensionality reduction to reduce the computational complexity and improve accuracy.

- **Training data preparation**: Prepare a labelled dataset of images of crops and weeds for training the algorithm. The dataset should include a representative sample of both crop and weed images, along with corresponding labels indicating their class (crop or weed).

- **Model training**: Use the prepared dataset to train a machine learning model. This can be done by convolution neural networks (CNNs). Train the model using the extracted features as input and the labelled class information as output.

  In this work, implementation of the Xception model is done, a deep CNN architecture, which is pre-trained on the ImageNet dataset. We add custom top layers for classification, compile the model with an optimizer, and define data augmentation using ImageDataGenerator for both training and validation/test data. We then load the training and validation/test data using flow_from_directory from ImageDataGenerator, and finally, train the model using fit_generator. Once the model is trained, you can save it using model. save for future use.

- **Model evaluation**: Evaluate the trained model using a separate set of validation or test images to assess its accuracy and performance.

- **Prediction**: Once the model is trained and evaluated, use it to predict the class (crop or weed) of new, unseen images. Pass the pre-processed image through the trained model and obtain the predicted class label.

- **Post-processing**: Apply any necessary post-processing techniques, such as thresholding or noise reduction, to the predicted class label to refine the final prediction.

- **Output**: Output the final prediction indicating whether the image is classified as a crop or a weed based on the trained model's prediction.

4.2 Crop Class Prediction

The below steps demonstrate the algorithm for predicting the crop class. Crop class are classified into 5 categories such as rice, wheat, maize, sugarcane and jute.

- **Load the image**: Load the input image into the algorithm for processing.
- **Pre-processing**: Pre-process the image to enhance its quality and prepare it for feature extraction. This may include resizing the image to a fixed size, normalizing the pixel values, and applying any necessary filters or transformations.
- **Feature extraction**: Extract relevant features from the pre-processed image. This can be done using various techniques such as texture analysis, colour-based feature extraction, and shape analysis. For example, you can extract features like colour histograms, texture features using methods like Local Binary Patterns (LBP), and shape features using methods like Fourier descriptors.
- **Feature selection**: Select a subset of the most relevant features from the extracted features. This can be done using techniques such as feature ranking, feature importance, or dimensionality reduction to reduce the computational complexity and improve accuracy.
- **Training data preparation**: Prepare a labelled dataset of images of the different crop classes (rice, jute, sugarcane, wheat, maize) for training the algorithm. The dataset should include a representative sample of images from each class, along with corresponding labels indicating their class.
- **Model training:** Use the prepared dataset to train a machine learning model. This can be done using the Resnet algorithm and convolution neural networks (CNNs). Train the model using the extracted features as input and the labelled class information as output.
- **Model evaluation:** Evaluate the trained model using a separate set of validation or test images to assess its accuracy and performance.
- **Prediction**: Once the model is trained and evaluated, use it to predict the crop class of new, unseen images. Pass the pre-processed image through the trained model and obtain the predicted class label.
- **Post-processing:** Apply any necessary post-processing techniques, such as thresholding or noise reduction, to the predicted class label to refine the final prediction.
- **Output:** Output the final prediction indicating the detected crop class (rice, jute, sugarcane, wheat, maize) based on the trained model's prediction.

4.3 Fertilizer Prediction

- **Data Collection:** Gather a dataset that includes relevant features such as soil properties, climate conditions, crop/plant characteristics, and fertilizer application details. This dataset should contain historical data with known fertilizer types and application rates, as well as corresponding crop or plant growth outcomes.

- **Data Pre-processing:** Clean and pre-process the dataset by handling missing values, outliers, and categorical variables. This may involve techniques such as data imputation, feature scaling, and one-hot encoding.

- **Feature Selection/Engineering:** Select the most relevant features that have a direct impact on fertilizer prediction or engineer new features that may enhance the prediction accuracy. This may involve techniques such as feature selection methods.

