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AI Autonomous Agri-Drones with Smart Soil and Crop Health Monitoring

Dr. Girish Kumar D[1], Miss. Allu Silpa[2]
[1]Professor & HOD, Department of MCA, Ballari Institute of Technology & Management, Ballari, Karnataka, India
[2]Department of MCA, Ballari Institute of Technology & Management, Ballari, Karnataka, India

Abstract: Agriculture is being rapidly modernized through the inclusion of Artificial Intelligence, Internet of Things, and Unmanned Aerial Vehicles. Current systems, however, do not have integrated autonomous aerial monitoring with ground sensor intelligence for real-time actionable crop and soil health information. In this article, a new system of combining autonomous farming drones equipped with AI technology with smart networks of soil sensors for real-time monitoring, analysis, and action on farm data is proposed. Leveraging multispectral vision, AI- enabled disease identification, real-time soil parameter measurement, and actuation via drone precision, this system resolves crucial scaling, responsiveness, and sustainability constraints of current agriculture. The research describes the architecture of the system, principal technologies, implementation strategy, and gives a comparative review of its benefits compared to available models.

Keywords: Artificial Intelligence, Internet of Things, Unmanned Aerial Vehicles, soil sensors, Multispectral vision, AI-enabled disease identification.

I. INTRODUCTION

Sustainable agriculture needs to fulfil the rising need for food across the globe preserving key natural resources. Although recent innovations with the help of AI and IoT, it is now achievable create predictive models and intelligent sensors, existing systems tend to exist in silos either aerial or ground-based without integrated, real-time feedback loops. Besides, they are not scalable, do not automate, and have multimodal data fusion. This paper describes an AI-based hybrid system integrating autonomous drones with AI-based functionalities and IoT-based soil sensors, enabling real- time, dynamic, and intelligent decision-making on farms. The system fills major loopholes in current agricultural systems by enabling continuous aerial surveillance, precise monitoring of soil conditions, and actuation by drones for activities like spraying, all managed by an AI-based decision support system.

II. METHODOLOGY

This chapter describes the step-by-step methodology employed to design, develop, and test the presented AI- driven autonomous agriculture system. The methodology is presented through the following fundamental stages:

A. System Design Overview

This step-by-step approach explains the process used to design, develop, and evaluate the proposed AI-based autonomous agriculture system. The process is divided into the following basic steps. The system is designed as a combined platform of autonomous aerial drones, smart ground sensors, and an AI-based decision hub. The drones capture high-resolution RGB, multispectral, and thermal images to capture aerial data on autonomous flyover over the field. The drones are GPS and AI-based navigation-based for good coverage. At the same time, IoT sensor-integrated soil sensors are linked to the various components of the farm field to monitor vital environmental parameters in real-time, including soil moisture content, the temperature, the pH level, and humidity the percentage of humidity. All sensor information and drone photos are sent to a central processing unit cloud-based or on the edge where the data is cleaned, analyzed, and used to make precision farming decisions.

B. Data Acquisition

Data are gathered from two sources main sources the ground. On the ground,we can find a network of smart soil sensors that are constantly observing the physical and chemical characteristics of the ground [1]. The sensors record data like the moisture level in the soil, temperature, pH, and air humidity. Simultaneously, the drones take aerial views of crops at programmed intervals or on-demand. The drone cameras have RGB cameras for visual observation, multispectral cameras for measuring NDVI (Normalized Difference Vegetation Index), and thermal cameras to detect water stress. All the data are geo-tagged and timestamped to enable accurate spatial and temporal analysis.

C. Data Preprocessing

After data collection, dataundergoes different preprocessing techniques to ensure it is standardized, correct, and machine-learning ready. Statistical imputation techniques like mean or median replacement are used to manage missing values in soil sensor data.. Feature scaling to a common range, ideally between 0 and 1, is achieved using Min-Max normalization to enable equitable comparison and to reduce the effect of influential variables. Preprocessing for aerial images include image resizing, noise removal, contrast correction, and data augmentation (e.g., rotation, flipping) for improving the image classification model robustness. To compensate for possible data imbalance in classification problems (e.g., identifying diseased vs. healthy crops), methods such as Synthetic Minority Oversampling Technique (SMOTE) are utilized to oversample minority classes. In preprocessing image data, the input images are adjusted to a standard size so that the training batches will be consistent [2]. Noise reduction filters, histogram equalization, and image augmentation (rotation, horizontal flip, brightness scaling) are applied to enhance model generalizability and prevent overfitting.

