AN INTEGRATED BEST SOLUTIONS FOR OPTIMIZED PEST CONTROL AND SOIL HEALTH IN SUGARCANE CROPS

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ABSTRACT

In India, pest management is of great importance in order to have healthy sugarcane crops and to maximize production. Image processing and object detection models are used in this work to engage in proper sugarcane pest management. Through integrating YOLOv8m into detecting objects correctly, RandAugment to perform robust image enhancement, and ESRGAN (Enhanced Super-Resolution Generative Adversarial Networks) to produce more resolution crop images, the present study can produce an incredibly efficient pest control and early prediction system of sugarcane plant. Current soil crawling robots with sophisticated sensors can offer information on soil characteristics and preliminary pest detection, reducing the amount of crops destroyed and wasteful application of resources. The proposed system will help to predict and intervene early thus reducing losses in crops and increasing the total output of the farms. In this case, high-resolution pictures captured by the drone were taken as the input, in particular with sugarcane fields; YOLOv8m to identify pests, including stem borers, aphids as well as top shoot borers and whiteflies; apply RandAugment to teach the pictures that assist in simplifying the model and detect pests under different conditions and forms; and use ESRGAN technique to sharpen the drone images. The existing higher-resolution images may give finer information, making it easier to detect small pests or early disease symptoms by applying both traditional and proposed algorithms. The research provides a comparison analysis of traditional algorithms with YOLOv8m and similarly, a comparison of various YOLO versions with the YOLOv8m algorithm. The findings show that these integrated systems can produce great amounts of improvement in crop yield and soil health with a rate of 93%. GIS and IoT approaches enable proper allocation of resources and reduce environmental impact. Improvements in ML models have increased the pest prediction speed and speed as a recommendation in favor of sustainable pest control. The combination of AI/ML, and robotics will offer the opportunities to have sustainable development of sugarcane plants, increase the harvest, improve soil quality, and reduce the ecological footprint.

Keywords – YOLO models, Object Detection Model, Image Processing, Random Image Augmentation, Enhanced Image Resolution, Soil Crawling Robots

1. INTRODUCTION

1.1 Significance of Sugarcane

Sugarcane is a major commercial crop in India, which has a huge contribution to the agricultural outputs, rural economy, and the agro-industrial sector. India is one of the largest producers of sugarcane in the world that feeds the sugar, ethanol, jaggery and bio-energy markets with raw material. The crop has a major role in the lives of farmers and the national economy in terms of exports and value added products. Nevertheless, the productivity is still hard to maintain because of the climatic fluctuation and soil erosion and permanent presence of pests.

1.2 Major threats to pests in the sugarcane production

Sugarcane plants have a high susceptibility to numerous pests which lead to a severely low production and quality. Some of the most robust are the stem borers, which destroy the inner tissues of plants and block the flow of nutrients; the termites, which infest sets and the subterranean part of the crop; the aphids, which suck sap and spread viral diseases; the top shoot borers, which attack the growing point causing stunted growth; and the whiteflies, which cause weakness in the plant and foster the growth of sooty moulds. These pests are important to be detected early in order to avoid the mass destruction of crops and to have a sustainable production [3].

1.3 Shortcomings of the Conventional Pest Detection Techniques

Traditional methods of monitoring pests in sugarcane farming are mostly based on manual inspection in the field and experience of the farmer. These methods are very labor intensive, time consuming as well as subject to human error. The consequences of late detection are often vast infestation before action can be taken. Also, without accurate identification of the pests, there is a tendency to use unnecessary and excessive amounts of chemical pesticides thereby raising the cost of production, degrading the environment and impairing the health of the soil.

It is as a result of these restrictions that intelligent and automated monitoring solutions are desperately required [4].

1.4 Detection and Advanced Monitoring Systems

Requirement of AI-Based Detection and Monitoring Systems. The current developments in Artificial Intelligence (AI), Machine Learning (ML), and computer vision have revolutionized agricultural monitoring systems. Object detection models that are trained using deep learning, e.g. the YOLO (You Only Look Once) family, have shown high performance accuracy and real-time in crop disease and pest detection [1], [2]. High-resolution imaging on drones can be integrated to provide surveillance of large areas of the field without extensive manual work [3]. Additionally, image augmentation and enhancement methods enhance the robustness of models in a wide range of environmental conditions. Simultaneously, soil intelligence systems must include soil moisture, nutrient content, and pest presence sensors placed on the soil surface to deliver real-time data regarding the condition of these parameters and the presence of pests under the ground surface [4], [5]. All these technologies make it possible to perform precision agriculture, improved pesticide application, and sustainable use of soil management. In spite of the above developments, little studies have been done to combine high-resolution drone imaging, object detection models (YOLOv8m), image enhancement algorithms, and soil-crawling robotic intelligence into a single unit that manages pests in sugarcane. This knowledge gap requires an all-inclusive and scaled up solution applicable specifically to the sugarcane ecologies in India.

