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E2E model from crop suggestion to harvesting time prediction in sugarcane plant utilizing machine learning and deep learning

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ORIGINAL RESEARCH PAPER

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ABSTRACT

The automated system for enhancing plant growth presents an innovative approach to optimize quality of sugarcane cultivation for four main sugarcane growing zones. It includes issues like recommendation of crops based on soil nutrients, diagnosis of disease in the leaf and stem images of sugarcane, weed detection and harvesting time prediction. The research work proposed in the article presents an innovative two-stage approach for object detection and classification in agricultural imagery. Initially, YOLOv8 (You Only Look Once) is employed to accurately detect objects within images, delineating them with precise boundary boxes. Subsequently, the focus of hybrid model integrating Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, known as Contextual Long Short-Term Memory (CLSTM), is employed. This dual-stage methodology harnesses the speed and accuracy of YOLOv8 for robust object localization, while the CLSTM model ensures nuanced classification, contributing to comprehensive and accurate approach for object detection and crop-weed differentiation in agricultural scenarios. The proposed approach is compared with the four DL algorithms for identifying weeds in sugarcane crops and subsequently assessed their accuracy and F1 score performance. At a learning rate of 0.002, the findings of CLSTM showcase superior precision at 98.5%, recall at 97.8%, F1 score at 98.1%, and an overall accuracy of 97.7%. The subsequent task is harvesting time prediction, which entails identifying the best time to harvest sugarcane based on the planting period, weather predictions, and sugarcane brix value. The implementation of this automated system not only enhances the productivity of sugarcane cultivation but also serves as a model for sustainable and resource-efficient agriculture.

KEYWORDS

crop yield, sugarcane plant, growth quality, soil fertilizer, weed detection, disease diagnosis, harvesting time

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1. INTRODUCTION

Crop yields essential to be increased for agriculture provide food for 1.2 billion people and take up 60% of the nation's land. Manual crop prediction has mainly failed. Farmers cannot select the optimal crops based on soil and environmental variables. In the present unique rural climate, it has become fundamental to expand crop efficiency while limiting ecological effects (Deshmukh et al., 2022). The execution of AI calculations has turned into a strong method for taking care of this issue. The challenge is optimizing sugarcane cultivation from crop suggestion to harvesting time prediction. Accurate predictions are crucial for maximizing yield and resource efficiency.

These algorithms hold the key to selecting the appropriate crop for the appropriate soil and advising on the most effective fertilizer usage by utilizing the capabilities of advanced data analysis and predictive modelling (Gupta et al., 2022; Sushil, 2023). Machine learning algorithms can offer insightful information that enables farmers to make knowledgeable decisions by examining the composition of the soil, climate data, past crop performance, and other pertinent elements (Militanteand Gerardo, 2019, December; Patra et al., 2017). This innovative strategy encourages sustainable practices while also boosting agricultural output, establishing a harmonic balance between crop yield and environmental preservation. Numerous variables, including crop illnesses the environment, the state of the soil, regional farming practises, novel pathogen variations, various illnesses, etc., influence the cultivation of a wide range of crops (Manavalan, 2021; Shingade and Mudhalwadkar, 2023a, b). Untrained pesticide use can harm crops and soil over time, and plant disease is one of the biggest threats to food security because it severely lowers crop yield and quality (Militante et al., 2019; Senthil Kumar and Vijay Anand, 2024). Currently, farmers are suffering losses as a result of climate change. Early identification of diseases in sugarcane plants is essential for reducing output losses and maintaining the health of the crops. Explainable AI models (XAI), enabled by deep learning-based techniques, have ushered in a new era of enhanced disease identification. Due to innovative technologies, experts can gather crucial new information on the variables impacting the onset of disease in sugarcane plants, which combines the strength of deep learning algorithms with interpretability (Bandi et al., 2023; Shingade and Mudhalwadkar, 2023a, b). The XAI model can reliably identify disease symptoms, offer justifications for its predictions, and help farmers take preventative actions to slow the spread of diseases by assessing vast datasets made up of photos, sensor data, and historical disease trends. This method supports the development of tailored disease management techniques in addition to lowering crop losses, thereby promoting sustainable sugarcane farming practices (Le et al., 2019).

Weed infestation has long been a serious problem that reduces farm production and crop yield. Precision real-time separation of weeds from crops will lead to advancements in precision crop and weed management, which prevents weeds in a field from competing with crops for light water and nutrients (Manikandakumar and Karthikeyan, 2023). The method of weed management that is currently most frequently utilized is blanket herbicide spraying. Effective weed identification methods are essential for boosting crop output and reducing weeds detrimental effects on agricultural productivity. A new age of precise weed detection has begun with the introduction of improved classification algorithms (Sarvini et al., 2019). Farmers can correctly detect and distinguish between desired plants and invasive weeds using these strategies since they accurately classify both the crop and the weed. This makes it possible to use targeted weed control techniques, such as selective herbicide treatment or manual weeding, to greatly lessen competition for resources and guarantee the best crop development (Jin et al., 2021). Utilizing the effectiveness of these methods, farmers may boost yield potential by reducing the negative effects of weeds and fostering a healthier and more fruitful agricultural environment (Raja et al., 2020). In site-specific weed management (SSWM) treatments, a tolerable dose of herbicides is advised based on reliable weed detection, which may ultimately increase chemical savings while increasing its effectiveness (Ahmad et al., 2021). One of the most crucial elements determining sugarcane productivity is harvest age. To reduce crop loss and maximize yield potential, it is fundamental to forecast the ideal sugarcane harvesting time. Farmers might select with sureness when is the best opportunity to collect their sugarcane crop by utilizing prescient demonstrating apparatuses. These algorithms can precisely predict the best time to harvest the crop by assessing a variety of characteristics like plant development stage, sugar content, meteorological conditions, and historical production data (Panakkal et al., 2022). This makes it possible for farmers to prevent both premature and delayed harvesting, which can result in sugarcane degradation and losses (Wang et al., 2022). This research addresses the problem by applying advanced machine learning and deep learning techniques to enhance prediction accuracy and crop management. Premature harvesting can lead to lower sugar content. Farmers may improve their harvesting techniques, cut down on crop waste, and assure the best return from their sugarcane crops by utilizing these predictive capabilities, which will lead to more effective and sustainable agricultural practices (Fu et al., 2022). The E2E model represents a ground-breaking advancement in sugarcane cultivation by combining YOLOv8 for accurate object detection with a hybrid CLSTM model for sophisticated crop-weed differentiation and disease prediction. This novel integration enables precise crop management and optimizes harvesting timing, significantly enhancing agricultural efficiency. Its potential impact extends beyond sugarcane, offering scalable solutions for crop management and yield prediction across diverse agricultural sectors. The remaining sections are arranged as follows: Section "Literature survey" covers the literature review; Section "Research problem definition and motivation" discusses the study problem identification and motivation; Section "Proposed research methodology" describes the proposed technique; Section "Experimentation and results discussion" discusses the results; and Section "Research conclusion" contains the paper's conclusion.

2. LITERATURE SURVEY

The literature survey on automated plant disease identification and diagnosis for enhancing sugarcane growth quality using machine-learning approaches reveals a growing body of research at the intersection of agriculture, technology, and data science. These efforts aim to mitigate the economic losses caused by plant diseases and enhance overall crop yield and quality. Gunjan et al. (2022) predicted crop yield precisely by employing SVM to produce accurate results and aid farmers in selecting a suitable crop for the region and climatic conditions in the systems prediction process; included are data on temperature, rainfall, subsurface water, and soil nitrogen, which could yield reliable advice about whether or not to invest in growing that crop. SVM outperforms other classifiers in terms of accuracy, scoring 95.48 per cent. This recommended model accomplishes 95.16%, which is greater in comparison to the other classifiers and equal to or better than the Naive Bayes classifier's precision rate of 94.31%. The recall rate for Naive Bayes is 92.16%, which is also higher than the recall rates for the other classifiers. This submitted ensemble learner has a 93.33% recall rate. Additionally, F-measure and Mean Square Error offer 87.71% and 0.105, respectively. Tanwar et al. (2023) employ a convolutional neural networks (CNN) model to predict and classify Red Rot disease in sugarcane. They delve into the issue of Red Rot infection in sugarcane plants. The research begins by capturing images of diseased plants through secondary sources. Utilizing the powerful features of CNN's deep learning techniques, they extract and analyze the disease-related characteristics, subsequently classifying them (Narmilan et al., 2022). Remarkably, the study achieves a high accuracy rate of 93% in predicting the presence of Red Rot Sugarcane Disease.

To identify WLD in crops of sugarcane, Amarasingam et al. (2022) assessed the execution of the current deep learning models like Faster R-CNN, YOLOR, DETR, and YOLOv5. The experimental findings show that the YOLOv5 network performed better than the other chosen models with precision, recall, mean average precision@0.50 (mAP@0.50), and mean average precision@0.95 (mAP@0.95) scores of 95%, 92%, 93%, and 79%, respectively. When measured for precision, recall, mAP@0.50, and mAP@0.95, DETR had the worst detection performance, scoring 77%, 69%, 77%, and 41%, respectively. Tamilvizhi et al. (2022) introduced a quantum-behaved particle swarm optimiztion-based deep transfer learning (QBPSO-DTL) model to accurately identify and categorize sugarcane leaf diseases. The outcomes showed that the QBPSO-DTL model generated a better classification output for each epoch. For example, the AUC, accuracy, measure, and recall of the QBPSO-DTL model utilizing 200 epochs are 94.1, 93.75%, 96.66%, 94.87%, and 92.50%, respectively.

Haq (2022) utilized the Convolution Neural Network (CNN) classification on a real dataset of 4400 UAV pictures with 15,336 segments to develop a novel automated weed detection method. The results were compared to existing ML and DL applications for categorizing weeds. Overall classification accuracy for the newly developed CNNLVQ is 99.44%, which is encouraging. El-Kenawy et al. (2022) proposed a novel method for classifying images of weeds and wheat captured by a sprayer drone. The proposed approach is based on a voting classifier composed of K-nearest neighbours (KNN), support vector machines (SVM), and neural networks (NNs), which are three basic models. The usefulness and superiority of the suggested strategy over the other competing optimization strategies were proven by experimental data. The suggested optimized voting classifier achieved a sensitivity of 98.10%, specificity of 95.20%, F-score of 98.60%, and detection accuracy of 96.70%. Sunil et al. (2022) used RGB image texture information to identify weeds and types of crops by comparing the Support Vector Machine classification algorithm with deep learning-based visual group geometry 16 (VGG16) models for classification. The average VGG16 model classifier f1-scores ranged from 93% to 97.5%, according to the results. A 100% f1-score value was attained for the corn class by the VGG16 Weeds-Corn classifier, which seems remarkable for the corn crop production system.

Modi et al. (2023) explored computer vision-based deep learning for autonomous weed identification. They used a dataset of 5,660 augmented images and trained six DL models with 90% for training and 10% for validation. DarkNet53 stood out with a >99% F1 score, surpassing various models (AlexNet, GoogLeNet, InceptionV3, ResNet50, Xception) in identifying weeds in sugarcane crops. Achieving >98% accuracy and <1% error rate was possible with a mini-batch size of 16 and 20 epochs. Johnson et al. (2023) utilized pigment and hyperspectral analyses to differentiate between sugarcane and weeds. Leaf samples from sugarcane varieties and common weed species were collected. Hyperspectral data successfully distinguished sugarcane from weeds in all cases. Classification accuracy ranged from 67% to 100% for various weed species and sugarcane varieties, with no misclassification of sugarcane as a weed.

3. RESEARCH PROBLEM DEFINITION AND MOTIVATION

Agriculture plays a critical role in global economies, underpinning food security and economic stability. Sugarcane (*Saccharum officinarum* L.), a key member of the Graminae family, is vital to India's agricultural sector, which is the second largest in the country after Brazil. India alone contributes approximately 25% of global sugarcane production. In 2018, 79.9% of sugarcane produced was used for white sugar, with 11.29% for jaggery and 8.80% for animal feed and seed. In 2019, India harvested 840.16 million tons of sugarcane. Understanding production levels is essential for effective policymaking, as sugarcane is crucial for generating sugar, biofuels, and other valuable by-products. Maximizing both yield and quality is vital to meet the growing demand for these products. Traditionally, farmers have depended on manual methods and personal experience for decisions related to soil management, disease detection, weed control, and harvesting timing. However, these conventional approaches can be labor-intensive, time-consuming, and often imprecise, leading to reduced productivity. To overcome these limitations, automated systems incorporating advanced technologies and machine learning present a promising solution. These systems aim to enhance plant growth, provide tailored soil recommendations, and optimize both yield and quality in sugarcane cultivation. By leveraging sophisticated algorithms and data analysis, these systems enable more efficient decision-making and precise interventions throughout the cultivation cycle. A critical function of these automated systems is predicting the most suitable crops for specific soil types through machine learning techniques. By analyzing soil characteristics and historical crop data, the system assists farmers in making informed crop selection decisions, ultimately enhancing productivity and resource use. Additionally, the integration of disease detection algorithms utilizing image processing can automate the identification of plant diseases, allowing for timely interventions that minimize crop losses and boost overall plant health. While the potential benefits are substantial, it is essential to acknowledge the challenges associated with implementing such technologies, including the need for farmer training and the importance of retaining human expertise in agricultural practices. Balancing technology with traditional knowledge may lead to the most effective outcomes in sugarcane cultivation.

4. PROPOSED RESEARCH METHODOLOGY

The automated system is implemented for the periodic monitoring of sugarcane fields from growing season to harvesting.