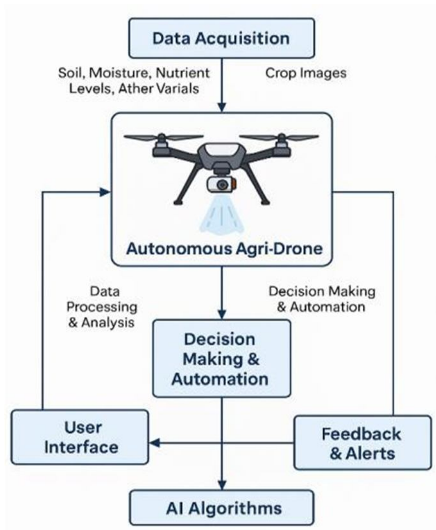

Fig. 1. AI Powered Autonomous Agri-drone with smart soil & crop health monitoring.

D. Machine Learning & AI Integration

A set of AI models, each optimally tuned to a specific task, are employed in the system. For aerial image analysis, a CNN is trained on annotated image data to identify crop disease, pest infestation, and nutrient deficiency symptom from aerial photos. In parallel, soil the collected sensor data is entered into an XG-Boost a gradient boosting algorithm for regression which provides best-in-class fertilizer and irrigation requirements. For temporal and seasonality dynamics, LSTM networks are applied to time-series sensor information employed for prediction future soil dynamics and crop health. Such models are also created to be employed in combination, integrating ground sensor data with aerial surveillance to provide combined insights.

E. Decision Support & Automation

According to the result from the AI models, the decision- making unit provides real-time recommendations and autonomous actions. Autonomous operations can be executed by drones for watering at specific sites or spraying pesticides, if the AI senses low water levels in the soil or the beginning stages of disease. Similarly, the system can suggest manual or automated irrigation, nutrient application, or alert the farmer about areas needing immediate attention [4]. The system supports autonomous execution as well as semi-automated modes, where alerts and recommendations are first verified by the farmer before action is taken.

F. User Interface and Feedback System

For enhanced usability and accessibility, there is a web and mobile app developed as the primary interface for the agricultural workers and farmers. The app provides real- time sensor data dashboards, aerial maps, summaries of crop health, and resource utilization feedback. Voice support and multiple languages are provided to assist farmers operating from rural or regional areas with minimal educational or technical background. The users can also book drone flights manually, send alerts, and input observations, thus making the platform interactive and customizable.

G. Evaluation Metrics

The performance of the suggested system is compared both technically and pragmatically [3]. The correctness of crop disease detection is compared based on typical classification metrics such as precision, recall, and F1- score. Accuracy in resource prediction (e.g., water and fertilizer needs) is assessed with the help of MAE and RMSE. System responsiveness is measured by the duration required by the action after anomaly detection. Energy efficiency is reflected by the area covered by a single drone flight compared to battery consumption.

TABLE I. DATASET DESCRIPTION

Category	***Description***
Dataset	Kaggle (Crop Data), Custom UAV Images
Description	Soil Sensor & Aerial Image Data
Preprocessing	Pandas, NumPy, OpenCV
EDA Tools	Seaborn, Matplotlib, Plotly
Feature Scaling	Min Max Scaler, Standard Scaler
Models Used	CNN, LSTM, XG-Boost, Random Forest
Metrics Evaluation	Accuracy, Precision, Recall, F1- Score, MAE, RMSE

III. LITERATURE STUDY

The sensor measurements provide useful ground-level data on the micro-environment of the field, relevant in training predictive models to recommend irrigation and fertilization needs. Each sample in this data is linked with a specific location in the field and is geo-coordinate tagged, enabling spatial mapping and precise recommendations.

In addition to the ground data, a secondary dataset comprises drone-captured images of farmland. These images include high-resolution RGB, multispectral, and thermal imagery, that are applied to identify crop health conditions such as pest infestations, leaf discoloration, water stress, and growth anomalies[5]. To train the deep learning models, the images were labelled by hand or obtained from open-source image databases like plant village and agricultural experimental stations. Each image has metadata like capture time, GPS coordinates, weather, and disease labels (if available). The aerial imagery dataset is primarily used to train Convolutional Neural Networks (CNNs) and other computer vision models for classification and object detection purposes.