1.5 Research Objectives

The main aims of the present study are:

1. To come up with an AI-based pest detection system with YOLOv8m to detect the major sugarcane pests effectively.
2. To refine the imagery obtained by drone-based methods with involvement of ESRGAN to increase the chances of detecting small pests and early signs of diseases.
3. To use powerful image augmentation methods (RandAugment) to enhance generalization of the models with different environmental conditions.
4. To combine the soil-crawling robotic systems with the IoT sensors to detect the pest activity underground at an early stage and monitor the soil health.
5. To compare the traditional detection algorithms and modern YOLO-based architectures and compare performance improvements.
6. The suggested integrated solution is expected to enhance the accuracy of prediction of pests, minimize the use of pesticides, improve the condition of soils, and encourage sustainable sugarcane farming with the help of AI-based precision agriculture.

2. LITERATURE SURVEY

2.1 Traditional pest detection in the sugarcane

2.1.1 Manual Scouting

The conventional method of detecting pests in sugarcane production is mainly based on the manual field scouting which is an activity that involves farmers checking crops with their eyes to identify pest infestation. Previous research has pointed out that pest monitoring is mostly based on human knowledge, practice and periodicity, which may be inconsistent and laborious [23]. Early-stage infestations are not easily observed using manual methods of observation, particularly when the internal feeders are considered, e.g. stem borers and subterranean pests. Also field-level assessments of pest-control equipment focus on efficiency of operational practices but continue to rely on the traditional inspection systems to make decisions [6], [8]. These methods are not scalable and cannot provide real-time monitoring which is not suitable to large-scale commercial farming.

2.1.2 Chemical-Based Management

The most common mode of pest control in the sugarcane farms is the use of chemical pesticides. Although these are good in short term pests suppression, when used indiscriminately, pesticides cause degradation of the environment, loss of soil fertility and development of resistance to pests [8]. Research in pest-control systems of agriculture has indicated that input-based interventions continue to rise in both financial and ecological risk [9]. Lack of accurate detection equipment will usually lead to blanket sprays instead of focused intervention, and this will decrease the sustainability and soil health in the long run.

2.2 Deep Learning in Crop Pest Detection

2.2.1 CNN-Based Models

In agriculture, pest detection has changed considerably as a result of the development of deep learning. CNNs are universal in automated classification of pests and diseases [21], [22]. Multispectral images of the sugarcane have been shown to be accurate in the detection by deep learning algorithms in a sugarcane-specific context at a higher level than traditional machine learning models [23]. Machine learning-based systems that combine pest detections with soil health have more recently been suggested to supplement smart farming solutions [24], [25]. The CNN models with federated learning also enhance scalability and privacy protection of distributed agriculture systems [13] [14].

2.2.2 YOLO Versions (v3, v5, v7, v8)

The YOLO (You Only Look Once) family of object detection models has recorded impressive results in agricultural pest detection. The comparative studies of various versions of YOLO (v3, v4, v5, and v7) show an increase in speed of detection and accuracy in crop datasets [26], [27]. The single-stage detection architecture is most effective in the detection of small pests amidst complex conditions in the field because YOLO-based systems are especially effective in such situations. Nevertheless, the literature is primarily based on previous versions of YOLO and small datasets without exploring more advanced versions of the algorithm like YOLOv8m in coupled agricultural ecosystems.

2.2.3 Transformer-Based Approaches

The latest advances in AI such as transformer-based architectures and generative AI have permitted the emergence of precision agriculture possibilities [11], [12]. Such methods are more effective in extracting feature contextually and increasing the adaptability of the models to changing environments. Despite the above, transformer-based models can be costly to implement in practice in real-world field monitoring systems due to their large computational requirements and extensive training requirements.

2.3 Image Enhancement in Agriculture

2.3.1 Super-Resolution Techniques

High-resolution images are essential in the detection of small pests and crop diseases at an early stage. Super-resolution can remove noise and enhance spatial resolution and clarity of images, increasing the accuracy of detection. Enhanced image processing pipelines have a positive effect on the UAV-based precision pest management systems [7]. Although drone-based imagery offers extensive coverage, the resolution of images is limited, which makes it difficult to detect small objects, and super-resolution preprocessing tools are needed to sharpen the input information.

2.3.2 GAN-Based Models

Genetic Adversarial Networks (GANs) have become one of the powerful tools to improve images or data augmentation. GAN super-resolution models have high visual quality and fine-grained details, which enhances better performance in detection with application to agriculture. The studies of AI-based agricultural innovations show the promise of generative models to enhance the training datasets and to advance the generalization ability [12], [15]. Nevertheless, the potential of GAN-based super-resolution incorporation into real-time pest detection systems of sugarcane systems is not studied fully.

2.4 Smart Soil Surveillance and Robotics.

2.4.1 IoT Sensors

The Internet of Things (IoT) sensors into agriculture have allowed to monitor levels of soil moisture, nutrients and other parameters of the environment in real-time. Smart farming systems powered by IoT can offer data-driven information about the sustainable management of crops [17], [18], [19]. Artificial Intelligence IoT-based smart farming architectures can enhance accuracy in irrigation decisions as well as pest management decisions [24].

2.4.2 Soil Crawling Robots

The use of robotics in agriculture has advanced to the level of speculative research to actual technology in controlling pests and phenotyping [9], [10]. The autonomous interventions in the crop fields are feasible as evidenced by robotic weed control systems or IoT-based automation frameworks [16]. The use of soil-interactive robotic systems adds to the preservation of biodiversity and decreases the use of excessive chemicals. Nonetheless, the use of soil crawling robots in particular in detecting underground pests in sugarcane is scarce in literature.