The collection of data plays a crucial role in understanding the complexities of sugarcane production. The overarching objective of this agricultural research is to address various crucial challenges in farming. Initially, it intends to assist farmers in choosing the best-fit crops for specific soil types and recommends the optimal fertilizer composition, utilizing machine learning techniques for accurate predictions. Further, the project focuses on the early identification of disease in sugarcane plants, offering a solution to the timely identification of diseases such as rust, smut, and mosaic viruses. This enables farmers to take proactive measures to protect their crops and ensure sustainable sugarcane production. Additionally, the study evaluates and suggests effective object detection models for weed management, promoting chemical savings and enhancing weed control precision in agriculture. Finally, the research includes a model for predicting the optimal harvesting time for sugarcane, considering factors like sowing periods, weather forecasting, and the brix value. Together, these objectives aim to improve farming practices, reduce environmental impact, and optimize crop yield while addressing critical agricultural challenges.

4.1. Crop recommendation for suitable soil

The study primarily aims to offer guidance on selecting the best crop for specific types of soil and recommends the optimal fertilizer composition. Addressing issues related to micronutrient deficits in the soil and imbalanced fertilizer application, the research explores various solutions, including soil and foliar fertilization, crop systems, and organic amendments. Previously, the study employed Barley, Rice, Wheat, Tomato, and Chilli as crops to predict yields in recommended soils (Rubini and Kavitha, 2022). The study predicted sugarcane as the best crop for the given soil type. Once the crop is determined, the research ensures the soil nutrient indices are adequate for healthy plant growth. If the nutrient levels fall below the required threshold, the model recommends the appropriate fertilizer dosage for farmers to apply in their farmland.

4.2. Sugarcane plant disease diagnosis

The current problem lies in the difficulty of timely identifying diseases in sugarcane plants. Sugarcane diseases, such as rust, smut, and mosaic viruses, can cause significant damage to crops if not identified and managed promptly. Traditional visual inspections by farmers may not always detect diseases in their early stages, leading to delays in implementing necessary control measures. There is a necessity for an accurate, efficient, and automated system that can detect diseases in sugarcane plants at an early stage, enabling farmers to take proactive actions. The purpose of this study is to develop a system that enables the early identification of disease in sugarcane plants. By detecting diseases at the beginning phase, farmers can take timely preventive measures to mitigate the spread of diseases, minimize crop losses, and ensure sustainable sugarcane production.

The task of automatically detecting and classifying sugarcane diseases is intricate, and the manual detection system faces challenges such as a lack of expertise, high expense, and a multitude of variations in leaf disease symptoms. The research makes use of a DNet-SVM: XAI comprehension that combines SVM and LIME translation with a thick net. DNet-SVM: several changes made to DenseNet201, such as expanding a Support Vector Machine classifier, were used to create XAI (Rubini and Kavitha, 2023). This trained the model using the labelled dataset of sugarcane leaf/stem images with identified diseases. This enhances the model's capability to understand complex examples and connections within the data, leading to improved disease prediction accuracy.

4.3. Weed detection model development

Controlling weed invasion through synthetic substances (herbicides and pesticides) is fundamental for crop yield. Regardless, overindulgence in these synthetics has resulted in major agronomic and ecological difficulties. As per precise weed discovery, a suitable portion of herbicides is suggested in Site-Explicit Weed Administration (SSWM) applications, which may at last advance substance saving while at the same time upgrading its adequacy. To enhance the effectiveness of weed detection models, several key strategies are recommended. The development of a weed detection model in YOLO (You Only Look Once) v8 involves leveraging the capabilities of this state-of-the-art object detection framework. YOLO v8 excels in real-time object detection, making it appropriate for applications like agricultural field monitoring. Within the framework of weed detection, the model is used to train a dataset. comprizing images containing both crops and weeds. The training process involves optimizing the neural network's parameters to precisely determine and classify objects, with a specific focus on distinguishing weeds from surrounding vegetation. YOLO's ability to detect multiple objects in a single pass enhances its efficiency in processing large-scale agricultural landscapes. The resulting model is then fine-tuned and validated to ensure robust weed detection performance. Once deployed, the YOLO v8 weed detection model offers a useful instrument for farmers, enabling them to identify and manage weed infestations promptly, contributing to more sustainable and effective crop management practices.

4.3.1. Image pre-processing. Pre-processing images is an important step in ensuring that all the images are identical or nearly identical, allowing them to be interpreted as having been taken with the same sensors and under the same environmental conditions. Pre-processing of the the collected sugarcane plant images is implemented to enhance quality, remove noise and extract relevant features from the images, such as colour, texture, shape, and size. Identifying and cleaning up irregular values is the most difficult task. The location calculates a weighted normal value over a given area based on the force difference between pixels and their Euclidean distance. The following formulas are to be applied to set the likeness between any two pixels.

$$\lambda\left(p_{k,l}, p_{m,o}\right) = exp\left(\frac{-\left\|\left(\overrightarrow{k,l}\right) - \left(\overrightarrow{a,b}\right)\right\|^2}{2\psi_\lambda^2}\right), p_{m,o}\varepsilon\Omega_{p_{k,l}} \tag{1}$$

$$\eta\left(p_{k,l}, p_{m,o}\right) = exp\left(\frac{-\left\|p_{k,l} - p_{m,o}\right\|^2}{2\psi_\eta^2}\right) \tag{2}$$

$$\theta\left(p_{k,l}, p_{m,o}\right) = \lambda\left(p_{k,l}, p_{m,o}\right) \tag{3}$$

Where, $\lambda(p_{k,l}, p_{m,o})$ shows the geometric distance between pixels coefficient of influence, $\eta(p_{k,l}, p_{m,o})$ represents the brightness difference between pixels coefficient of influence, (k, l) and (m, o) indicate the local area's pixel coordinates and a, b be the reference point of $p_{k,l}$. Ω, ψ_η and ψ_λ are the characteristics of the coefficients standard deviation. Introducing θ as identical to λ simplifies notation and clarifies that spatial influence directly affects prediction models, ensuring consistency. The sum θ is calculated as follows.

$$\varsigma_{x_{k,l}} = \sum_{x_{m,o}\varepsilon\Omega_{x_{k,l}}} \theta\left(p_{k,l}, p_{m,o}\right) \tag{4}$$

Assume that T is the threshold value selected empirically, and the array $g_{k,l}$ map of noisy pixels, then from (5).

$$g_{k,l} = \begin{cases} 0 \; if \; \varsigma_{x_{k,l}} < T \\ 1, if \; \varsigma_{x_{k,l}} \geq T \end{cases} \tag{5}$$

For the accommodation of a visual view of the consequence of cleaning the image, the Euclidean metric $L2$ was used. The L2 metric is well-suited for developing channel layers for clearing images from storage disruption using flexible intermediate filtering. The ability to measure the disparity in competence values between pixels is founded on the ability to create an absolute contrast between the handled pixel and other pixels in the surrounding window.

$$U\left(p_{k,l}, p_{m,o}\right) = \begin{cases} 1, if \; p_{k,l} = p_{m,o}, p_{m,o} \varepsilon \Omega_{p_{k,l}} \\ 1 - \frac{1}{q} \; log_2 \left| p_{k,l} - p_{m,o} \right|, if \; p_{k,l} \neq p_{m,o}, p_{m,o} \in \Omega_{p_{k,l}} \end{cases} \tag{6}$$

Where q is the image pixels bit depth. The lower the number of U the maximum brightness difference. Dividing by q keeps U non-negative. The logarithmic capability demonstrates the main piece of the distinction among pixels and is appropriate to make sense of the computerized idea of the information and to line up with the visual view of the natural eye, this is capable of efficient operation on complex data representations, such as images.

4.3.2. Dataset pre-processing. The raw images of sugarcane collected are imbalanced, so to balance the dataset, a data augmentation technique is applied and classes are balanced. To feed images in the YOLO model, the raw images need to be annotated. Annotation guarantees consistent and accurate labelling, which enhances the dependability and performance of the trained model. Roboflow is the tool used to annotate the images of sugarcane and weed and save them as a .txt file along with the original images as shown in Fig. 1.

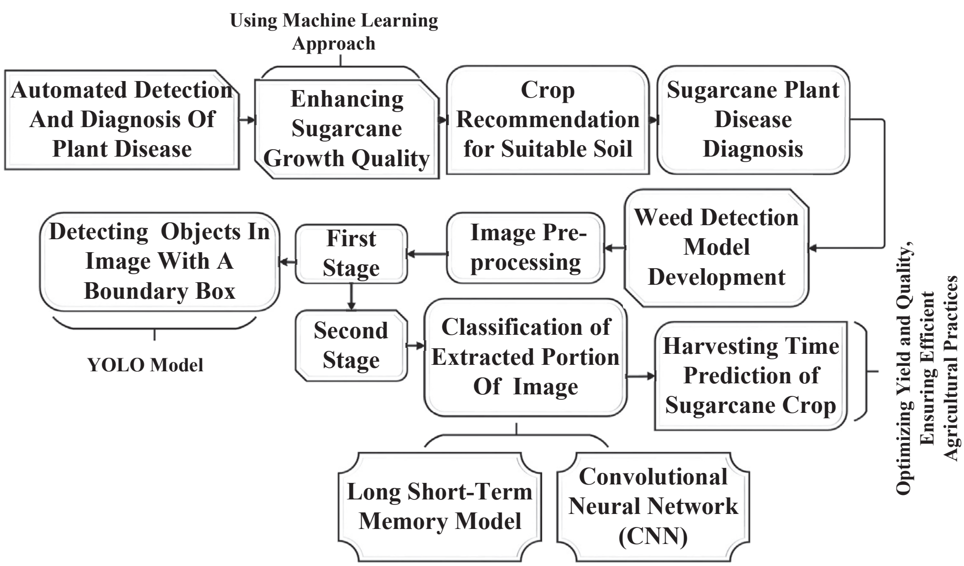


Fig. 1. Block diagram of the proposed work

4.3.3. Implementation of proposed work. The proposed work is implemented in the two-stage method for weed identification as shown in Fig. 2. The term "Detection" is defined as "Localization" and "Classification". In the proposed two-stage approach, the first stage involves the process of Localization which is a method of locating an object in the image utilizing YOLO version 8 for efficient object detection, employing bounding boxes to find items within the image. Following this, the second stage focuses on classification or further processing based on the identified objects, contributing to a comprehensive and accurate understanding of the image content that describes what is in the boundary box. For classification, the hybrid model approach of CLSTM was implemented, which is the combination of CNN and LSTM. This two-stage methodology enhances the overall efficacy of object recognition and facilitates more informed decision-making in applications such as computer vision and image analysis.

The E2E model improves sugarcane yield by optimizing crop management through precise suggestions and timely harvesting predictions. It enhances resource efficiency by minimizing inputs like water and fertilizers through accurate monitoring and analysis, leading to more efficient use of resources and higher productivity. To evaluate the E2E model for sugarcane cultivation, perform a comparative analysis by contrasting its performance with traditional methods and other systems, focusing on improvements in productivity and resource efficiency. Use before-and-after comparisons to highlight changes in key metrics, such as yield and resource use, due to the model's integrated approach. Benchmark the E2E model against existing systems and industry standards to validate its effectiveness. Provide detailed case studies and real-world applications showing the model's success in managing crops and optimizing harvesting. Include results from field trials to demonstrate its performance in diverse conditions. The measurement techniques used to assess productivity and resource use, ensuring accuracy and

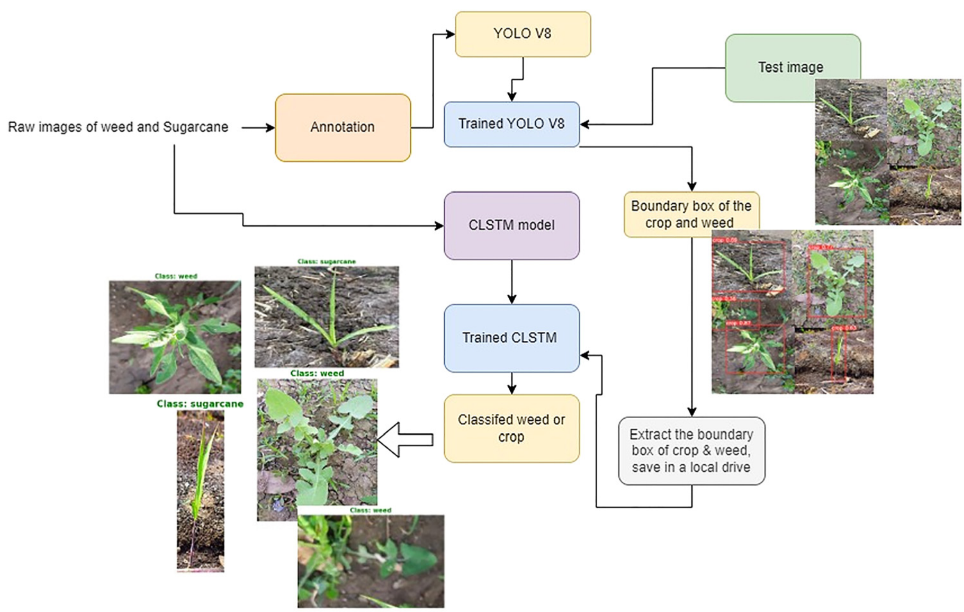


Fig. 2. Two-stage approach of weed detection

reliability. Define and utilize key metrics, such as yield per hectare, water and fertilizer usage, and harvesting time prediction accuracy, to comprehensively evaluate the model's impact.

4.4. First stage: detecting objects in the image

The initial step in the workflow involves the application of the YOLO (You Only Look Once) algorithm, the latest iteration in yolo series is yolov8 which improves upon earlier iterations by incorporating multiple changes like modules for context aggregation, feature fusion and spatial attention. One of the most significant object detection algorithms in use today is the YOLOv8 industry thanks to these advancements that lead to faster, more accurate object detection. There are 5 different-sized models of yolo n, s, m, l, x. The proposed approach selected Large sized model (yolov8l.pt) to object detection. The higher the model size that we select, the more accurate the predictions will be. So large model is chosen here and X is not chosen because it requires high computation time.

