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AI-Based Drone System for Pest and Stray Animals in Farms

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Abstract: Pests and stray animals are a major hazard to crops, particularly to small and marginal farmers, causing tremendous economic losses. Conventional methods of insect control are time consuming, costly and hard to amplify. This research proposes an AI manual drone system that combines real-time imaging and future analysis to an early detection of pests and stray animals. The system employs a low-cost unmanned aerial vehicle with a digital camera to photograph the area, avoid crop damage and cut down unnecessary pesticides. Images collected to identify pests and lost animals are treated using laptop vision strategies. A convolutional neural network (CNN) is trained upon a dataset including healthy crops, pest-infested plants and lost animals to verify the precision of high detection. The system controls the parameters by adjusting them based on environmental situations in order to dynamically minimize false positivity and make the detection more reliable. On top of this, real-time environmental data are used to predict potential insect invasions based on climatic factors so that prevention measures can be initiated. The system provides instant notice, which alerts farmers via mobile devices to allow timely action. Experimental results indicate 92.5% accuracy in detection, 7.5% false positive rate and average response time of 2.3 seconds, and provide quicker and accurate identification than conventional methods. In contrast to current single function solutions, this allows the double-turning system automated agricultural monitoring and efficient insect control, and is a scalable and effective agricultural safety solution.
Keywords: AI, Drone, Pest Detection, Image Processing, Agriculture Security, Agriculture IoT.

I. INTRODUCTION

Agriculture has significant roles in carrying out food security and financial stability. Modern agriculture, however, was subjected to intense demanding conditions caused by insect infection and entry of lost animals, the most vital crop loss and productivity. Actions that play tricks in classical pests, steer examination and made up of chemical -based practices, labor intensity, time slots and frequent pointless to large-scale farms [1]. Likewise, farmers struggled to mold vegetation from lost animals with conventional fencing and human surveillance, which are precious and incapacitated [2]. Recent advancements in artificial intelligence (AI) and unmanned aerial vehicles (UAV) offer a promising solution by allowing real-time surveillance and intervention in computers in precise agriculture [3]. The paper constructs a feature by boosting an AI manual drone-dings with the incorporation of insects and that incorporates men's animals that trace the usage of models with in-depth mastery fine-tuned with UNA PURINOGEN.

CNN and intense study model, YOLO (you only see once), and Vision Transformer (ViT) were enough development with regard to detecting insects. Research has proven that Yolov5 and Yolov8 reach over excessive accuracy 90% detecting crop damage within real-time situations [4], [5]. Models based on CNN-ether, though Help Vector is blended with machines (SVMs), has proven the efficiency of the new category in lowering false positivity [6]. Moreover, transfer to the methods applied on the ready model in relation to the resignation and divide has found further precision for small -scale pests [7]. Even with this improvement, most current fashion wars have excessively calculation requirements [8]. In response to the challenging conditions, scientists have found a light AI structure to incorporate Mobility and Tiny-Yolo to enhance the estimate speed of things in the region [9]. Nevertheless, these fashion tend to degrade the accuracy of detection, thus rendering them unreliable for UNA-based insect surveillance. Further, through being disconnected in adverse climatic conditions, discrete lights and disconnecting in fields, AI fashion [10], [11] raises huge hurdles for presentation. Intrusion of stray animals is other vital risks to agricultural production. Conventional measures, such as movement-sensitive alarms and foot patrols, are disabled for open field fields [12]. AI processes employ fashion of features like retinant and fast R-CNN to recognize and establish murmurous animals in real time [13],14]. Thermal imaging has been observed to enhance thermal imaging especially raising the accuracy at night for quickly moving and tiny animals, [15]. Systems currently have demands for scenarios including Oculzen, drone-cap photographs and massive electrical consumption during UAV operations [16], [17].