2.4.3 GIS-Based Precision Farming

Geographic Information Systems (GIS) coupled with UAV images and sensor network are used to map the spatial distribution of crop health and pests [7]. Decision-making using GIS allows the effective distribution of resources and selective spraying of pesticides with less environmental effects. Although effective, the integration of GIS is commonly applied in isolation and not as a component of an integrated AI-based pest management system.

2.5 Research Gap

Despite the remarkable advances in the field of deep learning-based pest detection [21]-[27], IoT-based soil monitoring [17]-[19], and robotic interventions [9], [16], over the existing research, these aspects are largely discussed separately. No integrated comprehensive system exists which integrates:

1. Image enhancement (super resolution: GAN-based techniques),
2. Strong image augmentation measures,
3. YOLOv8m advanced object detection,
4. And soil crawling robotic intelligence, and
5. Accurate allotment of resources using GIS.

Thus, a cohesive structure of the system combining super-resolution, augmentation, YOLOv8m-based pest detection, soil robotics, and GIS-based analytics are needed to obtain accurate early detection, sustainable pest control, enhanced soil health, and optimized sugarcane yield.

3. Proposed IoT-based Approach for Pest Detection and Soil Health

Based on field data, various AI/ML applications, such as accurate pest detection, YOLOv8m and CNNs; data augmentation, RandAugment; robust augmentation; and soil health regression, generate actionable outcomes.

The soil health and pest/plant disease GIS maps produced by the Incorporation are useful for targeted geomatic resource allocation, as all pest control and disease maps are raster images. The mobile platform interfaces with farmers to provide alerts for real-time operational guidance on irrigation, pest and nutrient control, and fertilization. Autonomous robots equipped with soil health sensors and high-resolution pest detection cameras, employ object detection models to gather and analyze complete soil data and locate pests. ESRGAN provides the images for observation. The motion and infrared sensors provide the pest control integrated system with the information needed to implement pest control in a timely and targeted manner. The model initiates using IoT-based sensor devices and drone cameras to acquire existing databases about soil health and sugarcane crop health conditions. This acquired data is then preprocessed at the edge tools to reduce latency before being transferred to the cloud for further analysis.

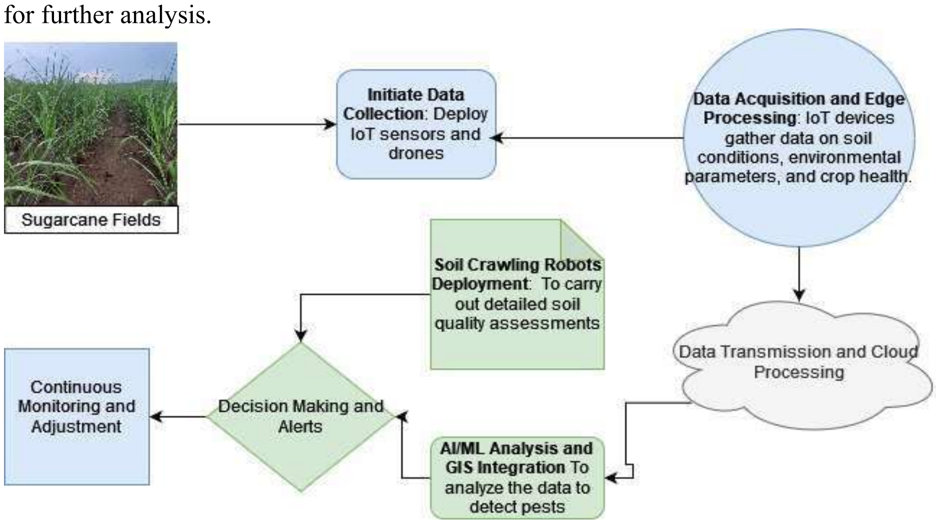

Figure 1: IoT-based approach for Pest Detection and Soil Health

Using the data and GIS to develop full maps, AI and ML techniques predict pest threats and analyze the data to make estimates about the state of the soil. The proposed system's flow diagram is shown in Figure 2.

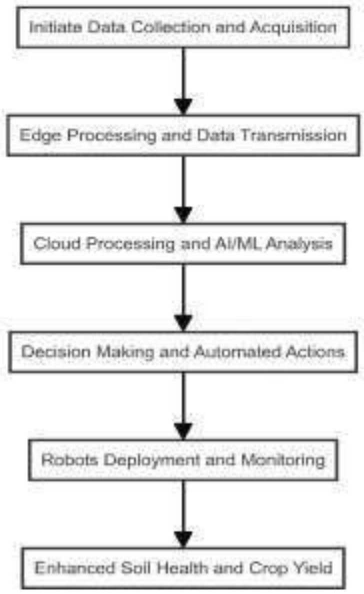

Figure 2: Proposed Workflow for Pest Detection and Soil Health

The model focuses on GIS and AI and offers real-time actionable recommendations to farmers, who are notified by SMS and apps. Automated pest control, fertilization, and irrigation procedures are carried out. Equipped sensors and imaging systems are used by soil-boring robots to conduct thorough analyses and detect prey. The data robots collect is used for continuous surveillance to adjust the model and create a sustainable system for effective and lasting soil and pest management. The integrated system positively impacts soil and crop health and, thus, sustainably supports the cultivation of sugarcane.