YOLOv8 detects objects within the given image and subsequently assigns bounding boxes to each identified object. YOLOv8 is well known for its ability to instantly identify objects. It works by dividing the image into grid cells and estimating bounding boxes and class probabilities for objects that are present in each grid cell. By analyzing the complete image in one pass, YOLO can efficiently and accurately localize and categorize multiple objects simultaneously. This process not only streamlines object detection but also yields precise boundary boxes, forming the foundation for subsequent stages in our image processing pipeline.

Annotating is necessary when using YOLOv8 technology to give the model accurate data labelling. Annotated photos are required to enable YOLOv8, an object detection algorithm, to discover and identify the objects. YOLOv8 can learn from past images and forecast future ones utilizing this annotated data. It is simple to begin using models that have already been trained on basic objects. However, in actual use, it can require a solution to identify particular items for a specific business issue.

There is probably not a free model that is fully informed, and this data is not readily accessible through open datasets. To detect these kinds of specific objects, it is essential to train own model. For that, the first process is to build a database related to the problem's annotated images and train the model used to make that happen. The steps that elaborate the image annotation before the training and evaluation phase are explained as follows.

Image annotation: To instruct the model, annotations of images must be created and separated into datasets of training and validation. The training set is utilized for both the validation set and model training, which also tests the study's conclusions, and is employed to assess the model's quality. The model undergoes training with 20% of the images in the validation set and eighty percent of the training set's images. Select and encode object classes to instruct the model to identify them. The training of the model is designed to localize only, not to classify, hence in this case, only one class—the crop class—is indicated as 0. No weed class is provided. The dataset is then divided into the images and labels subfolders. The dataset is then divided into the images and labels subfolders. Images are placed in the images subfolder, and a text file with annotations is made for each image in the labels subfolder. The names of annotation text files and their .txt extensions should match those of image files. To add documentation for every item present on the relevant image to the annotation files, use the format shown below:

{object_class_id} {x_center} {y_center} {width} {height}

Fig. 3. Weed image

For instance, the below weed image in Fig. 3 will be annotated as 0 0.589869281 0.490361446 0.326797386 0.527710843.

The following formula is used to calculate x_center, y_center, width and height

$$\text{x\_center} = (\text{box\_x\_left} + \text{box\_x\_width}/2)/\text{image\_width} \tag{7}$$

$$\text{y\_center} = (\text{box\_y\_top} + \text{box\_height}/2)/\text{image\_height} \tag{8}$$

$$\text{width} = \text{box\_width}/\text{image\_width} \tag{9}$$

$$\text{height} = \text{box\_height}/\text{image\_height} \tag{10}$$

For the image with the details as image_width = 612, image_height = 415, box_x_left = 261 box_x_top = 94, box_width = 200 and box_height = 219 then

$$\text{x\_center} = (261 + 200/2)/612 = 0.589869281$$

$$\text{y\_center} = (94 + 219/2)/415 = 0.490361446$$

$$\text{width} = 200/612 = 0.326797386$$

$$\text{height} = 219/415 = 0.527710843$$

So here, the annotation will be "0 0.589869281 0.490361446 0.326797386 0.527710843".

4.4.1. YOLOv8 model. Convolutional neural networks (CNNs) are the foundation of the one-stage, real-time object detection model used in the You Only Look Once model series. The reason for YOLO's widespread use is its effective feature fusion and capacity to generate extremely precise detection outcomes while upholding a thin network architecture. New features and enhancements over its predecessors are introduced by YOLOv8, the most recent YOLO version detection model, enhancing detection performance and flexibility. YOLOv8 adopts an anchor-free approach, reducing how many box predictions there are, expediting non-maxima suppression, and optimizing detection efficiency. To cater to diverse research needs, YOLOv8 offers five different scale models (n, s, m, l, x) based on scale factors akin to YOLOv5. The

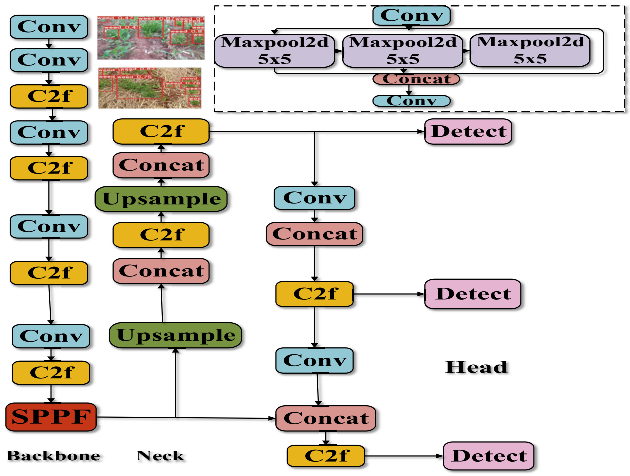


Fig. 4. YOLOv8's network structure

YOLOv8 network comprises Backbone, Neck, and also Head modules, responsible for prediction output, multi-feature fusion, and feature extraction, in that order. The network's structure is seen in Fig. 4, and it is adept at efficiently detecting objects in images by predicting bounding boxes.

Backbone module: Similarly to the YOLOv5 architecture, the YOLOv8 architecture also makes use of the Spatial Pyramid Pooling Fusion module, which greatly improves the model's capacity for generalization while successfully avoiding issues like image distortion brought through operations on the image regions such as scaling and cropping. The C2f module, which combines the two branches of a parallel gradient flow and reduces a convolutional layer based on the original C3 module, allows the YOLOv8 model to extract richer and more robust gradient flow information while maintaining its lightweight properties. The advancements introduced in YOLOv8, such as its anchor-free approach and multiple scale models catering to various research needs, showcase a commitment to improving flexibility and performance of detection. As fewer box predictions are made, expediting non-maxima suppression, and optimizing detection efficiency, YOLOv8 demonstrates its capability to meet the demands of modern computer vision applications. The integration of the network's Backbone, Neck and Head modules underscores its proficiency in prediction output, multi-feature fusion and also feature extraction. YOLOv8's efficacy in detecting objects with bounding boxes further solidifies its position as a robust and versatile real-time object detection solution for applications across various fields.

4.4.2. Training and validation phase of YOLO.

- Once all of the images have been annotated, the data is divided into combined with a train and validation dataset, along with a YAML descriptor file is produced and sent to the train approach.
- Run a random set of images via the method in the training stage. The model will then output the bounding boxes for each object it detects, along with its class.
- Send the outcome of the loss function, which compares the output that was received with the accurate results obtained from the files with annotations for the images. The degree of inaccuracy is computed by the loss function.

- The optimizer receives the loss function result and modifies the model weights according to the degree of inaccuracy in the right direction. The next cycle's errors are decreased as a result.
- Using the same methodology, the validation phase determines the model's precision by comparing the actual and predicted results.

4.4.3. Implementation of YOLOv8. YOLOv8 is a cutting-edge object detection model designed for real-time image analysis. It excels in detecting and classifying objects within an image efficiently, making it ideal for agricultural tasks such as differentiating between crops, weeds, and signs of disease. YOLOv8 achieves high accuracy with its advanced architecture, which includes a backbone network for feature extraction, a neck for feature aggregation, and a head for bounding box prediction and classification.

The CLSTM model integrates Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks to address both spatial and temporal dimensions of data. CNNs extract detailed features from individual images of sugarcane fields, identifying key traits and patterns crucial for distinguishing between crops and weeds. The LSTM component then analyzes these features over time, leveraging sequential data to forecast future conditions and identify trends based on historical observations. This hybrid approach enables comprehensive analysis by combining spatial insights with temporal predictions for enhanced crop management.

Data Sources for E2E Model: Image data for the YOLOv8 model is collected from field cameras, drones, or publicly available agricultural datasets, with each image meticulously annotated to identify crops, weeds, and disease symptoms. For the CLSTM model, temporal data is utilized, encompassing historical records of environmental conditions, crop growth stages, and resource inputs. This data is sourced from field sensors, weather stations, and agricultural records, providing a comprehensive basis for training the model to analyze and predict changes over time.

4.5. Second stage – classification

The subsequent phase of the pipeline employs a hybrid model CLSTM which combines Long Short-Term Memory and Convolutional Neural Network architectures. This integrated model is designed to classify the extracted portions of image is either crops or weeds. The CNN component is adept at capturing spatial features from the segmented regions, enabling robust feature extraction, while the LSTM component processes the temporal sequence of information, preserving contextual dependencies. The synergy between CNN and LSTM enhances the capacity of the model to discern between crop and weed instances, considering both spatial characteristics and temporal patterns in the segmented regions. This two-stage process guarantees a far-reaching and accurate analysis among the input image, providing valuable insights for agricultural applications such as precision farming and weed management.

4.5.1. Classification of the extracted portion of the image. Following the initial object detection with YOLO, the corresponding bounding box regions are taken out of the image and forwarded to the second stage. In this subsequent phase, a hybrid model combining Long Short-Term Memory and Convolutional Neural Network architectures is employed for classification. This Contextual Long Short-Term Memory (CLSTM) hybrid model excels in recognizing intricate patterns within the extracted image portions, enabling accurate differentiation between crops and weeds. The temporal modelling capabilities of LSTM, coupled with the spatial feature extraction of CNN, contribute to a complete understanding of the content, ensuring precise classification results. This two-stage process harnesses the strengths of both YOLO and the hybrid model, culminating in an effective approach for crop and weed identification in agricultural scenarios.

4.5.2. Convolutional neural network (CNN). The purpose of Convolutional Neural Networks is to efficiently extract spatial characteristics from images. Weight sharing, hierarchical feature learning, and convolutional layers are the main techniques that enable CNNs to capture spatial data.

Convolutional Layers: The fundamental components of CNNs used in feature extraction are convolutional layers. Small matrices called kernels, or learnable filters, make up a convolutional layer. These filters calculate the product of dots between the filter values and the matching input values at each point as they move above the source image in a predetermined pattern. The end product is a feature map that draws attention to the local features, patterns, and textures found in the input image.

Local Receptive Fields: Local receptive fields enable convolutional layers to focus on tiny, nearby spatial portions of the input. Within its receptive field, each filter has a speciality for identifying particular features.

Weight Sharing: A key idea in CNNs that lowers parameter numbers and improves the network's capacity for generalization is weight sharing. Throughout the input image, the same set of filters are applied at various spatial places. Because of this, the network can identify comparable patterns (textures, edges) in images irrespective of their location.

Pooling Layers: To downsample feature maps and lower computational complexity, pooling layers are frequently added after convolutional layers. The most notable properties in a particular region are retained by common pooling techniques such as average and maximum pooling.

Hierarchical Feature Learning: CNNs that use hierarchical feature learning include several convolutional layers layered on top of one another. Basic characteristics like borders, textures, and colours are captured by lower layers. Higher layers build on these fundamental characteristics as data moves through the network to acquire more knowledge of intricate and abstract representations.

Non-Linearity (Activation Function): To introduce non-linearity, an element-wise application of a function of nonlinear activation (often ReLU, or Rectified Linear Unit) is made following convolutional and pooling processes. The network can learn intricate correlations between features because of its non-linearity, which also increases the expressiveness of the model.

Global Context: The global context and relationships between various components of the image input are captured by higher layers in the network, which also have larger receptive fields. Understanding this global context is essential to identify intricate objects and conditions.

Convolutional layers are utilized by CNNs to extract hierarchical spatial characteristics from input images using localized operations. By ensuring that the same filters are applied to all areas of the image, weight sharing improves the generalization capacity of the model. CNNs are useful for a range of image-processing tasks because of their hierarchical structure, which enables them to capture both basic and complicated spatial patterns.

This novel method improves classification accuracy while guaranteeing flexibility in dynamic and changing visual environments. It works especially well in agricultural applications where accurate weed detection is crucial to productive farming methods.

4.5.3. Long Short-Term Memory model. Long Short-Term Memory (LSTM), a type of recurrent neural network (RNN), serves as a robust tool for classifying the extracted portions of images as either crop or weed. Renowned for its capacity to model sequential dependencies and capture temporal patterns, LSTM excels in analyzing image sequences and making informed classifications. Concerning agriculture, where distinguishing between crops and weeds is crucial for optimizing farming practices, the use of LSTM ensures that the model can effectively comprehend and categorize the dynamic features and variations within the image data. The application of LSTM in image classification contributes to the precision and adaptability required for accurate identification and decision-making in agricultural scenarios, ultimately enhancing the efficiency of crop management processes. Three layers: the output layer, the LSTM layer and the dense layer with a sigmoid activation function. Let x be a tensor that contains the input set values of a subject. x is fed as input to the embedding layer to generate the output tensor, $f(x)$, of the given dimensions:

$$f(x) = embedding(length(x), output - dimension, input - length(x)) \tag{11}$$

where $f(x)$ is the input for the LSTM layer.

$$g(x) = lstm(f(x)) \tag{12}$$

where $g(x)$ is the input to the Dense layer with a sigmoid activation function. Converging the output values among 0 and 1, this layer also serves as the output. Here, 0 denotes the absence of demented subjects, and 1 denotes their presence.

$$z = g(x) * W + b \tag{13}$$

$$y = 1/(1 + e^{-z}) \tag{14}$$

The implementation of Long Short-Term Memory for classifying extracted image portions as crops or weeds ends up being a promising approach. The unique temporal modelling capabilities of LSTM enable accurate and dynamic classification, essential for optimizing agricultural practices. This method not only enhances precision in the identification of crops and weeds but also showcases the adaptability required to handle diverse visual contexts. The utilization of LSTM holds significant potential for advancing image-based crop management, contributing to a more effective and informed decision-making realm of precision agriculture.