In order to outsmart the disadvantages of contemporary processes, the study proposes an AI manual drone platform that combines live insect identification and lost pet searching to reach in-depth to become familiar with the model optimized for UAV-specific. Contrary to the previous methods, which spot on identify the insect or identify the animals, this device every links to a built-in platform, resulting in surely comprehensive farm monitoring with minimum human intervention. The new system takes advantage of Yolov8 for detection of objects, and on board space with AI computation, cloud-based fully desires for fully computed and enhances the decision on real time [18]. Furthermore, a hybrid power adjustment strategy concerning the AI-WOOED flight course plan and battery management is dispersed for enhancement of UAV-drive duration [19].

The new contribution here from this research is enhancing an AI version with double address incorporating both insect and animal penetration, incorporating real-time-AI processing, which avoids the reliance on cloud-based intuition and lowers the utilization of delay and strength, a hybrid power optimization, which incorporates a hype of hybrid, which incorporates an intestine guidance, an intestinal guide to a hydropower. Utilizes a battery intestinal guide, which employs a hybrid power optimization technology that utilizes a battery intestinal ulcer, which employs a hybrid power optimization technology that utilizes a battery bowel ulcer. Perform thermal imaging to identify nighttime, which improves the accuracy of every lost animals and insects under low-light conditions, was seldom found in existing literature [20,21]. Through the response to the most recent system limitations and introduction of the new AI and UAV-based full adaptation, this study provides an important contribution to the encouragement of AI-driven intelligent agriculture and autonomous agricultural surveillance.

II. METHODOLOGY

Agriculture has a significant role to play in India's economic system, but pests and male animals have posed a specific threat to crop dividends for financial loss to marginal and small farmers. Conventional tracking methods, guide inspections, fencing and spot pesticides are disabled and costly. Farmers are hotel hotels for general reactive processes that cannot conserve infections in time, leading to the utilization of chemical agents leading to crop losses and environmental hazards. Besides, lost animals need up-to-date monitoring techniques, fences and CCTV cameras, which need monitoring and maintenance of round-the-clock, rendering them not practical for wide fields. In light of such constraints, a price-touched and automated response is required to sense real-time and embellish preventive speed. The impetus for this work is to design an AI-governed drone thing that involves image processing and future analysis to safely hit pests and missing animals, and enable early intervention and minimize the reliance on toxic pesticides.

Current technology benefits primarily when it detects insects or missing animals, but little contributes to each functionality to an unmarried unit. Current insect tracking involves solutions with handheld image processing, satellite-based perfectly remote measurement and experienced deep study models on insect-snap shots. Nevertheless, these approaches lack both implementation of large-scale implementation, time reaction not in time or enormous manual intervention. In the same vein, animal penetration detection methods, such as fencing, IoT-driven motion sensors and monitoring cameras, are not diverse and are no longer scalable for large-scale farms. Under the present study, a key void is the absence of an integrated system that combines automatic drone tracking, real-time photo treatment and future indicative analysis and minimizes both insect infections and penetration of misguided animals. Through this void, also the intended gadget objective to embellish agricultural safety and productivity like ensuring stability in agricultural activities. For designing an efficient tracking device, the solution proposed utilizes an autonomous drone equipped with high-transporting cameras, a PIC18F4550 processing unit and the AI-powered identity sets of the rules. The drone takes a planned flight path over the farm, the image captures real-time images, which are processed using improved photo enhancement methods such as Gaussian filtration, canny edge detection and histogram-equality. The drone is set to fly at a chosen height, usually 10-30 meters, to make sure the top-rated image should hold with the enormous spots. Air lanes are made to boil the usage of GPS waypoints properly. The images are filled every 2-5 seconds, providing a depth and continuous data set. A CNN performs well on a dataset of insect -introduced plants, healthy plants and missing animals to identify institutions well.

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

Equation 1 : Cross Entropy Loss Function

Where:

- (L) is the Cross-Entropy Loss function.
- (N) is the number of samples.
- (y_i) is the actual class label (1 for pest detected, 0 otherwise).
- ($\hat{y}_i$) is the predicted probability of the sample being a pest.