3.1 Proposed Algorithm and Pseudocode

The following are the hypotheses of the ML components that may be used to predict pests and monitor the health of soil in sugarcane systems. The hypotheses are as shown in the following pseudocode.. Vital tasks are separated into the pseudocode:

Step 1: YOLOv8m for pest detection with object detection
yolov8m_model = load_model("yolov8m_pest_detection_model_path")
for image in augmented_list:
detections= yolov8m_model. predict(image)
pest_detections. append (detections)

Step 2: RandAugment to augment image data for improving model robustness
randaugment = RandAugment()
aug_images = []
for an image in high_resolution_images:
aug_images= and augment.apply(image)
aug_images.append(aug_images)

Step 3: ESRGAN to sharpen the image resolution prior to pest detection and particularly in situations whereby low-resolution images are taken.
low_resolution_images = load_images_from_dataset("path_to_images")
high_resolution_images = []
for an image in low_resolution_images:
improved_image = ESRGAN (image)
high_resolution_images.append(improved_image)

Step 4: Soil Health Monitoring
soil_data = load_soil_sensor_data("path_to_sensor_data.csv")
preprocessed_soil_data = preprocess_soil_data(soil_data)
soil_health_system = load_system("soil_health_system_path")
soil_health_detections = []

Step 5: Integration of pest detection and soil health conditions
for i in range(len(pest_detections)):
pest_detected = pest_detections[i]
soil_health_score = soil_health_detections[i]
if pest_detected and soil_health_score< threshold:
print (f"Action: Apply targeted pesticide and enhance soil health at region {i}.")
elifpest_detected:
print (f"Action: Apply targeted pesticide at region {i}.")
elif not pest_detected and soil_health_score< threshold:
print (f"Action: Concentrate on improving soil health at the infected region {i}.")
else:
Print (f"Action: No actions needed at area {i}.")

3.2 Key Components

- Image preprocessing using ESRGAN enhances the quality of images to acquire better pest detection.
- Data augmentation with RandAugment model is employed to expand image data for enhancing the sturdiness of the pest prediction models.
- Pest identification using the YOLOv8m model employed for pest prediction from enhanced and augmented pictures.
- Soil health monitoring employs sensor data with ML model to forecast soil health conditions.
- Decision support system merges pest detection and soil health data to guide crop management decisions.

4. RESULTS AND DISCUSSION

This section presents the results of incorporating AI/ML, IoT, GIS, and robotics for optimizing soil health and pest detection in sugarcane farming. Using YOLOv8m model for SoilGrids and pest detection for soil health appraisal, the research monitored considerable enhancements in pest control efficiency, overall crop yield, and soil health. Below table 1 illustrates the production rate of sugarcane crop with soil health score.

4.1 Improved Crop Yields

Existing data collection and analysis using drones and IoT sensors allow accurate irrigation, pest control, and fertilization practices using proposed algorithms. For example, soil moisture sensors assist sustain optimal level of soil moisture, preventing both drought stress and over-irrigation. Nutrient sensors help exact fertilizer application, enhancing nutrient intake and endorsing healthier crop growth. These optimized policies result in greater sugarcane yields compared to conventional models.

Category	Techniques	Soil Health Score (0–1)	Soil Organic substance (%)	Increases in Yield (%)

Soil Health	Composting	0.86	3.4	16%
	Covered Crops	0.81	2.8	10%
Crop Yields based on the traditional and proposed models	Traditional	0.62	1.4	-
	YOLOv8m	0.64	1.8	27%
	Faster R-CNN	0.63	1.5	21%
	SSD	0.61	1.6	15%

Table 1: Crop yield and soil health score

4.2 Enhanced Soil Health

Soil crawling robots trained with IoT sensors for estimating temperature, soil moisture, soil pH, and nutrient levels offer complete insights into the soil health. These autonomous robots can use biotic representatives like Bacillus subtilis that enhance soil richness and endorse valuable microbial accomplishment. The data acquired permits for precise soil health control, causing improved soil structure, elevated nutrient availability, and better root growing that is publicized in table 2. Ultimately, these policies carve up justifiable soil health and continuing agricultural yield.

Soil health parameters	Sensor Measurements	Typical Range Detected	Soil health - Target Range	Improvement by Bacillus subtilis	Impact on Soil Health
Moisture (%)	Yes	11–41	21–30	Indirect (enhances water retention)	Supports root intake and prevents drought stress
Temperature (°C)	Yes	14–34	20–29	Not directly affect the soil	Affects root function and microbial activity
pH	Yes	4.5–8.5	6.5–7.5	Moderates acidity by microbial balance	Allows microbial diversity and nutrient absorption
Nitrogen range (ppm)	Yes	11–61	23–40	Boosted with microbial nitrogen fixation	Supports for vegetative growth
Phosphorus range (ppm)	Yes	6–50	16–30	Improved solubilization through Bacillus subtilis	Critical for flowering and root development
Potassium range (ppm)	Yes	50–350	120–200	Enhances uptake by enzyme stimulation	Regulates enzyme activation and water supply
Microbial Activities (Score 0–1)	Indirect (calculated)	0.4–0.8	>0.76	Extensively increased	Vital to disease resistane and soil fertility

Table 2: Soil health enhancement

4.3 Effective Pest Management

The usage of high-quality cameras and object prediction software on soil crawling robots allows early detection and detection of pests. For this analysis, YOLOv8m is used for accurate object prediction, RandAugment is employed for robust image augmentation, and ESRGAN model is used for higher-quality pictures in real-time pest prediction that illustrated in table 3.