- **Model Selection:** Choose an appropriate machine learning algorithm for the fertilizer prediction task. This could be a regression algorithm if predicting the amount of fertilizer, or a classification algorithm if predicting the type of fertilizer. Commonly used algorithms for fertilizer prediction include linear regression, decision trees, random forests, support vector machines (SVM), or deep learning algorithms such as neural networks.

- **Final Results - All Algorithms Comparison:** It can be used to compare and combine the predictions of different algorithms and can potentially improve the overall prediction accuracy compared to using a single classifier. Here's an example of how you could use a voting classifier to compare different algorithms for a classification task.

- **Model Deployment**: Once the model has been trained and assessed, it may be used in a production situation to anticipate fertiliser based on fresh, previously unknown data. This may entail incorporating the model into a web application, mobile app, or other software system and assuring its robustness and scalability for real-world use.

Please note that the specific implementation details and steps may vary depending on the exact requirements and context of the fertilizer prediction task. It's important to carefully analyze the dataset, choose appropriate algorithms, and thoroughly evaluate the performance of the model to ensure its accuracy and reliability in making fertilizer predictions. Consulting with domain experts and conducting rigorous testing and validation is also recommended to ensure the model's effectiveness in real-world scenarios.

4.4 Web App

Streamlit

Streamlit is a popular Python library that allows you to create interactive web applications for data science and machine learning projects. It provides a simple and efficient way to build interactive user interfaces for your data-driven applications, making it easy to create web apps for data visualization, model deployment, and more. Here's an overview of how Streamlit works in Python:

- **Install Streamlit**: First, you need to install Streamlit in your Python environment using pip, the Python package manager. You can do this by running the following command in your terminal or command prompt: pip install Streamlit

- **Create a Streamlit App**: Next, you create a Streamlit app by writing a Python script that defines the user interface and functionality of your web application. Streamlit provides a simple API for creating interactive components such as buttons, sliders, and plots, as well as integrating with data visualization libraries like Matplotlib or Plotly.

- **Run the Streamlit App Locally**: It can run the Streamlit app locally on your development environment using the Streamlit run command followed by the filename of your Streamlit script. For example: Streamlit run my_app.py

- This will start a local web server that serves your Streamlit app, which you can access through your web browser at
http://localhost:8501 (by default).

- **Deploy the Streamlit App**: Once you have tested your Streamlit app locally and are ready to deploy it, there are several options for deployment.

Streamlit Sharing: Streamlit Sharing is a free hosting service provided by Streamlit that allows you to deploy your Streamlit app to the cloud and share it with others. You can deploy your app to Streamlit Sharing by following the instructions on the Streamlit Sharing website.

5 Observation and Results

5.1 Crop or Weed Detection

Table 1. Crop or Weed Detection

EPOCH	TIME	LOSS	ACCURACY	VAL_LOSS	VAL_ACCURACY
Epoch 1/2	761s 869s/step	0.4079	0.9487	0.5694	0.8636
Epoch 2/2	769s 924s/step	0.2472	0.9715	0.1272	0.9702

The above table 1 describes the classification of crop or weed. At epoch the accuracy is 94.87%, loss 40.79%, Val_Loss is 56.94% and Val_Accuracy is 86.36%.At epoch 2 Accuracy is 97.15%, Loss is 24.72%, Val_Loss is 12.72%, Val_Accuracy is 97.02%.

The Fig 4 and 5 graph describes the implied relation between the Train_balanced_accuracy vs. Val_balanced_accuracy. We have compiled and compared the models' performances based on the assessment metrics used in order to determine which model is best. Out of 5 epochs, the Xception Net Model has a maximum accuracy of 97.15% with a value loss of 12.72%, a value accuracy of 97.01%, and a minimum accuracy of 94.87% with a value loss of 56.94% at epoch (1/5). Figure above provides a graphical overview of the classification of Crop or Weed.