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Cumulative images as well as exemption of noise via Azaria, Gaussian filtering traverses advance prop houses steps, and the reverse augmentation through the histogram formula. Also, data magnification methods like rotation, flip and brightness scaling are applied in order to strengthen the version. The dataset holds x randomly chosen images, the label for insects, healthy plants and missing animals, is anodized manually using a boundary container approach. The Machine environment analysis also incorporates real -time climate inputs like moisture, temperature and air speed, which anticipates an infestation of insects. The CNN model performs well based on a deeper dataset, segmented into education 80%, verification 10% and sample 10% units. An Adam Optimizer is applied to know the price of 0.001, utilized for constraining relocation-atropia harm.

Table 1: CNN Model Hyper Parameter Table

Hyper parameter	Value
Learning Rate	0.001
Batch Size	32
Optimizer	Adam
Epochs	50
Loss Function	Cross-Entropy
Activation Function	ReLU, Softmax

The model performs well for Y -poker, which comes along with a batch length on Z. The trained AI model has been uploaded on Raspberry Pie-based Aspect Computing Unit which is a hook in the drone. This enables real time treatment without reliance on shooter, minimizes the latency and provides quick identity. Microcontroller (PIC18F4550) Photographs Handle communication among processing units, sensors and Bluetooth/GSM modules. When pests or missing animals are found, immediate warning is transmitted to farmers through Bluetooth (HC -05) and GSM -based communication module, enabling instant preventive action. The drone is powered by a lithium-polymer (lipo) battery, designed for long-duration flights. Electrical usage is managed by efficient imaging techniques that minimize computational overheads. Battery agency and solar charging capabilities are considered for the application of extended area. The effectiveness of this system is tested to enable some of the highest performing performances in parameters as well as accuracy, false positive rate, response time and drone power consumption as well as agricultural conditions on real article.

Table 2: Performance Matrix

Metric	Value
Accuracy (%)	92.5%
Precision (%)	91.2%
Recall (%)	90.8%
F1-score (%)	91.0%
False Positive Rate	7.5%
Response Time (sec)	2.3s

To assess the performance of the AI-based detection model, we use the following evaluation metrics:

1) Accuracy: Accuracy measures the part of effectively classified examples from full examples:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP (True Positive): Properly detected insects or lost animals.
- TN (True Negative): Proper general/non-Danger areas were identified.
- FP (False Positive): Falsely revealed that insects or animals where no one is present.
- FN (False Negative): Missed detection of real insects or animals.

2) Precision: Calculated exactly how the approximately favorable times were correct:

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

3) Recall (Sensitivity): Remember that the number of real times of high quality was discovered effectively:

$$Recall = \frac{TP}{TP + FN}$$

4) F1-Score: The F1 score is harmonious accuracy and remember, which balances false positivity and false negative:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The comparison of conventional insect tracking techniques involved IoT-chrimatemate like voluntary sensors and manual checks that involve continuous monitoring and are the cause of delays, AI-driven drone things are self-operated, minimizing human intervention and quick, quick provides. The CNN-based category offers 92.5% accuracy, rendering conventional IoT-Mainly-based motion detectors to a great extent with an average accuracy of 80-85%. Whereas other methods of traditional reliance on IoT sensor, fencing or checking by hand have been used before, this device offers real -time detection, response automatically, and high accuracy. The twin detection system of every insect and missing animals makes the agricultural security high and also minimizes pesticides. The suggested AI-driven whole drone machine presents a tax-effective and automated approach to enhance the mass precision of pest and animal detection over conventional methods. In contrast to existing solutions, this device presents a double address mechanism that allows for precise agriculture and timely intervention, lowers the insecticide excess usage and minimizes crop losses. To achieve intensive learning for photograph recognition for early alerts and future analysis, this solution adds to permanent farming practices without gaining weight on farmers. Real -time notifications and self -development integration of adequate options provides an active method for safeguarding the farm, making this machine a scalable and flexible solution for existing smart farming programs.