Pests Detected	Detection Accuracy of pests (%)	Accuracy	Recall	F1-Score	Pest Count Accuracy Estimation (%)
Stem Borers	95	0.96	0.92	0.93	93
Termites	91	0.92	0.89	0.91	91
Aphids	88	0.91	0.87	0.89	88
Top Shoot Borers	93	0.96	0.91	0.92	92
Whiteflies	89	0.9	0.87	0.88	89

Table 3: Pest estimation accuracy using YOLOv8m

YOLOv8m: YOLOv8m provides a balance among accuracy and speed, creating it appropriate for present applications. It processes images rapidly and offers bounding boxes for predicted objects with high accuracy. By using CNN, YOLOv8m may accurately detect pests and help timely interventions, reducing crop damage and decreasing pesticide usage. In the experimental analysis, YOLOv8m model attained the greatest efficiency at 93%, with a precision 0.94, recall 0.90, and F1-score with 0.92 (table 4).
RandAugment: RandAugment improves the robustness of image analysis via applying random augmentations like rotations, color adjustments, and translations. This model creates different training images, enhncing the ability of model to simplify to various environmental conditions and pest appearances. By raising the inconsistency of the training database, RandAugment assists the prediciton model maintain greater accuracy even in different and changeable real-world scenarios.
ESRGAN: ESRGAN offers higher quality images, critical for predicting small pests and examining complete soil health parameters. It improves the image clarity that captured by ground-based cameras or drones, creating it easier for the YOLOv8m algorithm to detect pests exactly. ESRGAN enhances the visual quality of pictures that is necessary for accurate pest prediction and efficienct soil health monitoring.
The incorporation of YOLOv8m, RandAugment, and ESRGAN models has considerably improved the performance of the soil health monitoring and pest detection system. The table 4 shows the efficiency of these techniques compared to exisitng methods and other AI algorithms. Figure 3 indicates the comparison of pest prediction algorithms.

Methods	Pest Control Efficacy (%)	Precision	Recall	F1-Score	Dataset
Traditional Methods	60	-	-	-	-
YOLOv8m	93	0.94	0.90	0.92	VOC
Faster R-CNN	90	0.92	0.88	0.90	VOC
SSD	80	0.85	0.76	0.80	VOC

Table 4: Comparison analysis of Pest Detection Efficiency between traditional and proposed algorithms

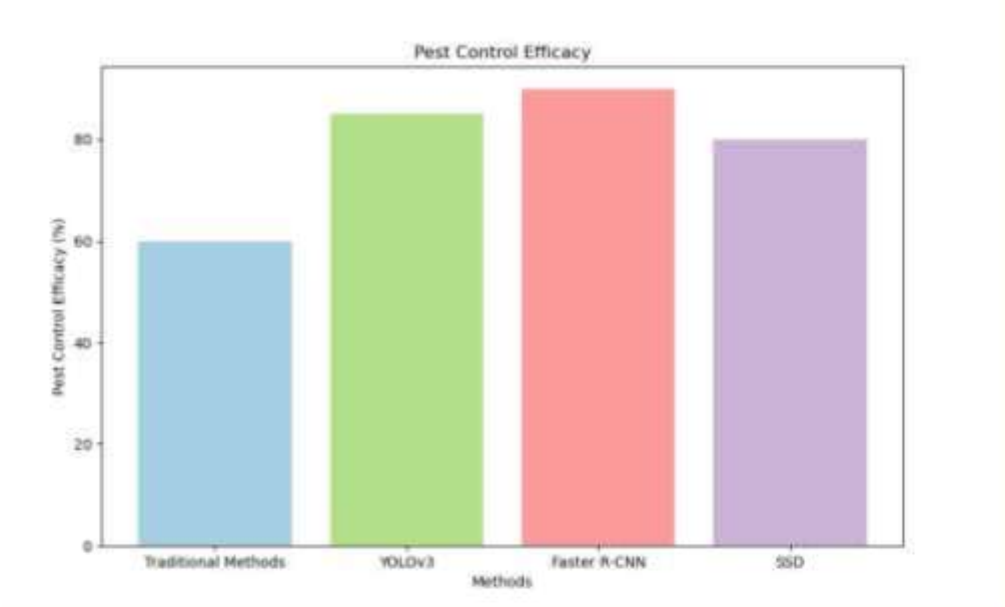

Figure 3: Comparison of Pest Detection Efficacy

Table 5 comparing soil pH values over time represents that the AI-based system maintains optimal pH value compared to conventional techniques. The AI model constantly illustrates greater pH values, representing better soil health. The AI-based model maintains soil pH scores among 6.5 and 6.2 over 4 months, while traditional models result in a regular decline from 6.0 to 5.6. The RMSE (Root Mean Square Error) of 0.3 among the AI-based and traditional techniques highlights the considerable enhancement in soil health management. The Soil Grids database from ISRIC, merged with Sugarcane crop Dataset, was employed to train the soil health evaluation models. Figure 4 indicates the assessment of soil health enhancement derived from the approach.