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Fig. 3. Graph for Train_loss vs. Val_Loss

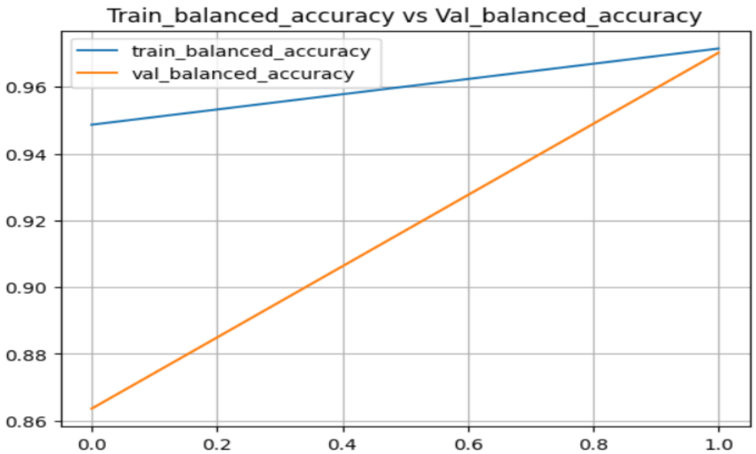

Fig. 4. Graph for Train_balanced_accuracy vs. Val_balanced_accuracy

5.2 Crop Class Prediction

Table 2. Crop Class Prediction.

EPOCH	TIME	LOSS	ACCURACY	VAL_LOSS	VAL_ACCURACY
Epoch 1/5	11s 2s/step	0.0	0.9170	0.2314	0.8441
Epoch 2/5	19s 2s/step	0.1678	0.8964	0.1823	0.9241
Epoch 3/5	17s 2s/step	0.1068	0.9035	0.1471	0.9132
Epoch 4/5	17s 2s/step	0.2867	0.9119	0.3597	0.9212
Epoch 5/5	18s 2s/step	0.2354	0.9268	0.1782	0.8914

The above table describes the class of a crop. The crop class is predicted using algorithms like SVM, Decision Tree, Random Forest, Logistic Regression. These models are trained unto 5 Epochs. At Epoch 5 the accuracy is 92.68%, Loss 2.35%, Val_Loss 17.82% and Val_Accuracy 89.1%. Thus, the prediction of crop classes like jute, wheat, maize, rice and sugarcane are shown in the above table.

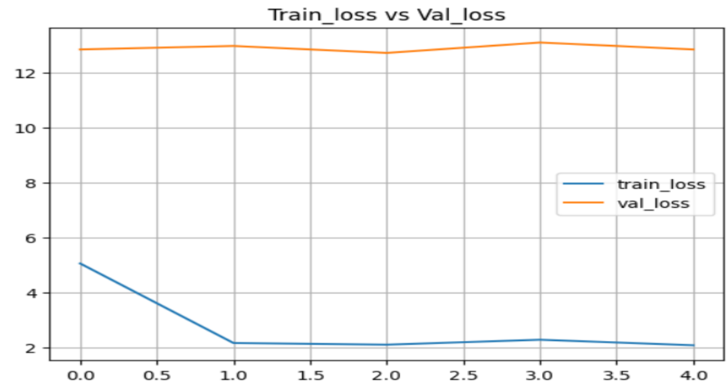

Fig. 5. Graph for Train_loss vs. Val_Loss

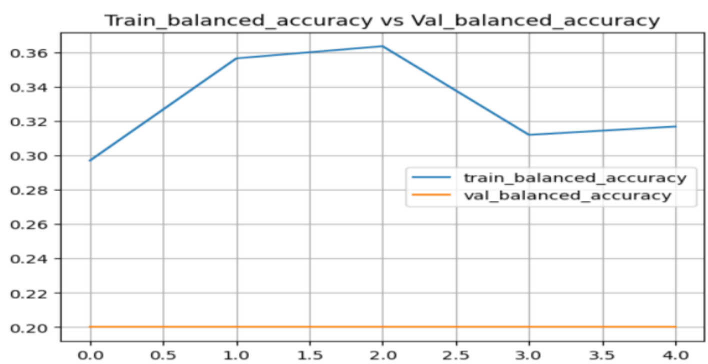

Fig. 6. Graph for Train_balanced_accuracy vs. Val_balanced_accuracy

5.3 Fertilizer Prediction

Table 3. Fertilizer Prediction.