4.5.4. CLSTM model. Figure 5 explains a hybrid model of Contextual Long Short-Term Memory (CLSTM) that is utilized for image classification tasks where the data will be recorded for both spatial and temporal dependencies. Hierarchical spatial features among the input data are extracted using CNN as the first feature extractor. To capture temporal dependencies across the images, the CNN's output features are then input into the LSTM network. For eventual classification, the LSTM's resultant output is coupled to two fully interconnected layers. The spatial and temporal data that the CNN and LSTM components learned are combined in these layers. The final layer usually generates class probabilities for the image sequence using a sigmoid activation function. Using labelled data, the entire model is trained from end to end The

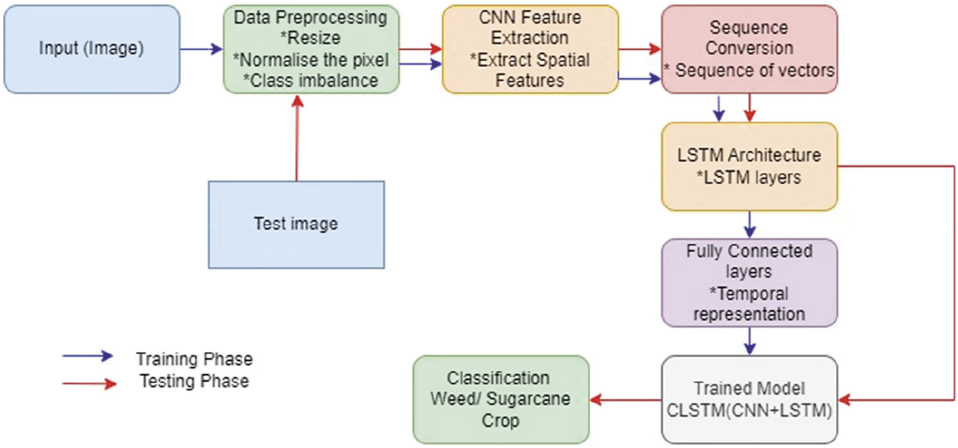


Fig. 5. Hybrid model -CLSTM

CNN is used during training to teach the model how to extract spatial characteristics from each image, while the LSTM is used to collect temporal dependencies throughout the series. Temporal dependencies between frames are captured by LSTMs as they process the sequence of these spatial properties.

4.6. Training phase

During the training cycle, each image is converted into a sequence of features through a combination of a Long Short-Term Memory and Convolutional Neural Network architecture involves the following algorithmic steps:

- Data Preprocessing:
  a. Load and preprocess image dataset.
  b. Resize images to a consistent size.
  c. Normalize pixel values.
- CNN Feature Extraction:
  a. CNN architecture is designed for image feature extraction.
  b. The Convolutional layers are employed to remove hierarchical spatial features from each image.
  c. The output will be a set of features representing spatial information within the image.
- Sequence Conversion:
  For every image, the extracted spatial features are reshaped into a sequence of vectors.
- Padding
  These sequences have different lengths, so to ensure uniform length padding or truncating is essential.

- Long Short-Term Memory Architecture:
  a. LSTM architecture is intended to process sequences of features.
  b. The input shape based on the sequence length and dimensionality of each feature vector is passed.
  c. LSTM layers are added with 512 units in the proposed approach.
- Fully Connected Layers:
  a. Two fully connected layers are added after the LSTM layers to further process the learned temporal representations.
  b. Flatten layer and dropout layer with 0.4 is added before the output layer.
  c. The layer that is output is included with a Sigmoid activation for the classification of weed or a sugarcane crop.
- Training:
  a. The dataset is split into instruction and verification sets of 80:20.
  b. Then the combined CNN-LSTM model is trained utilizing a loss function as categorical cross-entropy and an optimization algorithm as Adam.

4.7. Testing phase

When a test image is transported via the combined Contextual Long Short-Term Memory model for classification, the process involves the following steps:

- Preprocess the Test Image:
  Preprocess the test image similarly to preprocessing for the training images. This includes resizing, and normalization steps used during training.
- Extract Spatial Features using CNN:
  a. Pass the preprocessed test image via the CNN portion of the model.
  b. The CNN extracts hierarchical spatial features from the image.
- Convert Features into Sequences:
  Reshape the extracted spatial features into a sequence of vectors with the same sequence length used during training.
- Pass Sequences through LSTM:
  a. Pass the sequence of feature vectors via the LSTM segment of the model.
  b. The LSTM captures temporal dependencies within the sequence.
- Make Predictions:
  a. Then the combined trained model is used to make predictions on the test sequence.
  b. The model outputs probabilities for each class.

4.7.1. Hyperparameter tuning of the suggested model. The model's parameters, such as the number of epochs, batch size, learning rate, etc., were determined before the training process occurred. The model underwent training using training data. For a determinate validation of the prototype, the validation set was employed. This assisted in optimizing the model's hyper-parameters. The model was retrained with these parameters after the appropriate ones were determined. Upon completing the instruction procedure, the test set was utilized to verify the model's correct operation by providing an additional practical validation of the unseen data points.

Table 1 displays the performance metrics of the CLSTM model across different epochs and batch sizes, providing a comprehensive view of its effectiveness in handling the given task. When the quantity of epochs rises, there is a discernible improvement in key metrics such as precision, recall, F1 score, and overall accuracy. For instance, at epoch 10, with a batch size of 16, the model achieves a precision of 92.0%, recall of 99.2%, F1 score of 99.5%, and an accuracy of 94.6%. Moreover, the impact of varying batch sizes is evident, with performance variations observed across different configurations. As the model undergoes training for more epochs, it consistently refines its capacity to forecast with accuracy, as reflected in the escalating precision, recall, and F1 score values.

4.8. Harvesting time prediction of sugarcane crop

Predicting when to harvest is another important aspect of agriculture. It entails figuring out when to harvest sugarcane in order to maximize sugar content and crop quality overall. The estimation of sugarcane harvesting time is influenced by a number of variables. Based on variables such as the cane's brix value, weather forecasts, and the planting period, the sugarcane harvesting time can be estimated. In the world of sugarcane farming, knowing when to plant is essential to achieving strong crop growth and maximum yields. The upgraded datasets and features mentioned below are added to the existing methods in the climate-forcing datasets to provide new datasets that support and connect to agricultural applications. Various conventional methods, such as manual crop disease and pest detection and statistical calculations to estimate quantity and forecast crop production and loss, were often labour-intensive and prone to human error because farmers lacked experience before the development of information technology. Machine learning is one area in which technology can learn from recognitions and experiences. Large volumes of crop field data are available for this study to extract the most important findings for machine learning and data analytics. It reveals hidden relationships and patterns between variables that affect horticulture, like humidity, soil salinity, and temperature.

Predicting the optimal harvesting time for sugarcane is a critical task in agriculture. It involves determining the most suitable time to harvest sugarcane to achieve the highest sugar content and overall crop quality. Several factors influence the prediction of harvesting time in sugarcane: The harvesting time can be predicted for sugarcane based on parameters like the sowing period, weather forecasting, and the brix value of the cane. Figure 6 displays the flow diagram of the harvesting time prediction model.

Table 1. Performance metrics of the CLSTM model

Epoch	Batch size	Precision (%)	Recall (%)	F1 Score (%)	Accuracy
10	16	92.0	99.2	99.5	94.6
	32	93.4	99.2	96.2	95.5
20	16	94.9	99.2	97.0	96.4
	32	97.8	97.8	97.8	97.3
30	16	98.5	97.8	98.1	97.7
	32	94.4	99.2	97.8	97.0

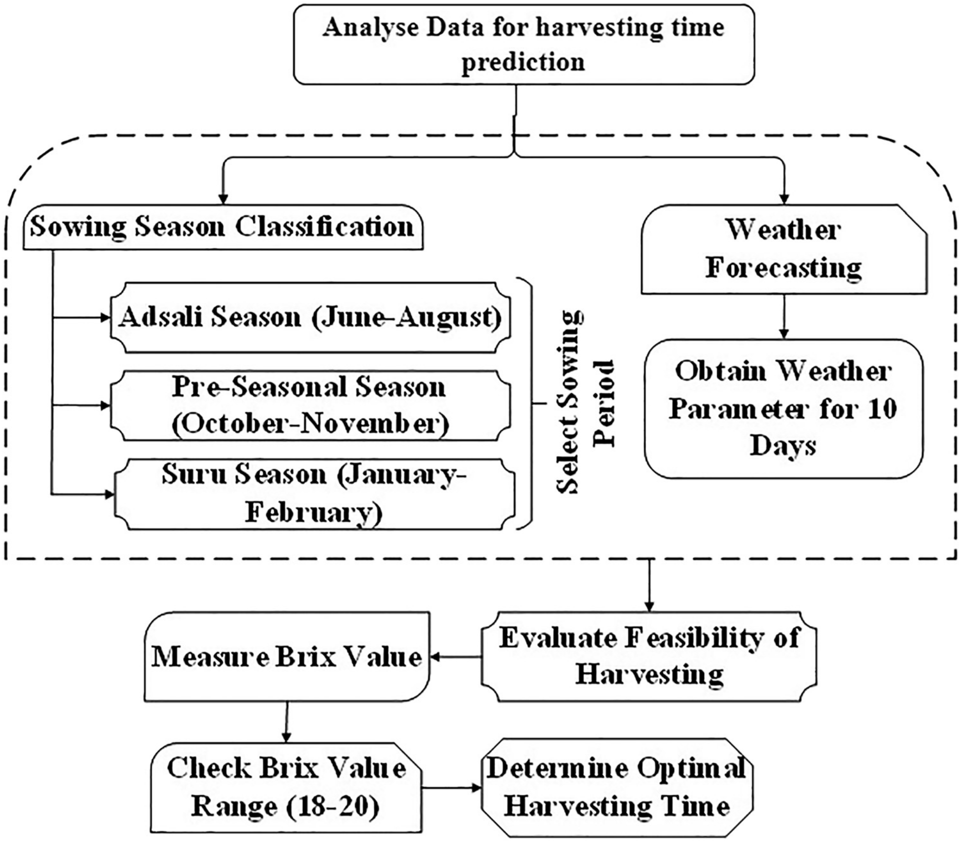


Fig. 6. Flow diagram for harvesting time prediction

Sowing Season Classification: In the realm of sugarcane cultivation, understanding the optimal sowing season is paramount for ensuring robust crop growth and maximizing yields. This crucial decision is often categorized into three primary periods, each with its distinct characteristics and considerations. This section delves into the classification of sowing seasons for sugarcane, shedding light on the factors that influence this pivotal agricultural choice. The sowing season for sugarcane is categorized into three main periods.

- Adsali Season (June–August)
- Pre-seasonal Season (October–November)
- Suru Season (January–February)

In regions like Maharashtra and Karnataka, Adsali planting typically occurs from July to August, and the crop takes about 16–18 months to mature. This extended growing season often leads to higher yields and better sugar recovery. One key advantage of Adsali planting is that it only spans one summer season. However, in recent times, the area under Adsali planting has been decreasing due to limited availability of irrigation water. Pre-seasonal planting is prevalent in northern India, taking place September through October, although in Bihar and the Indian Peninsula, it occurs in October-November. In Gujarat and Maharashtra, this is additionally known as autumn planting. In 13–15 months, the pre-seasonal crop reaches maturity and provides sugarcane early in the crushing season. Spring planting in Northern India takes place in February–March, However, in the Indian Peninsula, it occurs in January–February. Spring-planted crops are referred to as Eksali in Gujarat and Andhra Pradesh and Suru in Maharashtra.

Selecting the appropriate sowing period is crucial for predicting the harvesting time accurately. The developed algorithm offers three options for farmers to select a suitable sowing period. For instance, if a farmer chooses to sow the crop during the June-August Adsali season (option 1), the model requires input regarding the sowing date, month, and year. Since it is an Adsali period, the crop needs a minimum of 18 months to mature. Option 2 indicates a 15-month maturity period, while option 3 corresponds to a 12-month duration, allowing farmers to align their sowing decisions with the desired harvesting timeline.

Weather Forecasting: While the model estimates the harvesting time based on the chosen sowing period, it's important to note that the sowing season alone isn't the sole determinant of the ideal harvest time. Weather conditions have an important part, and farmers must consider local climate forecasts. Specifically, sugarcane crops should be harvested prior to the start of frost, necessitating a minimum temperature of above 20 degrees Celsius. The weather forecasting model provides valuable insights by offering 14 key parameters for the next 10 days, aiding farmers in assessing the feasibility of harvesting. These parameters include [temp_prediction,tempfeels_like_prediction, temp_min_prediction,temp_max_prediction,pressure_prediction,sea_level_prediction,grnd_level_prediction,humidity_prediction,temp_kf_prediction,main_weather_prediction,main_weather_description_prediction,clouds_prediction, wind_speed_prediction, wind_degree_prediction] as the output for the next 10 days so the farmer can check the possibility for harvesting. These predictions are obtained through an API call, empowering farmers to decide with knowledge based on upcoming weather conditions and ensuring a successful harvest.

Brix Value and Maturity Assessment: Another important feature that defines the optimal harvesting time for sugarcane is the Brix value. The method of sucrose growth in sugarcane stalks begins during the elongation stage and continues even after this stage ends. However, it's during the ripening stage that sucrose accumulation accelerates significantly. This ripening stage is characterized by growth in the brix value. To assess whether the sugarcane is ready for harvest, the farmer should measure the brix value using a hand brix refractometer. When the brix value reaches the range of 18–20, it indicates that the crop has reached maturity and is suitable for harvesting. If the estimated harvesting time is approaching the current month and year, the model recommends performing weather forecasting for the next 10 days to predict the local climatic conditions. This prediction is obtained through an API call. Together, these insights aid farmers in making knowledgeable judgements on harvesting their sugarcane, ensuring that it reaches the desired maturity stage for optimal yield.