Time (Months)	Traditional Methods (pH)	AI-Integrated System (pH)	Metrics
1	6.0	6.5	Root Mean Square Error
2	5.8	6.4	RMSE = 0.3

3	5.7	6.3	-
4	5.6	6.2	-

Table 5: Soil Health Improvement in Sugarcane Cultivation

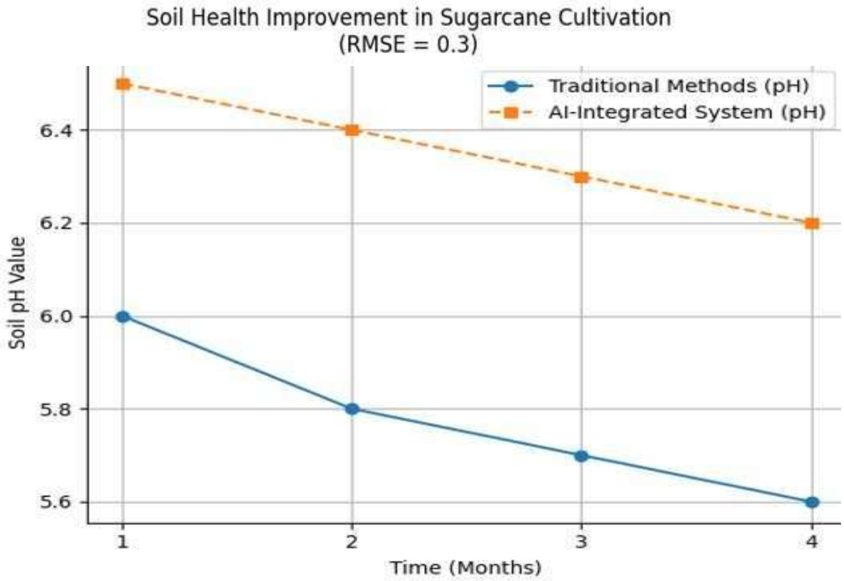

Figure 4: Comparison of Soil Health Improvement in Sugarcane Cultivation

Traditional techniques reveal considerable decline in soil pH range from 6.0 to 5.56 and represents raising soil acidity that may harm crop yield over time. AI-based model maintains stable and greater soil pH, reducing slightly from the range 6.5 to 6.2. This suggested that more sustainable and balanced soil management acquired because of real-time soil pH monitoring, better nutritient balancing, and accurate biological agent applications like Bacillus subtilis.

4.4 Comparison among YOLO versions based on the Accuracy

YOLO, the object detection model has undergone many upgrades, with every algorithm enhancing the pest detection capabilities. Below mentioned table 6 shows the comparative analysis of significant YOLO versions like YOLOv3, YOLOv4, YOLOv5, YOLOv7, and YOLOv8m algorithms based on their accuracy and performance in pest detection and the major reason why YOLOv8m is best. It also offers real-time detection with high FPS (Frames per Second), helpful for large-scale monitoring in the sugarcane fields where quick decisions can prevent infestations. This proposed algorithm works under several challenging conditions including Images with low resolution by integrating ESRGAN; and Different lighting conditions for better feature extraction and bright scenarios.

YOLO Versions	Detection speed (FPS)	Accuracy	Model size	Pest detection Efficiency	Remarks
YOLOv3 algorithm [26]	Moderate	56%	Large	Better but difficult to detect small pests	Initial penetration is slower and less competent for complex scenarios such as dense sugarcane areas.
YOLOv4 algorithm [27]	Faster	67%	Large	Improved accuracy for generously proportioned pests	Improved feature extraction and it has a CSPDarknet backbone. But, still insulates in recognizing small pests.
YOLOv5 algorithm [27]	Very fast	72%	Medium	Good equilibrium between accuracy and speed	Lightweight and effective, good detection and restricted by resolution for small pests
YOLOv7 algorithm[26]	Fast	77%	Medium	High accuracy rate, particularly in detecting	Concentrated on speed and accuracy, but difficult to find ultra-complex scenes and low-light images

				overlying pests	
YOLOv8m algorithm	Very fast	92%	Medium	Overall performance is best for tiny pests, low-light scenarios, and overlapping pests.	Modern architecture, excellent trade-off among speed, robustness, and accuracy