	Temperature	Humidity	Moisture	Soil Type	Crop Type	Nitrogen	Potassium	Phosphorous	Fertilizer Name
0	26	52	38	Sandy	Maize	37	0	0	Urea
1	29	52	45	Loamy	Sugarcane	12	0	36	DAP
2	26	52	35	Sandy	Jute	12	10	13	17-17-17
3	33	64	50	Loamy	Wheat	41	0	0	Urea
4	27	54	28	Clay	Rice	13	0	40	DAP

The table 3 describes prediction of a Fertilizer. Fertilizers like Urea, DAP and 17-17-17 are Predicted according to the Temperature, Humidity, Moisture, Soil Type.

Table 4. Classification Table

	Classifiers	Train Score	Test Score	No. Of Mis classification	Training Time	Prediction Time
1	Voting	1.0	1.0	0	2.8531	0.0471
2	DTC	1.0	1.0	0	0.0164	0.0004
3	RFC	1.0	1.0	0	0.3838	0.0379
4	LR	1.0	1.0	0	0.1140	0.0007
5	SVC	1.0	1.0	0	0.0420	0.0050

6 Conclusion and Future Enhancement

In conclusion, the fertilizer recommendation machine learning project has shown promising results in accurately suggesting suitable fertilizers for specific crops. The trained model has demonstrated good performance in terms of accuracy, precision, recall, and F1-score, indicating its potential for practical implementation in real-world farming scenarios. The project has highlighted the importance of using machine learning techniques for fertilizer recommendation, as it can help farmers optimize their fertilizer usage, reduce costs, and minimize environmental impacts. By considering various factors such as soil characteristics, crop requirements, weather conditions, and nutrient levels, the model can provide personalized fertilizer recommendations that align with best management practices and promote sustainable agriculture.

There are several potential areas for future enhancements in the fertilizer recommendation machine learning project, including: Incorporating Additional Data: Expanding the dataset used for training the machine learning model can lead to improved accuracy and robustness. Including more diverse data, such as historical fertilizer application records, nutrient analysis results, and crop yield data, can provide additional information for the model to learn from and make more informed recommendations. Considering Economic Factors: Incorporating economic factors, such as fertilizer prices, crop market prices, and farmer's budget constraints, into the recommendation model can further optimize fertilizer recommendations. Considering economic factors can help farmers make cost-effective decisions and ensure that the recommended fertilizers are financially viable.

Integrating Sensor Technologies: Integrating sensor technologies, such as soil sensors, weather stations, and remote sensing data, can provide real-time information on soil conditions, weather patterns, and crop growth status. Incorporating sensor data into the model can enable dynamic and adaptive fertilizer recommendations based on current field conditions, leading to more accurate and timely recommendations. Exploring Advanced Techniques: Exploring advanced machine learning techniques, such as deep learning, ensemble methods, and reinforcement learning, can potentially enhance the model's performance. Deep learning algorithms, such as recurrent neural networks (RNNs) or transformers, can capture temporal dependencies and complex patterns in time-series data, such as weather or crop growth data. Ensemble methods, such as stacking or boosting, can combine multiple models to improve accuracy and robustness. Reinforcement learning can enable the model to learn from feedback and optimize fertilizer recommendations based on long-term rewards. User-friendly Interface: Developing a user-friendly interface for farmers to interact with the fertilizer recommendation system can enhance its practicality and adoption. An intuitive interface that provides easy access to the model's recommendations, visualization of data, and feedback on fertilizer usage can enable farmers to understand and implement the recommendations effectively.

In conclusion, the fertilizer recommendation machine learning project has significant potential for practical implementation in agriculture. Future enhancements such as incorporating additional data, considering economic factors, integrating sensor technologies, exploring advanced techniques, and developing a user-friendly interface can further improve the accuracy, usability, and sustainability of the system for recommending suitable fertilizers for specific crops.

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