This holistic and integrated approach, which encompasses sowing season classification, precise weather forecasting, and meticulous brix value assessment, empowers farmers with a robust toolkit for making well-informed decisions throughout the entire sugarcane cultivation and harvesting journey. Moreover, the meticulous assessment of the brix value is a critical milestone in the sugarcane cultivation journey. This value serves as a reliable indicator of sucrose accumulation and ripeness. With the control of the model, farmers can precisely determine when their sugarcane crop has reached the optimal maturity stage for harvesting. This not only ensures maximum sugar content but also enhances the overall quality of the yield.

4.9. Integration of YOLOv8 and CLSTM

YOLOv8, a cutting-edge object detection algorithm, excels in real-time identification of objects in sugarcane fields, distinguishing crops, weeds, and disease signs with speed and accuracy. CLSTM combines CNNs for image feature extraction with LSTMs for analyzing sequential data, enabling predictions about crop growth and optimizing harvesting schedules by leveraging time-series data and historical trends.

YOLOv8 and CLSTM work synergistically to enhance crop management in sugarcane fields. YOLOv8 first detects and classifies objects in real-time, providing crucial data for the CLSTM model. This data, encompassing current field conditions, is then used by CLSTM to analyze temporal patterns and predict future trends, optimizing harvesting schedules. YOLOv8's rapid, precise detection ensures that CLSTM receives accurate, up-to-date information, leading to comprehensive analysis and improved decision-making. This integration not only offers a holistic view of crop health and growth but also enhances yield and minimizes waste through better-informed management strategies.

5. EXPERIMENTATION AND RESULTS DISCUSSION

The integration of artificial intelligence, computer vision, and machine learning has significantly improved weed detection and management in agricultural fields. Our findings indicate that AI-powered systems can accurately identify and classify weeds, reducing the need for manual detection. The technology has demonstrated substantial efficiency gains, streamlining the farming process and enhancing productivity. Key metrics, such as detection accuracy and time saved, have shown considerable improvements with the adoption of these advanced technologies.

The results highlight the transformative impact of integrating advanced technologies in weed management. By automating weed detection, AI and machine learning not only reduce labour and time but also contribute to more precise and sustainable agricultural practices. This evolution in technology supports the broader goals of precision agriculture, enhancing resource optimization and boosting overall crop yield. The implications suggest that further advancements could continue to refine and expand these benefits, offering a more efficient approach to modern farming challenges. This separation clarifies the findings and their implications, making the information more digestible and actionable.

5.1. Performance analysis of YOLOv8

In assessing the YOLO model's performance in weed detection, a range of performance metrics was employed, including precision, recall, F1-score, average precision (AP), and mean average precision (mAP). These metrics provided a quantitative evaluation of the model's effectiveness in identifying weeds within the dataset. The mAP score, often considered a comprehensive metric for identifying object models, served as a key indicator of overall performance. This score was compared to baseline models or other relevant benchmarks when applicable. Furthermore, a detailed analysis was conducted to examine the compromize between recall and precision, shedding light on the capacity of the model to minimize false positives and maximize the detection of actual weed instances. The significance of these trade-offs within the framework of specific applications was discussed. These images highlighted instances of correctly detected weeds, false positives, and false negatives, contributing to a comprehensive assessment. A ground truth value was obtained by manually calculating the quantity of weeds in each image. Therefore, using this data, the evaluation metrics for weed detection were recall (R) and precision (P). The following is a definition of these model evaluation metrics:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{15}$$

$$\text{Recall} = \text{TP}\,\frac{TP}{TP + FN} \tag{16}$$

The training progress of the model YOLO is comprehensively depicted in Fig. 7 across 50 epochs. This graphical representation unveils the model's evolution through key metrics and losses. In the inaugural epoch, the model encounters a training box loss of 1.6208, a classification loss of 1.94, and a regression loss of 1.808. Precision, recall, mAP50, and mAP50-95 metrics are detailed with initial values of 0.00048, 0.02864, 0.00023, and 5.00E-05, respectively. Throughout the training, fluctuations in these metrics are evident, signifying the model's adaptation to the dataset. Notably, nan or inf values are observed, particularly in early epochs, warranting thorough investigation. Validation losses and metrics on unseen data are also presented, offering insights into the functionality of the model. Continuous monitoring facilitates a nuanced understanding of convergence and generalization, guiding potential adjustments for enhanced performance. In early epochs, the model grapples with high variability, yet as training progresses, stability emerges, showcasing refined object detection capabilities and minimizing erroneous negative and positive results. The recorded learning rate adjustments in the final columns underscore the optimization process crucial for the model's convergence.

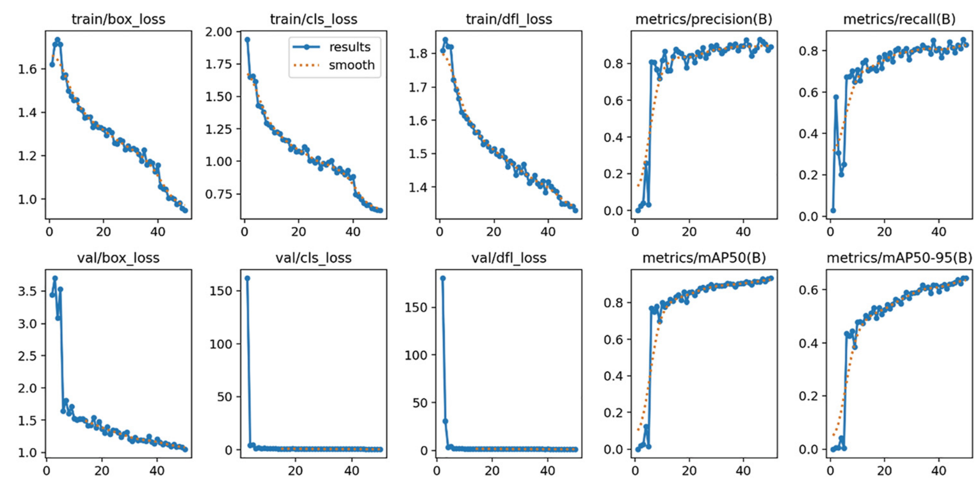


Fig. 7. Training progress and evolution for YOLO of metrics over 50 epochs

Figure 8 displays the curve that illustrates the trade-off between confidence levels and the corresponding recall rates. At a confidence threshold of 0.99, the model demonstrates high confidence in its predictions, resulting in a lower recall for detecting instances. Conversely, at a threshold of 0.000, the recall is maximized, indicating a more inclusive approach with lower confidence requirements for identifications. This analysis offers insightful information about the model's performance level. across different confidence thresholds, aiding in the selection of an appropriate operating point based on specific application requirements.

The presented Fig. 9 showcases the model's performance at a level of confidence of 0.930 for crop detection and an overall multi-class detection scenario with a mean Average Precision of 0.930 at 0.5 Intersection over Union. This curve offers a thorough understanding of the trade-off between recall and precision, offering valuable insights into the capacity of the model to balance sensitivity and accuracy across different confidence levels. The achieved mAP@0.5 metric further quantifies the overall effectiveness of the model in accurately identifying and localizing objects within the specified IoU threshold.

Figure 10 presents a thorough examination of the model's performance for both crop detection and multi-class detection. At a high confidence threshold of 1.00, the model exhibits a precision of 0.828, indicating a robust association between the confidence levels assigned by the prototype and the precision of its predictions. This figure offers insightful information about how reliable the model's detections are, particularly when considering perfect confidence levels, and offers a nuanced understanding of precision across different confidence thresholds for both crop-specific and overall object detection scenarios.

Figure 11 displays an assessment of the model's performance through the Confidence and F1 curves for all classes. At a level of confidence of 0.86, the model achieves an F1 score of 0.432. This analysis sheds light on the capacity of the model to balance precision and recall at varying confidence levels, providing insightful information for selecting an optimal operating point

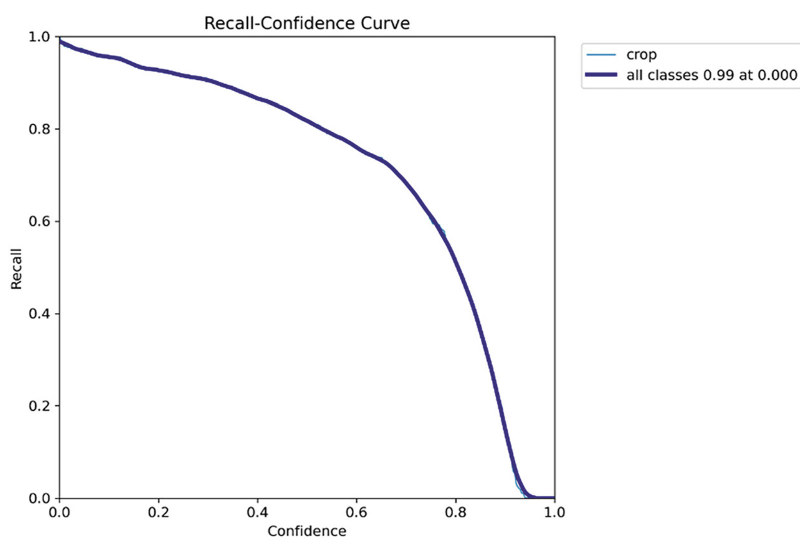


Fig. 8. Confidence-recall trade-off curve analysis

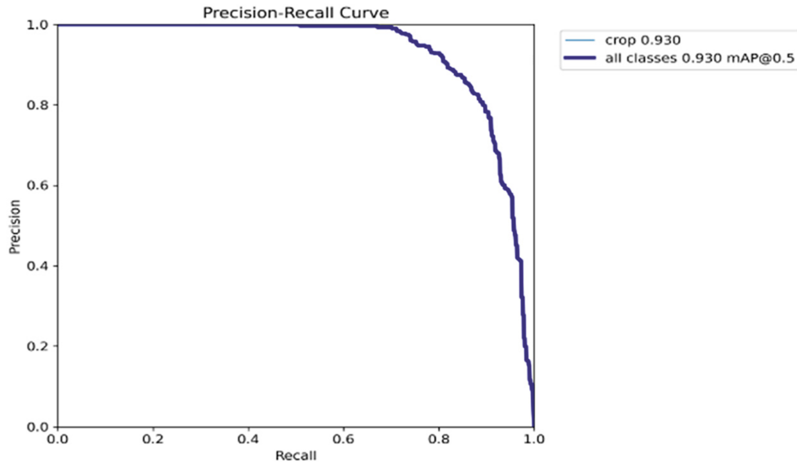


Fig. 9. Performance evaluation curve for crop detection and multi-class situation at confidence threshold

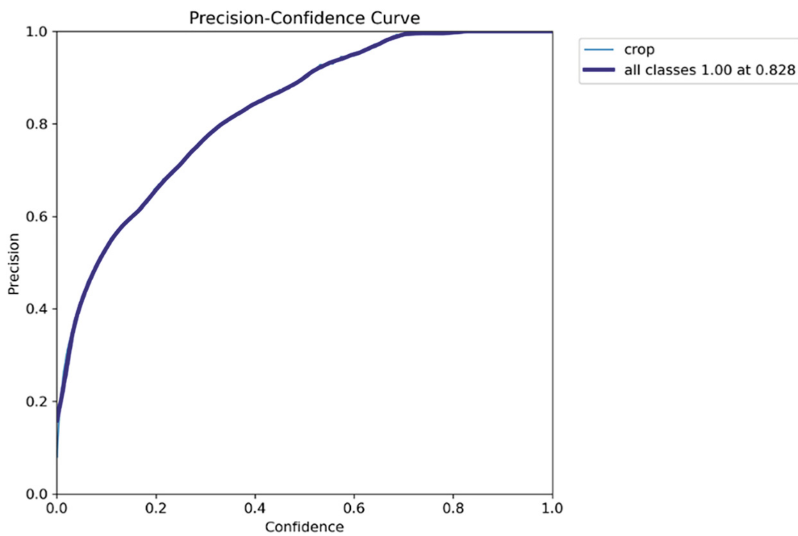


Fig. 10. Precision analysis at high confidence threshold for crop and multi-class detection

based on specific application requirements. The figure contributes to a nuanced understanding of the trade-offs between confidence levels and overall model performance, providing crucial information for decision-making in real-world scenarios.

After the Yolov8 model has been trained using 5,800 images, the instruction and verification output are shown in the images below. In this instance, Yolov8 recognizes the objects and gives the boundary box of each crop and weed in the field image. In this case, crop refers to both the sugarcane and the field's weeds.