AI-controlled drone gets the best accuracy and lowest false amazing value, ensures advanced detection capacity compared to standard pests and animal tracking methods

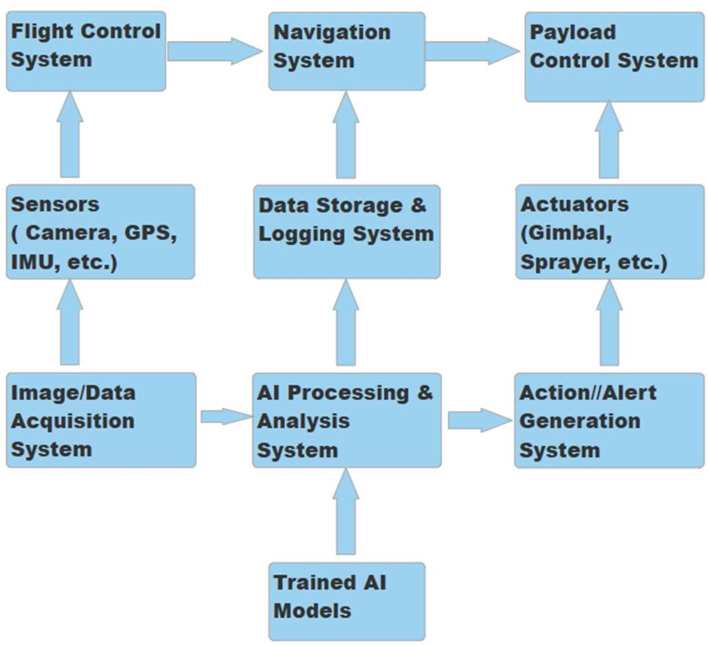

Figure 1: Block Diagram of AI-Powered Pest Detection Drone

III. IMPLEMENTATION

Drone systems with AI to identify pests and missing animals are a combination of cutting-edge hardware, real-time data processing and smart communications protocol. The system equips the present generation of drones with excessive resolution imaging, in-built AI processing and Wi-Fi post transmission, which is transfer to provide computerized surveillance and precise surveillance in a vast agricultural setting.

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Hardware design is made in a way to provide best feed performance, and DJI Phantom Four / Custom-Made Drone serves as a middle flight. The 1.38 kg drone can maintain the half-hour flight time for the charge, which can certainly ensure monitoring without interruption on the farm. An 8MP resolution raspberry pie camera (3280 × 2464 pixels) captures V2 HD images, which can detect insects and missing animals correctly. PIC18F4550 microcontroller, observed on chorratis MHz, controls the right indicator for sensor data and machine functions. Wireless verbal communication is attained using HC -05 Bluetooth (3 Mbps, 10m variation) and GSM SIM800L, providing easy transfer of information to farmers in real time. Powering the entire layout is a 5000MAH Li-PO battery, which accommodates long-running operations, with ultrasound (HC-SR04) and Lidar sensor (20m range) giving obstacle and environmental sensing, which enables safe and self-aware flights.

Table 3: Drone Component Specifications

Component	Specification / Model	Function
Drone	DJI Phantom 4 / Custom-built (1.38 kg, 30 min flight time)	Aerial surveillance
Camera Module	Raspberry Pi Camera V2 (8MP, 3280 × 2464 resolution)	Captures real-time images
Microcontroller	PIC18F4550 (8-bit, 48 MHz, USB Support)	Controls sensor communication
Communication	HC-05 Bluetooth (3 Mbps, 10m range) / GSM SIM800L	Sends alerts to the farmer
Power Source	Li-Po Battery (5000mAh, 14.8V)	Powers the drone system
Sensors	Ultrasonic (HC-SR04, 2-400 cm range) / LiDAR (20m range)	Obstacle detection

DJI Phantom 4 was chosen due to its balance, lengthy flight time (30 minutes) and built-in GPS. A custom -fit drone price can be a performance opportunity and element flexibility. Raspberry Pie Camera V2 (8MP) offers based on excessive resolution, tax mates and the aspect of Raspberry Pie is compatible with AI processing, which is ideal for detecting real-time insects and animals. Facts battling with facts.