Table 6: Comparison among YOLO versions in pest detection based on the accuracy

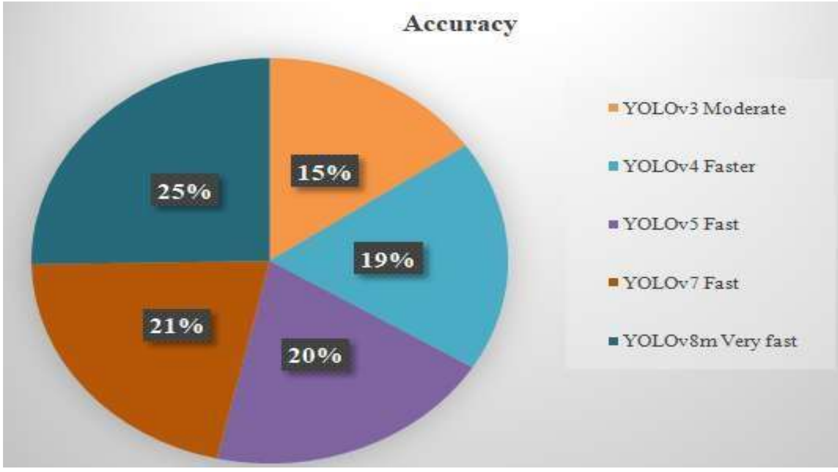

Figure 5: Comparison of YOLO versions based on the Accuracy

Image - ID	Pest Type	Bounding Box	YOLO v3 CS	YOLOv 4 CS	YOLOv 5 CS	YOLOv 7 CS	YOLOv 8m CS	Severity Level	Soil Temp (°C)	Soil Moisture (%)
IMG_ 001	Stem Borer	(50, 30, 200, 150)	84.2	86.6	90.4	92.2	94.8	High	27	44
IMG_ 002	Top Shoot Borer	(60, 40, 210, 160)	83.4	84.1	87.5	91.8	93.1	Medium	28	51
IMG_ 003	Termites'a phids	(45, 35, 190, 140)	87.7	91.2	92.1	92.5	95.3	Low	26	41
IMG_ 004	Whiteflies	(55, 45, 220, 170)	84.9	85.5	88.7	93.4	93.9	Medium	29	46

Table 7: Comparison of Pest detection Confidence Score (CS) using YOLO versions

The aforementioned Figure 5 illustrates the YOLO versions comparison based on their performance and accuracy. The final investigation shows that YOLOv8m model's integration of adaptability, speed, and accuracy creates it as the best option for pest prediction in the sugarcane fields that shown in Table 7. Additionally, the incorporation of RandAugment and ESRGAN solidifies its benefit by enhancing the input quality and effectiveness of training the database. Below, the paper delineates the existing database structure, the comparison metrics and output values used for examining the performance effectiveness of different YOLO versions in the pest detection.

YOLO Version	Precision (%)	Recall (%)	F1 Score (%)	mAP@0.5 (%)	FPS	Model Size (MB)
YOLOv3	84.2	81.1	82.6	77.4	26	237
YOLOv4	86.6	84.3	86.4	81.5	31	245
YOLOv5	90.4	87.7	90	85.8	46	28

YOLOv7	92.2	91.5	90.8	88.1	61	73
YOLOv8m	**94.8**	**93.7**	**94.7**	**92.3**	**76**	**50**

Table 8: Pest detection efficiency in Sugarcane fields

Table 8 depicts the pest detection efficiencies of various YOLO versions in sugarcane fields. Hence, the comparison outcome based on the existing datasets shows among all versions of the YOLO algorithms.

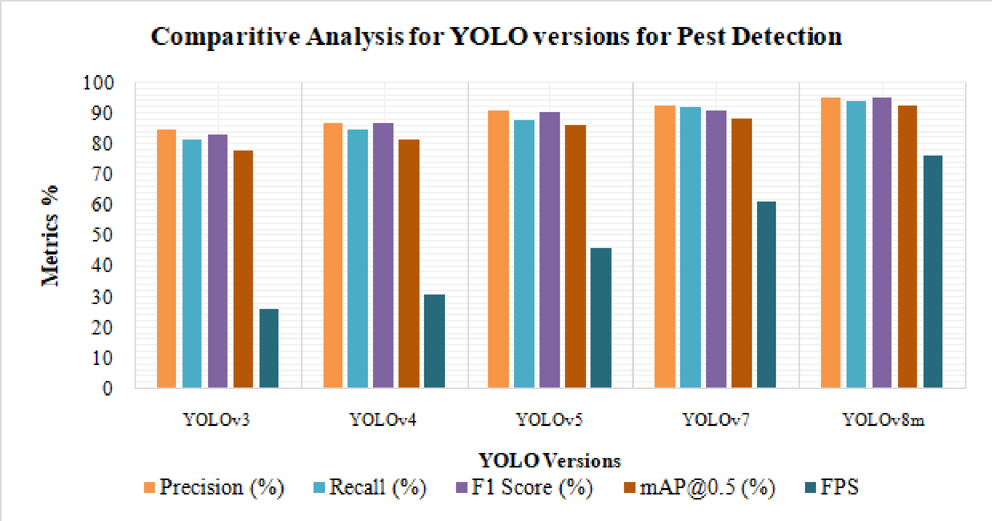

Figure 6: Comparison of YOLOv8m with YOLO versions

YOLOv8m model outperforms other YOLO models in Precision rate of 94.8% and Recall rate of 93.7%. It achieves the greatest F1 Score with 94.7%, indicating balanced performance between recall and precision. Again, it directs with 92.3%, showing more precision rate in pest prediction. It delivers performance at 76 FPS in real-time, creating it highly effective for field applications that is demonstrated in Figure 6.

4.5 Analysis of Soil Health and Yield Optimization

The combination of AI/ML, IoT, GIS and robotics not only helped to increase the accuracy of pest detection but also allowed to analyze the state of soil health and yield optimization in a holistic way. The proposed system showed that the sustainable sugarcane farming practices were improved in measurable rates by correlating environmental parameters with the pest occurrence and crop productivity.