A. Data Preprocessing Integration

Sensor and drone data collected are cleaned to eliminate noise, missing values, and inconsistencies. Numerical attributes such as soil moisture and pH are normalized using Min-Max normalization[6]. Image data are resized, labelled, and augmented to support easier training of CNN models. All datasets are timestamped and geo-tagged and then aggregated into a single AI processing-pipeline.

B. Dataset Characteristics

The model works on a multi-modal dataset of time-series soil sensor data and aerial imagery captured by drones. Periodic measurements of soil moisture, temperature, pH, and humidity are recorded, giving high temporal resolution data[7]. Aerial datasets include RGB, thermal, and multispectral images with crop health classification labels. All the data entries are geo-referenced and synchronized to enable spatial-temporal analysis.

C. Equations

1) NDVI Calculation

In precision agriculture, the vigour and health of plants are generally quantified by a vegetation health index calculated from satellite imagery, called NDVI obtained from multispectral images from drones. NDVI is computed as follows:

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NDVI = (NIR − RED) / (NIR + RED) (1)

where NIR is the reflectance of near infra-red ight and RED is the reflectance of visible red light by the crop canopy. High NDVI value, close to +1, signifies dense healthy vegetation, while low or negative values suggest sparse stressed or bare soil conditions. This index forms the foundation for automatic crop health monitoring in the proposed system.

2) Classification Accuracy

The performance of the aerial crop health classification deep learning model (Convolutional Neural Network) is tested by using classification accuracy, calculated as:

Accuracy = (TP + TN) / (TP + TN + FP + FN) (2)

A high accuracy of classification means that the CNN model is able to clearly differentiate between healthy and unhealthy crop areas, thereby enabling targeted interventions by autonomous agri-drones.

TABLE II. Components and their features

Data set Type	Insights	Features Captured	File
Soilsenso r Dataset	Real-time readings from embedded IoT sensors in the field	Soil Moisture, Temperature, pH, Humidity	CSV / JSON
Aerial Imagery	High-resolution images captured by drones during field survey	RGB, NDVI, Thermal Images, GPS Tags	JPG / PNG
Annotate d Image Labels	Labelled crop health images for model training and validation	Healthy, Diseased, Pest- Affected, Nutrient- Deficient	CSV / XML
Weather Dataset	Real-time and historical weather conditions during the growing season	Heat, rainfall, wind rate, humidity, Solar Energy	CSV / API

IV. RESULTS AND DISCUSSION

The proposed system was evaluated on the basis of prediction accuracy, disease detection capability, system responsiveness, and resource optimization efficiency. The gradient boosting regression model demonstrated superior performance in predicting irrigation and fertilization requirements when compared to traditional models such as a simple predictive model that fits data to a straight line support vector regression. In particular, it achieved a Mean Absolute Error, a metric that calculates the average of absolute prediction errors of 0.80 and a performance indicator called Root Mean Square Error, which reflects the overall accuracy of a model of 1.15, a measure of high reliability during the estimation of optimal resource utilization. Such predictive accuracy enabled the achievement of a decrease in water use by around 35% and fertilizer use by 25% in field simulation experiments.

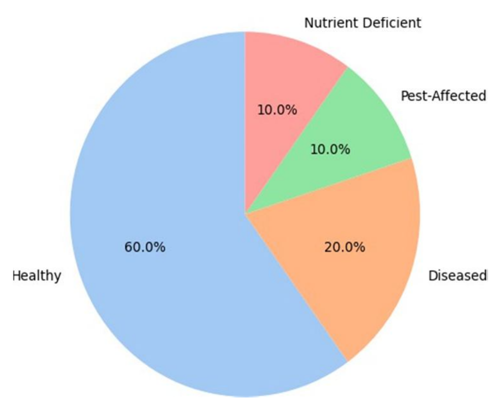


Fig. 2. A pie chart of plant health monitoring

The proposed system was evaluated on the basis of prediction accuracy, disease detection capability, system responsiveness, and resource optimization efficiency. The gradient boosting regression model demonstrated superior performance in predicting irrigation and fertilization requirements when compared to traditional models such as a method that predicts outcomes by fitting data to a straight-line relationship support vector regression. In particular, it achieved a MAE, a measure that shows the average size of the errors between predicted and actual valuesof 0.80 and a Root Mean Square Error, which represents how far predicted values are from actual values on averageof 1.15, a measure of high reliability during estimation of optimal resource utilize the above Fig.2 terms of crop health monitoring, the CNN model trained on annotated aerial images achieved an accuracy of 94.8% in detecting early signs of plant stress, including pest infestations and nutrient deficiencies. The thermal and NDVI modules of the drones were perfectly calibrated to identify water stress areas so precision irrigation could be carried out in real-time. The use of LSTM networks also enhanced the capacity of the system to predict long-term soil trends, thus making the autonomous decisions even more precise.