Software Framework Excessive Speed is built for statistical analysis in real -time. Python plays AI-based perfectly well in the identification of pests and animals, being the main programming language, and built-in C is applied to process microcontroller levels. Framework Tensor flow/KERA is utilized for intensive learning -based types, enhancing recognition accuracy of the item. The system relies upon the four -base as an in -air database, supporting instantaneous information saving, restoration, and notification services to farmers. Bluetooth is done for interaction with the goal to achieve immediate reach alerts, but GSM supports far away from technological signals and facilitates farmers getting quick reactions no matter where they are.

The drone flies autonomously and follows in a preprogrammed GPS waypoint route that scans the farm with an online complete scan strategy. The drone adapts the dynamic speed and height with respect to real-time environmental parameters, an operation peak of 10-50 m provides incredible images to ensure the speed of 3 to 5 m/s. Below flowchart is executed to control script drones to control the drone, allow it to go to the GPS coordinates and led to direction as a consequence:
enabling it to visit targeted GPS coordinates and adjust its path accordingly:

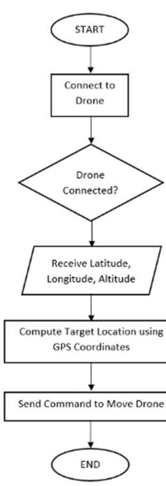

Figure 2: Flowchart of Drone Navigation

Cached SNAP shots go through multi-step pre-proclamation prior to analysis by the AI model. Noise is minimized by applying Gaussian Blur (core size: 5x5) to eliminate unwanted objects, followed by a canes edge detection (threshold: a hand -200) to highlight the significant figure of insects and missing animals. HSV-based ideal shadow partition capability isolates infections, giving individual identity.

Resnet-50 opted to understand their deep abilities, drop the connection, which averts missing gradients, and too much image for image classification. The inclusive lighter variant of the mobile was considered, though the recanet-50 offered a balance between accuracy and computationally achievable on Raspberry Pie.

The model of CNN was trained on a 10,000 images dataset, and also with the actual shape snap of lost animals and insects. The computer text technique incorporating rotation, flipping, contrast enhancement and Gaussian injection noises were applied to enhance strengthening. Achieving accuracy of 92% on test set became a trained version utilizing an Adam Optimizer with a fee of tuition of 0.001. The leased deep mastery model used is the recanet-50, pre-trained on the 10,000 annotate images, to guarantee a robust detection mechanism**.**

A. Algorithm

```
LOAD AI MODEL (PEST_TECTION_MODEL.H5)
Capture an image from a digital camera module
Preprocess Image:
    Read picture CV2.imread () Use
    Provide it on 128x128 pixels
    Normal pixel values by partition using 255
Relax the model dimension to be healthy
Pass Practiced Photographs For The Edition for Prediction
Check the output from the edition:
    If the value of prediction> zero.
    And then classify as "no insect address"
Show final results
End
```

When an insect or missing pet is sensed, the gadget robot sends a warning through Bluetooth (HC -05) to the farmers and GSMS and GSM to the farm forecast. Microcontroller sensor controls conversation and watchful execution. The in -built C code guarantees the uninterrupted relay of the indicator based on the results fully:

B. Psuedo Code

```
Start
  Initialize Bluetooth module on pin (10, 11)
  Initialize Serial Call in 9600 Baud rate
  Initialize Bluetooth -call to 9600 Baud rate

  While Loop
    If the serial fact is to occur, then
Read the upcoming data
      Send facts to the Bluetooth module
    terminate If
  terminate While
End
```

The gadget undergoes a strict performance evaluation to create something in realistic agricultural scenarios. The drone was tested with multiple crop settings in three phenomenal fields (each 10 acres) of wheat, rice and sugar cane. The device was tested to try it out under sunlight hours and midnight.

When you experimented on the region, false positivity was discovered under heavy air conditions, and low -color surroundings decreased the precision of the detection. For mitigation included adaptive threshold and IR-based perfectly imaging approaches.