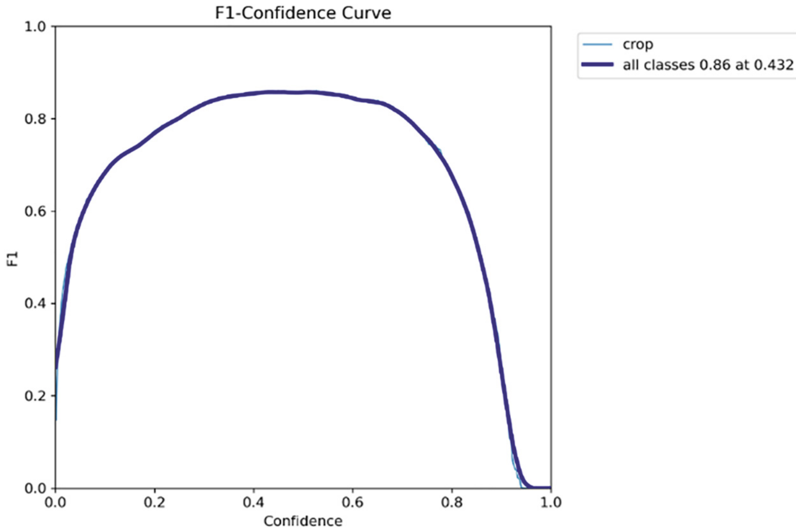


Fig. 11. Confidence-F1 trade-off curve for multi-class detection at threshold

Figure 12 represents the E2E model for sugarcane, the graph displaying mean monthly temperatures (200, 400, 275, 375, 25, 100, 200) represents the variation in temperature over different months. This temperature data is crucial for both crop suggestion and harvesting time

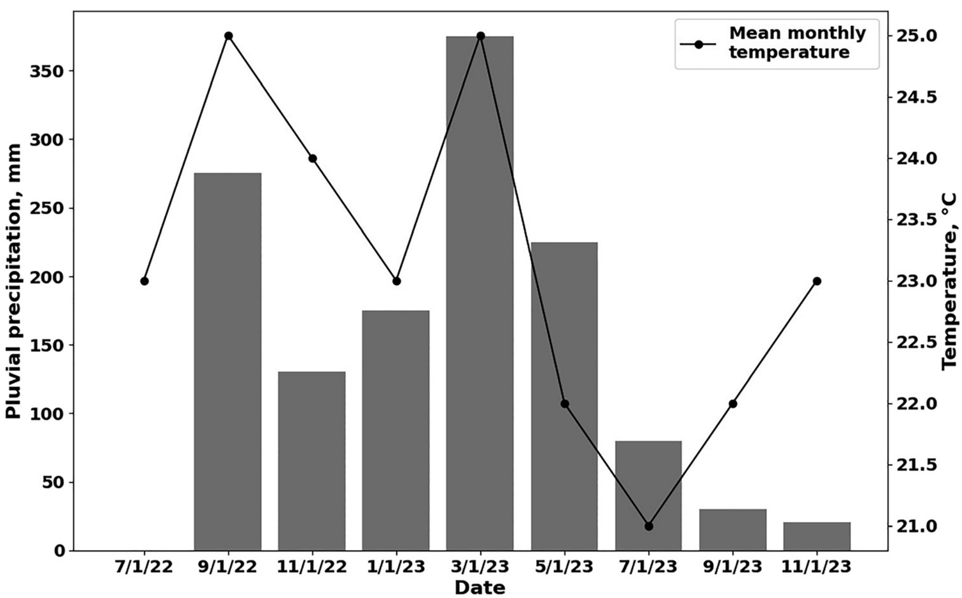


Fig. 12. Optimizing sugarcane planting and harvesting in monthwise

prediction. Machine learning and deep learning algorithms analyze historical temperature trends to optimize planting schedules and predict harvest times. By incorporating temperature data, the model can determine the most suitable planting periods and forecast ideal harvest times to maximize yield. The goal is to align agricultural practices with climatic conditions, ensuring optimal growth and productivity of sugarcane crops throughout their growth cycle.

Figure 13 presents the 12–16 month cycle for sugarcane cultivation using the E2E model shows the timeline from crop suggestion to harvesting time prediction. Initially, the model suggests suitable crop varieties based on environmental and soil data (months 2–3). As the crop grows, the model uses machine learning algorithms to predict growth patterns and adjust recommendations (months 4–5). Advanced deep learning techniques refine these predictions as the crop matures (months 6–6.5). Finally, the model provides accurate harvesting time predictions to optimize yield (month 12). The cycle reflects a comprehensive approach, integrating data at various stages to improve the efficiency and accuracy of sugarcane farming.

Figure 14 represents the E2E model for sugarcane cultivation tracks key metrics over time, including surplus, deficit, withdrawal, and replacement. Surplus values (150, 100, 50, 75) indicate the excess resources available at different stages, initially high but decreasing as the crop matures. Deficit values remain at 0, showing no shortage of resources throughout. Withdrawal

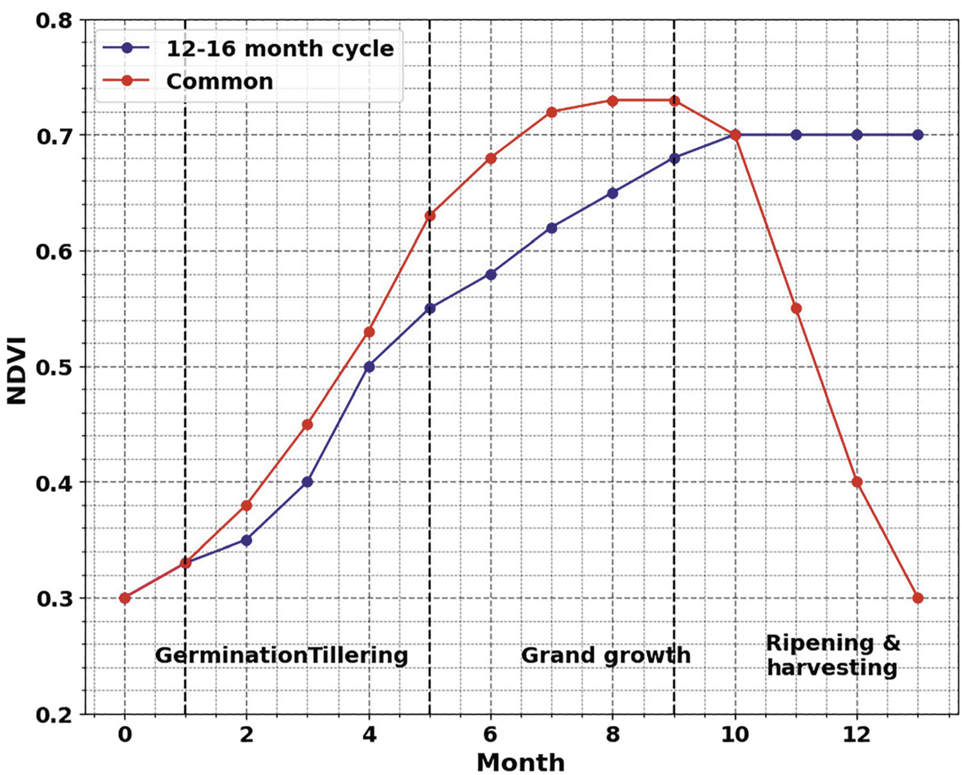


Fig. 13. Optimizing sugarcane cultivation a 12–16 month E2E model

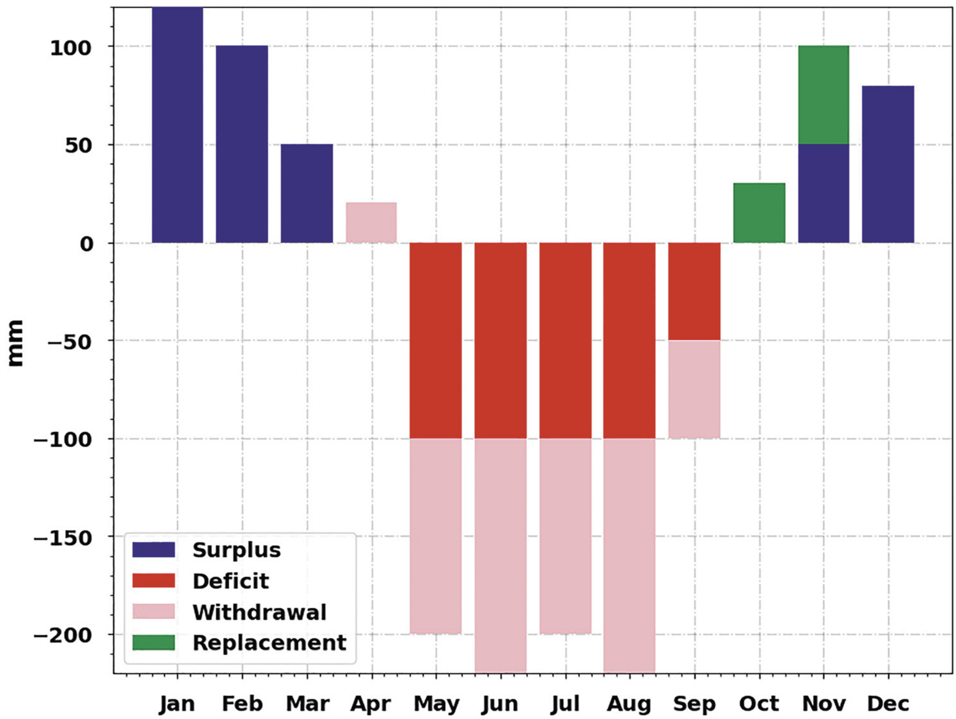


Fig. 14. Resource management in sugarcane cultivation surplus, deficit, and replacement metrics

values (25, −100, −50) represent resource consumption or depletion, with a significant drop indicating high resource use or potential over-extraction at certain points. Replacement values (25, 100) reflect the addition or replenishment of resources, with an initial small replacement and a larger one later to sustain crop growth and health. This data helps optimize resource management and ensure efficient sugarcane production using machine learning and deep learning insights.

Figure 15 shows Brix levels for different sugarcane varieties of RB 867515, RB 863129, and RB 92579 throughout the cultivation cycle in the E2E model. RB 867515-17% exhibits stable Brix levels, indicating consistent sugar content throughout growth. RB 863129-18% shows a gradual increase, suggesting improved sugar concentration as the plant matures. RB 92579-18% demonstrates fluctuating Brix levels, with periods of higher and lower sugar content. The graph helps evaluate the sugar content potential of each variety, informing optimal harvesting times. By leveraging machine learning and deep learning, the model predicts and maximizes yield quality based on these Brix trends, guiding better crop management and selection for efficient sugarcane production.

Figure 16 represents maximum temperatures recorded over several days: 32, 34, 38, 40, 37, 28, and 30 °C. In the context of an end-to-end (E2E) model for sugarcane cultivation, these temperature values play a crucial role in crop suggestion and harvesting time prediction. Machine learning and deep learning techniques can analyze this temperature data alongside other

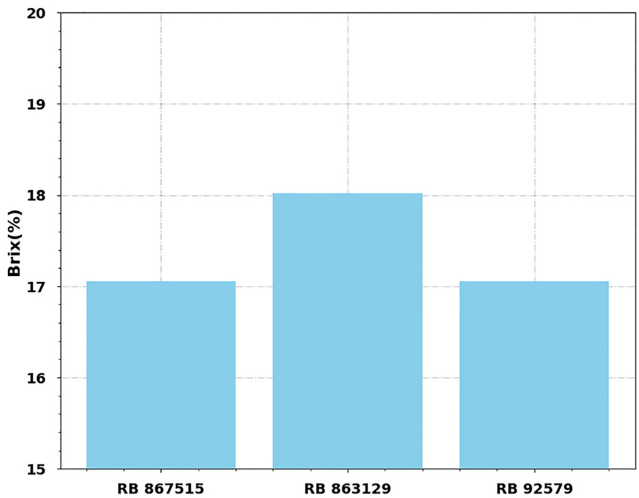


Fig. 15. Brix levels for sugarcane varieties

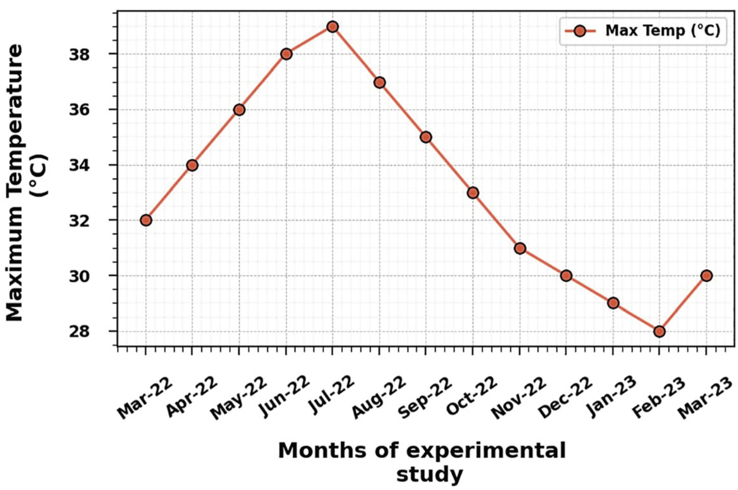


Fig. 16. Impact of maximum temperatures on sugarcane growth and harvesting prediction

environmental factors to determine optimal planting times and predict growth cycles. High temperatures may accelerate growth but also increase stress, impacting yield. By integrating this data, the model helps farmers make informed decisions, ensuring efficient resource use and maximizing crop yield. The analysis ultimately supports better management practices for sugarcane cultivation.