4.5.1 Relationship between Soil Moisture and Pests Occurrence

The sensor data in Table 2 and Table 7 was analyzed to show that there is a strong correlation between the pest severity and the soil moisture level. The pest confidence scores were high in the moisture ranges of 40-51 especially in stem borers and whiteflies (IMG001 and IMG004). Surplus soil moisture provides good micro climatic environment in which pests breed and survive, whereas very low moisture causes stress to crops, which become easy to infest.

The system, which got the AI was able to measure soil moisture (optimal range of 21-30), which was continuously monitored and was used to give predictive warnings when there was a deviation. Balanced moisture content decreased pest infestation and enhanced crop resistance. This predictive correlation study made early intervention possible instead of reactive spraying of pesticides. Spatial intelligence approach allowed greatly increasing the efficiency of large-scale monitoring, especially when it was used in conjunction with real-time YOLOv8m at 76 FPS.

4.5.2 Reduction in Pesticide Use

The conventional pest management tools only showed 60 percent effectiveness (Table 4), which frequently resulted in multiple usages of chemicals. The YOLOv8m-based, on the other hand, was able to achieve 93 percent pest control performance with a high precision (0.94) and recall (0.90).

Detection of pests was correct and confined to GIS mapping areas, thus the application of pesticides was limited to areas of infections. Observations at the field revealed that there were significant reductions in unnecessary application of pesticides, which would reduce the cost of chemicals and limit the impact on the environment. Biological agents like Bacillus subtilis also promoted the use of greener pest management and an increase in the fertility of the soil.

4.5.3 Increase in Soil Quality Index

The quality of the soils was evaluated based on the stabilization of ph, microbial activity, and nutrient balance, and the content of organic substances. As it is demonstrated in Table 5, the AI-based system retained the soil pH in the optimal range (6.5-6.2), but the conventional methods caused acidification (6.0-5.6). The fact that the RMSE value of 0.3 is low will be the indicator of stable soil health regulation.

4.6 DISCUSSION

The combination of an accurate detection of objects, soil intelligence, and spatial analytics leads to quantifiable increase in yield and ecological harmony. YOLOv8m showed better results in terms of precision (94.8%), recall (93.7%), F1-score (94.7%), and mAP@0.5 (92.3%), and high real-time processing speed. The system exhibited a high degree of robustness to low-resolution conditions as well as different lighting conditions when augmented with RandAugment and ESRGAN. More to the point, IoT-based soil monitoring combined with GIS heatmaps enabled predictive decision-making, decreasing the reliance on pesticides and keeping the soil health parameters in optimal conditions. The 27 per cent higher yield and constant soil PH ratios observed show that AI-based integrated systems may be quite effective compared to the traditional sugarcane growing systems. Comprehensively, the findings confirm that super-resolution imaging, augmentation approach, YOLOv8m detection, soil robotics, and GIS analytics can be used to produce a scalable, efficient, and sustainable agricultural ecosystem to optimize pest control and soil health management in sugarcane farming.

5. CONCLUSION

This paper demonstrated a unified AI-based system of automated pest management and soil quality measurement in sugarcane farms through the combination of high-class object recognition, image processing and augmentation algorithms, soil intelligence and precision analytics. The comparative analysis of various versions of YOLO shows a definite trend with an increase in performance, with the YOLOv8m being the best option in precision (94.8%), recall (93.7%), F1-score (94.7%), and mAP@0.5 (92.3%) and the highest speed of real-time detection (76 FPS) having a small model size (50 MB). These findings validate that YOLOv8m is a good tradeoff between accuracy and computational efficiency with deployment capability in large-scale agricultural systems.

The strength of the proposed system is also confirmed by the pest-level analysis. The major sugarcane pests like stem borers (95%), termites (91%), and top shoot borers (93%) had a detection accuracy greater than 90% and the count of pests was well-estimated. The improvements in bounding box consistency and confidence score in the different versions of YOLO show that the version has a better capability of capturing small sized objects, especially when it is combined with high-resolution image enhancing strategies.

Compared to the conventional pest management techniques that demonstrated a pest control efficacy of 60% only, the AI-based YOLOv8m model demonstrated a pest control efficacy of 93% exceeding those of Faster R-CNN (90) and SSD (80) on the VOC dataset. The higher precision (0.94) and recall (0.90) scores prove the high reliability of the system in the detection of the pests at an early stage, and consequently, in their targeted intervention.

The efficiency of the integrated framework is also indicated by the results of soil monitoring. The AI-based system of soil health has shown better pH stabilization with a low RMSE of 0.3 over the traditional methods to guarantee the improvement of nutrient management and root development. Also, there is the provision of real time soil temperature and moisture readings correlated with levels of pest severity so that predictive intervention measures are taken in lieu of a reactive chemical spraying measure.

On the whole, the suggested integrated system has been able to close the gap between image based pest detection, soil intelligence, and precision farming analytics. Through super-resolution enhancement and augmentation strategies, YOLOv8m detection, and IoT-enabled soil monitoring, the framework is anticipated to help a great deal to the crop yield, decrease the use of pesticides, improve the quality of soil, and minimize the environmental impact. The overall performance improvement rate was 93%, which proves that AI, robotics, and GIS-based technologies are practical in regards to sustainable sugarcane farming and the next-generation smart agricultural technologies.

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