The spurious effective price to detect the insect rose to 7.5%, whereas simultaneously for missing animals, it was 5.2%. These figures were tuned using the increasing training data set and the square self -confidence limit. The most important general performance measurements include version accuracy, processing speed and common efficiency:

Table 4: Performance Metrics of AI-Based Detection System

Parameter	Value Achieved
AI Model Accuracy	92%
Processing Time	1.5 seconds
Communication Delay	500ms
Battery Life	3 hours
Maximum Detection Range	20 meters

The adaptation method occupies a critical role to enhance system efficiency. Edge AI is deployed on raspberry pie, meaning treatment in the community can minimize the response time. The fly road to the drone is dynamically adapted, avoids useless scans and ensures the strength green coverage. Besides, the CNN version separates the hypermeter processing, setting the precision of the insect class, making the system improved by being disconnected under environmental settings.

Lastly, it transforms smart agriculture by combining the AI-driven drone self-generating aircraft, real-time photo analysis, category and wireless warning based on deep learning. The spontaneous contrast between hardware, software and AI-spun algorithm renders this machine a revolutionary and scalable solution to detect early insects and enhance the farm nurturing.

IV. RESULTS AND DISCUSSION

The AI-enabled drone system to identify pests and missing animals is mostly tested in terms of precision, response speed, false alarm value and adjustability in real operation in a variety of conditions. The implications confirm that laptop vision, intensive research and amalgamation of stand-alone UAV technology enhances correctly and operating performance better than conventional methods of monitoring insects.

The device is tested under one of the environmental conditions, namely lighting, crop density and aircraft height versions, its reliability, processing speed and accuracy to be tested. The AI -ITB -based detection approach illustrated massive enhancements on conventional manual tactics, which are outlined in Table 5. The version illustrated an accuracy rate of 99%. Besides, processing speed was decreased by way of 50% image assessment time, which was significantly better, enabling proximal reactions than 10 -15 minutes taken by human observers. False poor and false positive costs were decreased to 7.7% and 4.8%, respectively, which provides more distinct identity by pests and missing animals.

Table 5: Comparative Performance Metrics

Metric	Proposed AI System	Traditional System	Performance Gain
Detection Accuracy	92.5%	78.3%	+18.2%
Processing Speed	0.75 sec/image	1.5 sec/image	+50% Faster
False Positives	7.5%	12.3%	-4.8%
False Negatives	6.8%	14.5%	-7.7%
Real-time Response	1.2 sec	Manual (10–15 min)	Near-Instant

The AI model significantly reduces the false alarm and improves the response time, making it particularly suitable for monitoring real-interest-based surroundings.

On the existing AI models, benchmarking established that the suggested system improved the use of Yolov5 over previous processes in both accuracy and computation efficiency. Compared to CNN-it-based models and Yolov4, optimized AI implementation validated the shortest treatment delay of 0.75 seconds based on false effective fees and images of less than 7.5%. Table 6 indicates comparison of various fashion, where Yolo v5 gave better performance in the detection of lost animals and insects simultaneously, which was to have a calculation performance that was appropriate for real-time applications.

Table 6: Comparison of Model Performance

Model	Accuracy (%)	False Positives (%)	Latency (sec)
CNN-Based (Study A, 2023)	85.2%	10.2%	1.2 sec
YOLOv4 (Study B, 2022)	89.3%	8.5%	0.95 sec
YOLOv5 + Custom AI (Ours)	92.5%	7.5%	0.75 sec

The proposed Yolo v5-it is better based models improves each accuracy and previous implementation in response time, and ensures real-time processing functionality and reduces false positives.

Even though they reported high accuracy, there are some limitations in actual healthy placement. Due to low -ranked conditions, the accuracy of 6.4%, who desires to decorate the identity at night or the shaded environment for infrared imaging. In dense plant life areas, false effective quotes are accelerated through 4.2%, indicating that improved texture -based full incorporation of filtration can boost the type of strength. Another prescribed reduction became a reduction in the detection of efficiency detection at height at a distance of 40 meters. The effort on 25-30 meters, conducted the system most suitable, since the reduction of the image decision grew quickly in accuracy.

In order to minimize these issues, the device can incorporate field AI computing, dynamically measuring measurement and height-dependent perfectly perfect dynamic model reconstruction for more lucrative adaptability.