Figure 17 shows two sets of relative humidity data: Relative Humidity 1 (160, 165, 180, 160, 145, 140, 150) and Relative Humidity 2 (140, 150, 160, 140, 125, 120, 130). In an end-to-end (E2E) model for sugarcane cultivation, these humidity readings are vital for crop suggestion and

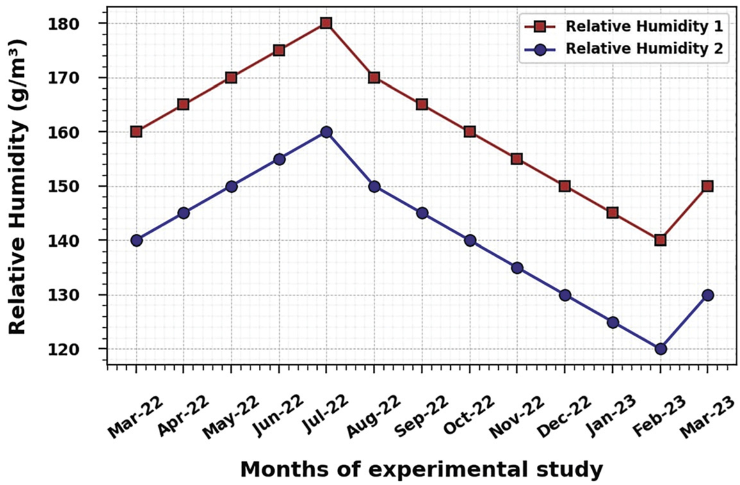


Fig. 17. Role of relative humidity in sugarcane growth and harvesting optimization

harvesting time prediction. Machine learning and deep learning algorithms analyze these humidity levels alongside temperature and other factors to optimize growth conditions. Higher humidity can enhance sugarcane growth but may also foster diseases if excessive. By correlating humidity data with growth stages, the model assists farmers in making timely decisions on planting, irrigation, and harvesting, ultimately improving yield and sustainability in sugarcane farming.

Figure 18 illustrates minimum temperatures recorded over time: 22, 24, 26, 28, 26, 18, 15, and 15 °C. In the context of an end-to-end (E2E) model for sugarcane cultivation, these

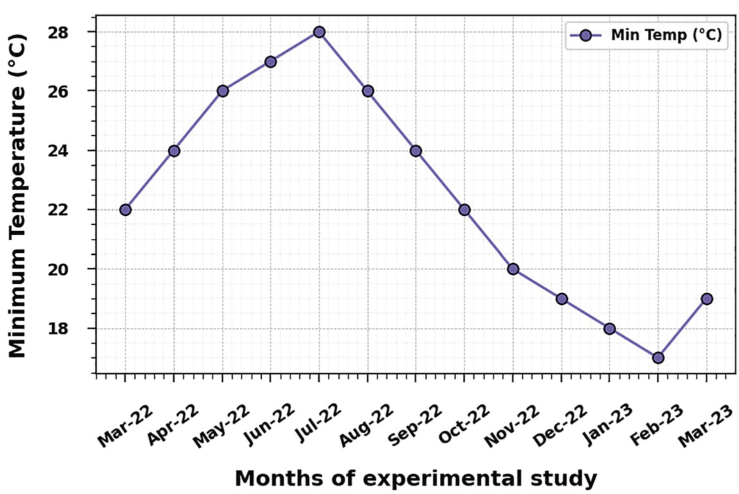


Fig. 18. Impact of minimum temperatures on sugarcane growth and harvest timing

minimum temperatures are crucial for crop suggestion and harvesting time prediction. Machine learning and deep learning algorithms utilize this temperature data to assess growth conditions. Lower temperatures, particularly those below 18°C, can hinder sugarcane growth and affect yield quality. By analyzing these temperature fluctuations along with humidity and maximum temperatures, the model helps predict optimal planting times and harvesting schedules. This data-driven approach enables farmers to make informed decisions, ultimately enhancing crop management and improving overall productivity in sugarcane farming.

Figure 19 presents the performance metrics of the K-Nearest Neighbors (KNN) model versus a proposed model for predicting sugarcane cultivation outcomes in the E2E model. The KNN model shows an accuracy of 89.3%, while the proposed model achieves a higher accuracy of 97.7%, indicating improved overall prediction reliability. Precision for KNN is 91.2%, compared to the proposed model's 98.5%, reflecting better accuracy in identifying relevant results. The F1 score for KNN is 88.5%, whereas the proposed model scores 97.5%, showing enhanced balance between precision and recall. These metrics highlight the proposed model's superior performance in predicting optimal harvesting times and improving sugarcane yield management, driven by advanced machine learning and deep learning techniques as shown in Fig. 20.

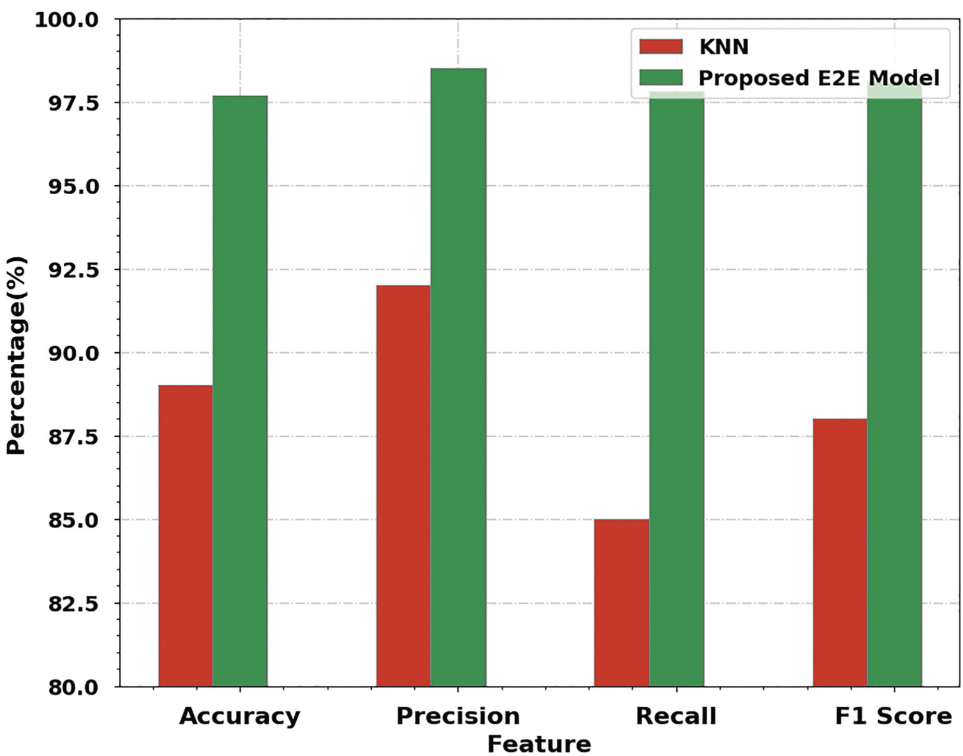


Fig. 19. Performance comparison: KNN vs. proposed model in sugarcane prediction

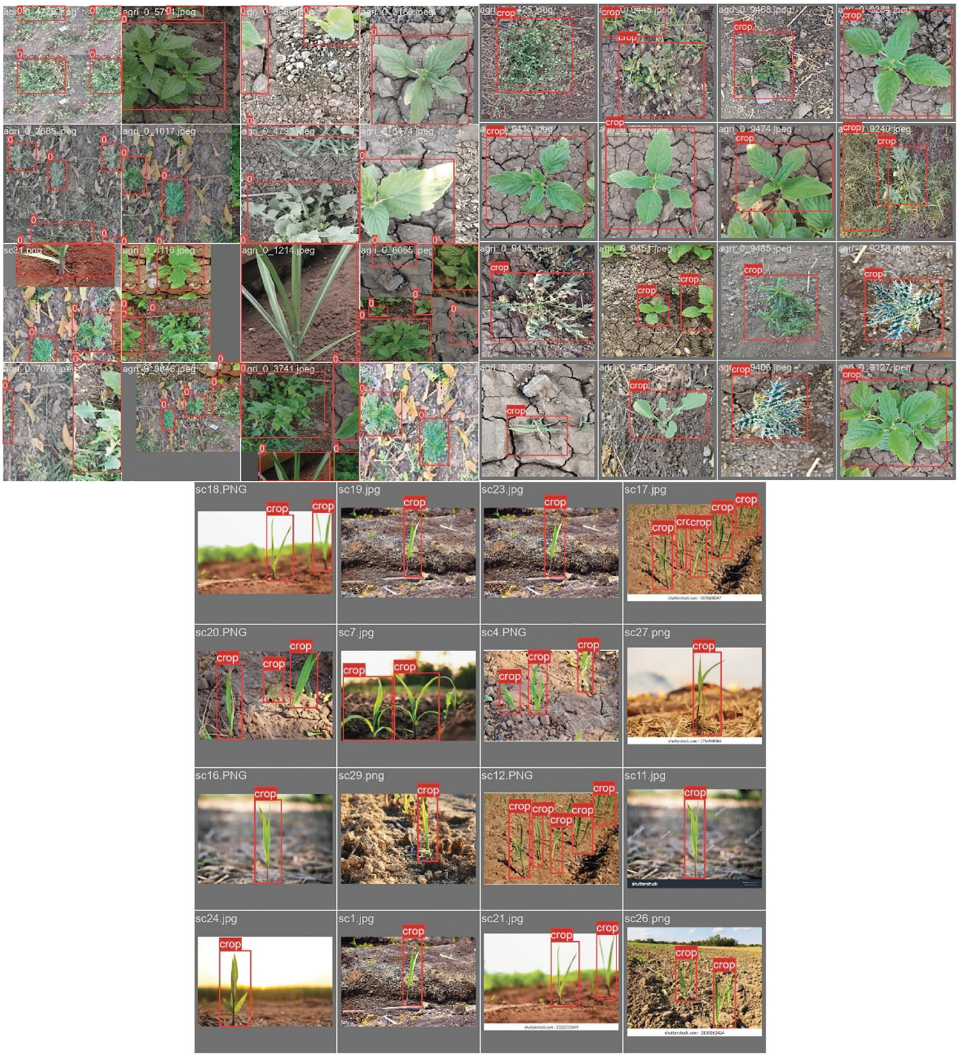


Fig. 20. Training and validation batch images

The model attains the best precision with the optimizer learning rate hyper tuned to the description: optimizer: AdamW (lr = 0.002, momentum = 0.9) with parameter groups 97 weight (decay = 0.0), 104 weight (decay = 0.0005), 103 bias (decay = 0.0).

Once the Yolo model is trained then the below image in Fig. 21 is passed to Yolo to detect the boundary box of objects (either a crop or a weed) in the field image.

The following is Yolo's output upon its identification of the input image's boundary box (Fig. 22).

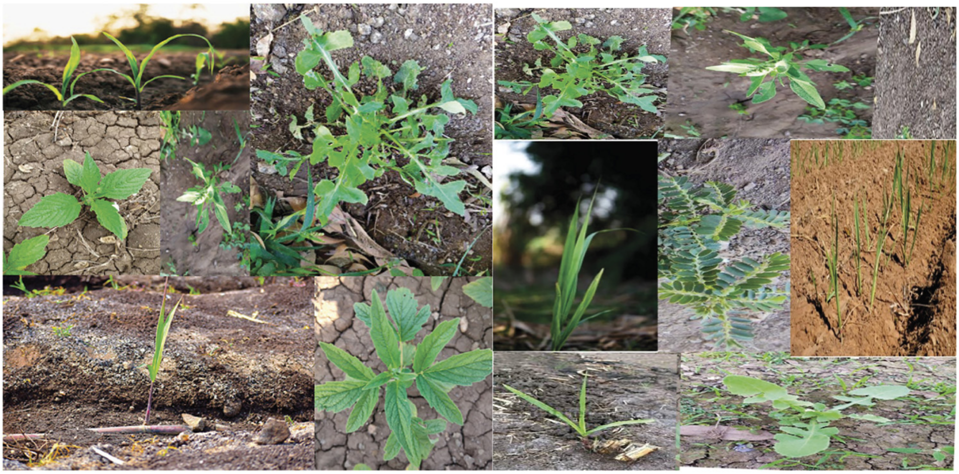


Fig. 21. Test image passed to YOLOv8 model

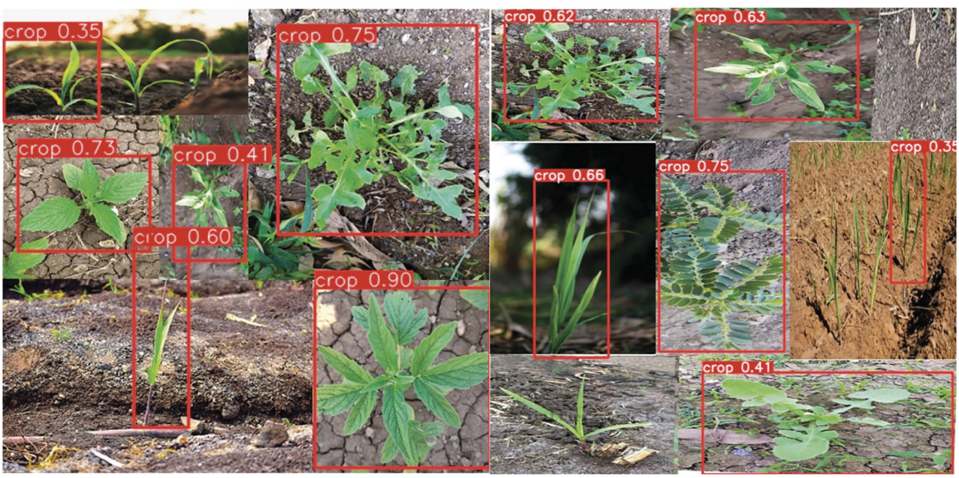


Fig. 22. Output of YOLO with Boundary box for the test image

5.2. Performance analysis of CLSTM

The output of yolo (You Only Look Once) in the image (Fig. 22) is passed for the CLSTM model showcasing the initial data fed into the proposed system for weed and sugarcane crop classification. This image serves as the foundation for the subsequent processes in the model, highlighting the importance of accurate and representative input data for achieving precise classification results. The clarity and relevance of the input image significantly influence the capacity of the model to make informed distinctions between weed and sugarcane crop instances, contributing to the overall effectiveness of the classification system.

In the comparative analysis, the research work delves into the performance evaluation of three distinct models for CNN, DenseNet, and the hybrid proposed approach CLSTM (CNN+LSTM). Each model is meticulously assessed based on specific metrics to gauge its effectiveness in handling the given task. Furthermore, a detailed examination of the CLSTM model's performance across various epochs and batch sizes offers insightful information about its adaptability and accuracy. This comparative study aims to elucidate the strengths and weaknesses of each model, aiding in the choice of the most suitable architecture for the designated application.