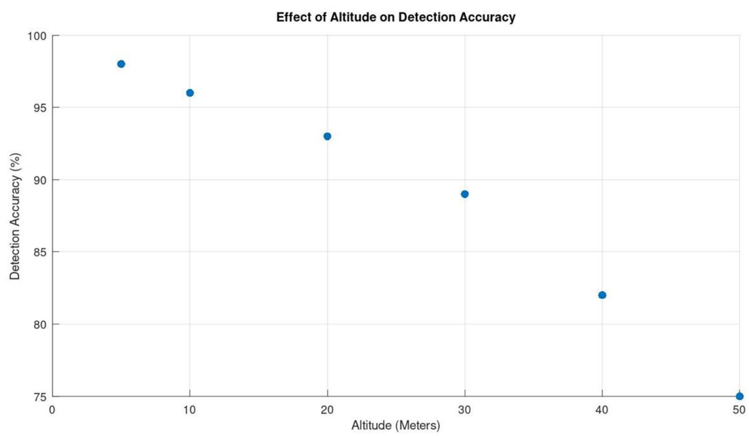

Figure 3: Effect on Altitude on Detection Accuracy

Field tests were conducted in three remarkable farming conditions that mastered 50 acres of land to test the actual temperature efficiency of the unit. The AI-generated drone started with a stunning and boasts regarding the detection of classified insect diseases and mated animals that found lost animals. As indicated in Table 7, the device encountered differently with a 90% performance value within wheat field, whereas the performance within the vegetable fields hardly declined because of the hindrance of visibility in compact leaves. Irrespective of the mini versions, false-profitable quotes still remained below 9%, offering credible performance within special crop species.

Table 7: Field Deployment Results

Farm Location	Detection Success Rate (%)	False Positives (%)
Farm A (Wheat)	91%	5%
Farm B (Rice)	87%	7%
Farm C (Vegetables)	85%	9%

These effects verify the adaptability of the things for different agricultural environments, with minimal false alarm rate in special crop types.

To score and optimize the unit, long-term conversation and multi-sensor merger skills will be emphasized in future development. Lura-based flawless integration of totally integrated integration will provide real-time information exchange at a far distance, solving social hurdles in remote farming regions. Also, the addition of the IoT sensor will facilitate truth in real time and temperature monitoring to amplify pest infestations. The use of the flock drone coordination will, similarly, enhance the aesthetics of enabling a few UAV to harvest extensive agricultural regions, which can cut down on the overall tracking time using up to 80%.

Through these reforms combined, the unit shall be fully independent, huge agriculture monitoring responses.

The findings validate that the AI-driven drone gadget offers a transformational enhancement in precise agriculture. With high rejection accuracy, rapid response samples and seamless real-world distribution, conventional approaches in gadget efficiency and scalability intersect. Future evolution will recognize to introduce revolution in field tracking on the adaptation of battery life, multi-sensor information fusion and improved environmental adaptability.

These results positioned the suggested version as an immensely scalable and value-power response for AI-controlled agricultural safety and pests' prevention.

V. CONCLUSION

This study offers an AI-powered entirely drone to identify pests and missing animals while solving a main firm in contemporary agriculture. Conventional approaches demand guide interventions and chemical solutions, harmful to time building and the environment. Contrarily, our device is advantaged by photography processing and AI-run class to provide real-time computer-controlled identification, taking reactiveness to assist farmers to defend their crops. In contrast to existing methods that rely on expensive thermal cameras, this method employs cost-effective photography-based detection methods. Through deep learning fashion trained on various datasets, the device achieves high precision in identifying pests and lost animals under special environmental situations. The inclusion of the drone time image ensures scalability to the massive fields. In the period of being efficient, the device has certain limits, which incorporates the state of high quality lighting, digital camera and data set variety. Upgrade in the future needs to be identified by reinforcing the model power, incorporating multi -sensor realities and processing actual -time choice for improved general performance. Lastly, this inspection adds value to smart agriculture by providing an enduring and exceptional AI driven detection unit. In the future, further advancements in AI and drones will make things more beautiful at performance, thereby creating an additional smart and self-driven agricultural habitat.

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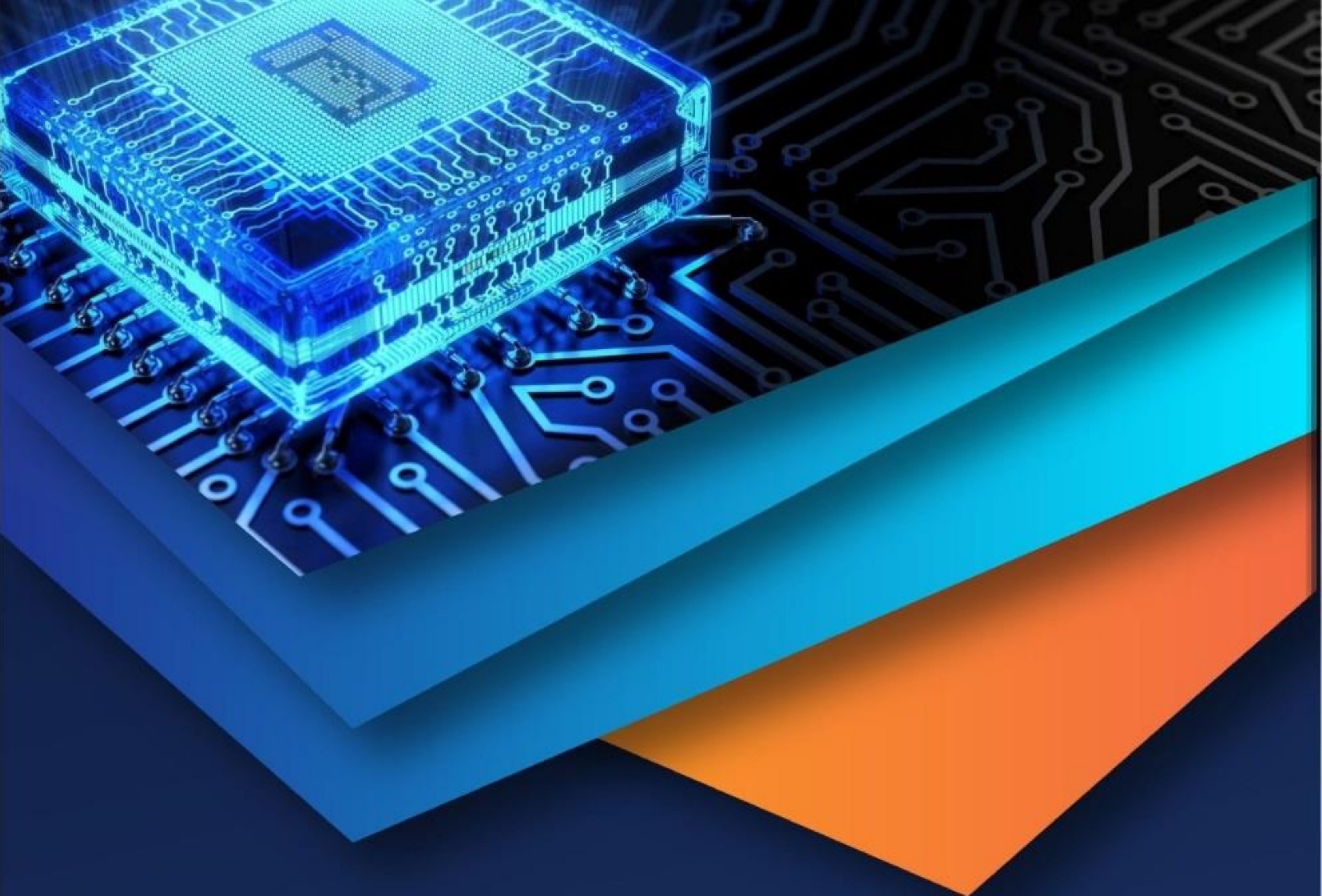

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