Technical specification: YOLOv8 features a sophisticated architecture that incorporates convolutional layers, attention mechanisms, and enhanced detection heads to enhance object localization and classification. It is trained on a diverse dataset of sugarcane fields, which includes annotated images of crops, weeds, and disease symptoms. The model supports various input resolutions, typically ranging from 416 × 416 pixels to 640 × 640 pixels, balancing detection accuracy with computational efficiency. Optimized for real-time performance, YOLOv8 can process images at high frame rates, making it well-suited for live monitoring and rapid analysis applications.

The presented Table 2 encapsulates the performance metrics of different models, namely CNN, DenseNet, and CLSTM, based on precision, recall, F1 score, and overall accuracy. Notably, the CNN model exhibits a precision of 95.6%, recall of 98.5%, F1 score of 97.0%, and an impressive overall accuracy of 96.4%. Similarly, DenseNet demonstrates robust performance with a precision of 94.9%, recall of 98.5%, F1 score of 96.7%, and an accuracy of 95.9%. Lastly, CLSTM showcases superior precision at 98.5%, recall at 97.8%, F1 score at 98.1%, and an overall degree of precision of 97.7%. These quantitative results provide a comprehensive assessment of the models' capabilities in terms of precision, recall, and overall classification accuracy, aiding in the selection and enhancement of the most effective model for the given task.

Figure 23 explains the relationship between epochs and accuracy, showcasing the training accuracy and validation accuracy. At the designated epoch, the model achieves a remarkable training accuracy of 97.6% and a corresponding validation accuracy of 99.35%. This analysis offers insightful information about the convergence and generalization capabilities of the model over training epochs, contributing to an improved understanding of its overall performance. The figure helps evaluate the model's learning dynamics and reliability in accurately classifying instances.

Figure 24 displays the training process's epochs and losses. The model's performance on the training dataset is demonstrated by the training loss, which is measured at 0.0827, and its ability to generalize to new data is demonstrated by the validation loss, which is measured at 0.0152. A succinct summary of the model's learning process is given by this visualization, where lower loss values indicate better convergence and efficiency in identifying underlying patterns in the data.

Table 2. Performance of models CNN, DenseNet and CLSTM (Epoch = 30, Batch size = 16)

Model	Precision (%)	Recall (%)	F1 Score (%)	Accuracy
CNN	95.6	98.5	97.0	96.4
DenseNet	94.9	98.5	96.7	95.9
CLSTM	98.5	97.8	98.1	97.7

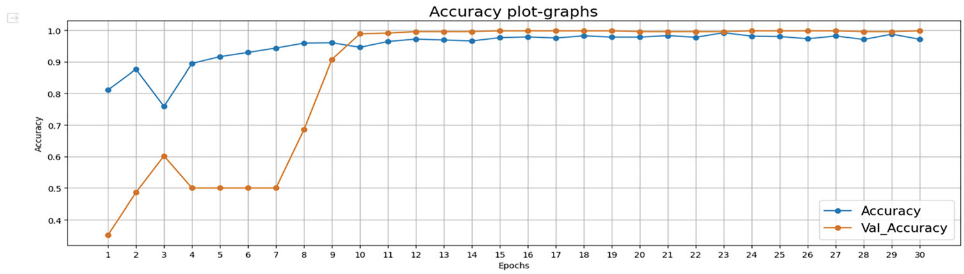


Fig. 23. Epochs vs accuracy of validation and training

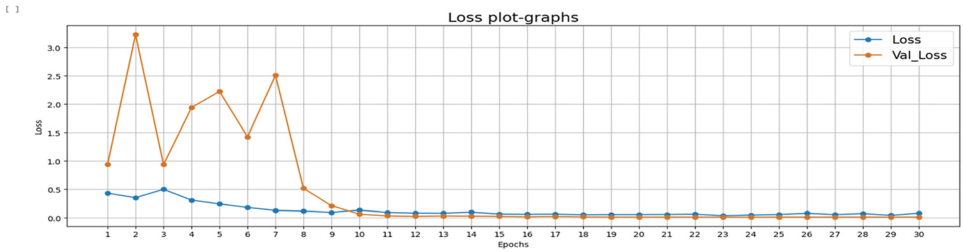


Fig. 24. Training loss and validation loss

The model's training processes and generalization skills can be evaluated with the assistance of the figure.

The boundary box portions in the output of the YOLO model are extracted and saved in the local drive and passed to CLSTM regarding the categorization of weeds or crops. The below image in Fig. 25 represents the input and also output flow of the CLSTM.

5.3. Analysis of harvesting time prediction

The output of harvesting time prediction is displayed in the below representation in Fig. 26.

Figure 26 provides a comprehensive weather forecast for Bengaluru City, India, over the next 10 days, which is vital for determining the optimal time to harvest a sugarcane crop. This includes various weather-related parameters for each time prediction, including the date and time of the prediction, city-related information such as latitude and longitude, population, time zone, sunrise, and sunset times, as well as temperature predictions, atmospheric pressure, sea level pressure, ground level pressure, humidity, and temperature fluctuations. The user's input data, including the sowing date of the sugarcane crop (November 1, 2021) and the estimated harvesting time (May 1, 2023), is calculated based on the sowing date, and suppose the current date is (May 13, 2023) according to this calculation, the sugarcane crop is ready for harvesting at the time, so the model generates the next 10 days' weather prediction to verify the optimal harvesting time. Furthermore, the user is prompted to enter the Brix saccharometer value, which is essential for assessing the maturity of the crop. Here, the user enters a Brix value of 21, indicating that the crop has matured and is suitable for harvesting.

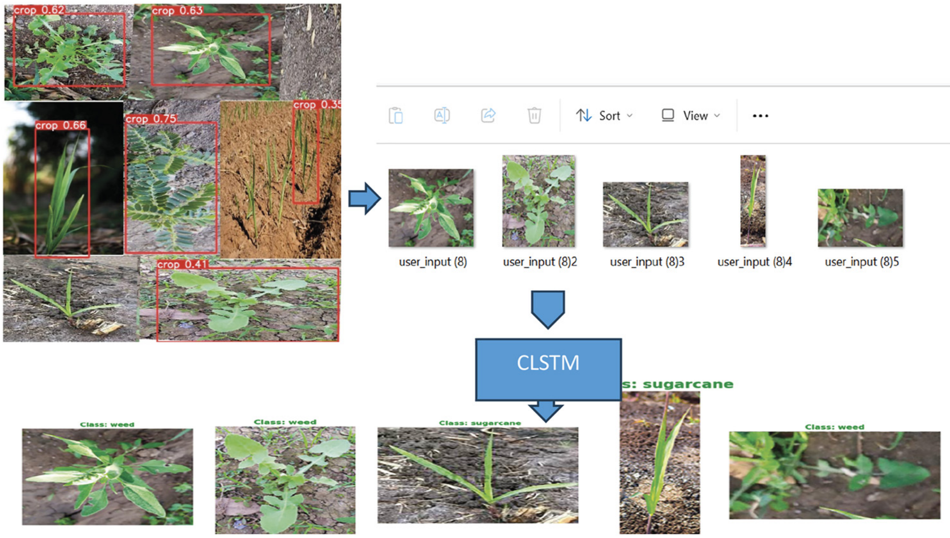
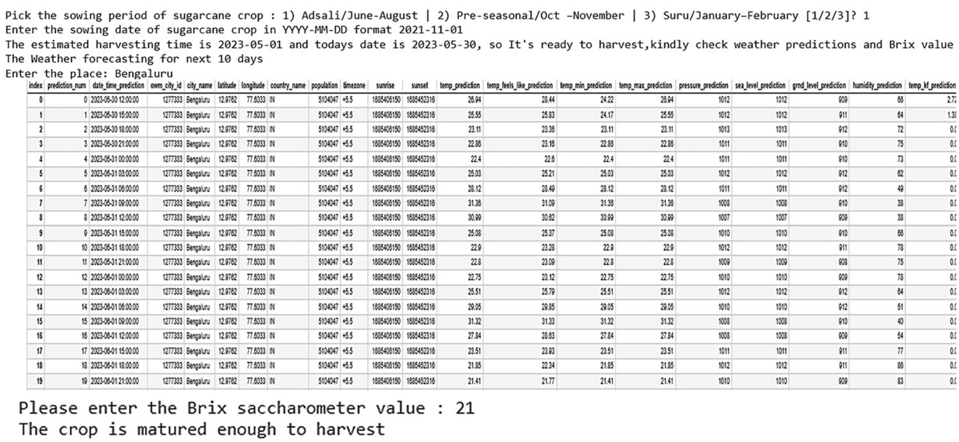


Fig. 25. Input and Output flow of CLSTM



```
Pick the sowing period of sugarcane crop : 1) Adsali/June-August | 2) Pre-seasonal/Oct –November | 3) Suru/January–February [1/2/3]? 1
Enter the sowing date of sugarcane crop in YYYY-MM-DD format 2021-11-01
The estimated harvesting time is 2023-05-01 and todays date is 2023-05-30, so It's ready to harvest,kindly check weather predictions and Brix value
The Weather forecasting for next 10 days
Enter the place: Bengaluru
```

index	prediction_num	date_time_prediction	owm_city_id	city_name	latitude	longitude	country_name	population	timezone	sunrise	sunset	temp_prediction	temp_feels_like_prediction	temp_min_prediction	temp_max_prediction	pressure_prediction	sea_level_prediction	grnd_level_prediction	humidity_prediction	temp_kf_prediction
0	0	2023-05-30 12:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	26.94	28.44	24.22	26.94	1012	1012	909	66	2.7
1	1	2023-05-30 15:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	25.55	25.83	24.17	25.55	1012	1012	911	64	1.3
2	2	2023-05-30 18:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	23.11	23.36	23.11	23.11	1013	1013	912	72	0.0
3	3	2023-05-30 21:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	22.86	23.16	22.86	22.86	1011	1011	910	75	0.0
4	4	2023-05-31 00:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	22.4	22.6	22.4	22.4	1011	1011	910	73	0.0
5	5	2023-05-31 03:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	25.03	25.21	25.03	25.03	1012	1012	912	62	0.0
6	6	2023-05-31 06:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	28.12	28.49	28.12	28.12	1011	1011	912	49	0.0
7	7	2023-05-31 09:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	31.36	31.09	31.36	31.36	1008	1008	910	38	0.0
8	8	2023-05-31 12:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	30.99	30.62	30.99	30.99	1007	1007	909	38	0.0
9	9	2023-05-31 15:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	25.08	25.37	25.08	25.08	1010	1010	910	66	0.0
10	10	2023-05-31 18:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	22.9	23.28	22.9	22.9	1012	1012	911	78	0.0
11	11	2023-05-31 21:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	22.8	23.09	22.8	22.8	1009	1009	908	75	0.0
12	12	2023-06-01 00:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	22.75	23.12	22.75	22.75	1010	1010	909	78	0.0
13	13	2023-06-01 03:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	25.51	25.79	25.51	25.51	1012	1012	912	64	0.0
14	14	2023-06-01 06:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	29.05	29.85	29.05	29.05	1010	1010	912	51	0.0
15	15	2023-06-01 09:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	31.32	31.33	31.32	31.32	1008	1008	910	40	0.0
16	16	2023-06-01 12:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	27.84	28.63	27.84	27.84	1008	1008	909	54	0.0
17	17	2023-06-01 15:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	23.51	23.93	23.51	23.51	1011	1011	911	77	0.0
18	18	2023-06-01 18:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	21.85	22.34	21.85	21.85	1012	1012	911	86	0.0
19	19	2023-06-01 21:00:00	1277333	Bengaluru	12.9762	77.6033	IN	5104047	+5.5	1685408150	1685452316	21.41	21.77	21.41	21.41	1010	1010	909	83	0.0

```
Please enter the Brix saccharometer value : 21
The crop is matured enough to harvest
```

Fig. 26. Harvesting time prediction in Bengaluru city

6. RESEARCH CONCLUSION

The research work presents an innovative and advanced automated system with the potential to transform sugarcane cultivation practices. Its core objectives revolve around enhancing yield, improving crop quality, and advocating for sustainable farming methods. The study leverages the power of five machine learning algorithms working in tandem within an ensemble learning model for recommendations of the most suitable crop according to the soil conditions and suggests optimal fertilizer compositions. Notably, the execution of the DNet-SVM model, a fusion of Dense Net, SVM, and LIME interpretation techniques, substantially elevates the accuracy of the disease prediction. This breakthrough is a cornerstone in disease management, as it effectively reduces crop yield losses and promotes sustainable agricultural practices. Furthermore, the research extends its focus to the critical aspect of precise weed detection. Through the utilization of deep learning and a comprehensive analysis of object detection models, this study advances site-specific weed management approaches. This not only diminishes the reliance on herbicides but also amplifies their efficiency, aligning with eco-friendly and sustainable weed control practices. Beyond disease and weed management, the study takes a holistic approach by predicting optimal sugarcane harvesting times. This prediction accounts for multiple factors, including sowing periods, weather forecasts, and brix values, all aimed at maximizing sugar content and overall crop quality. The system's predictions empower farmers with valuable insights to make well-informed decisions regarding their harvesting schedules. In future research, enhance model generalization by diversifying datasets with more challenging images. Improve real-world agricultural performance by incorporating data from diverse locations, seasons, and weed species to enhance the detectors' performance. Consider semi-supervised and weakly-supervised learning approaches to reduce reliance on fully annotated datasets, alongside domain adaptation techniques for better performance in new agricultural fields.

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