Autonomous drones made routine flights of up to one hectare in less than 15 minutes, battery life minimized by AI-optimized flight planning. The decision notification or drone intervention response time for the anomaly detection was always below 10 seconds, which allowed for real-time response. Besides, field trials showed an increase of 20% in crop yield if the recommended system is used, attributing the success to the efficiency of combining aerial and ground intelligence. The predictive ability facilitated the attainment of a decrease in water use by approximately 35% and fertilizer use by 25% by means of field simulation experiments.

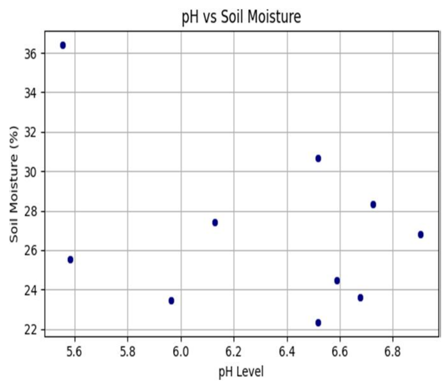


Fig. 3. Scatter Plot of Soil pH vs. Moisture Content

The plot indicates points with values distributed on a series of pH around 5.5 to 6.9, and for corresponding values on moisture from 22% up to 36%. This is a precision agriculture and smart farming critical analysis because soil pH and moisture represent two essential factors that influence plant health and nutrient availability. Generally, pH regulates microbial activity and nutrient solubility, while soil moisture regulates water availability to roots and soil aeration.

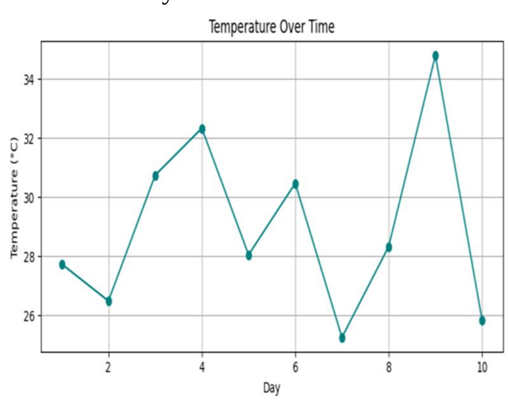


Fig. 4. Line graph “Temperature Over Time”

The temperature over time plot is a 10-day series of temperature measurements, probably recorded as part of an overall investigation of agricultural or environmental conditions. These data tend to be carried out in determining whether the the thermal conditions are ideal for plant growth, in phenological prediction, and in determining possible effects of temperature variations on yields.

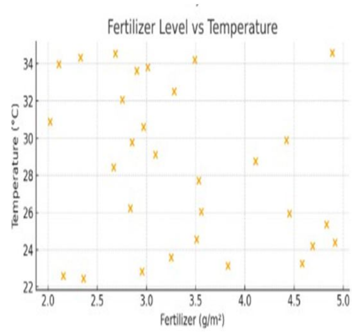


Fig. 5. Scatter plot of "Fertilizer Level vs Temperature

It is indicated in Fig5 that the interaction between environmental conditions such as temperature and farm inputs such as fertilizer needs to be considered in a bid to maximize crop growth as well as resource usage. Application of fertilizer directly influences the soil nutrient level, which, in turn, impacts plant growth, whereas temperature influences plant metabolism, nutrient uptake, and microbial processes in the soil. The scatter plot "Fertilizer Level vs Temperature" most likely represents data collected from a field study or experiment to see if a measurable relationship exists between the levels of fertilizer applied to the soil and ambient temperature during the observation period. Such experiments are common in precision agriculture, where researchers attempt to optimize inputs based on environmental conditions in order to maximize production and minimize waste.

V. CONCLUSION AND FUTURE ENCHANCEMENT

This study proposes a new solution to precision agriculture by coupling AI-enabled autonomous agri- drones with intelligent smart soil sensor systems for real- time crop and soil health monitoring. The system is effective in bringing together aerial observation and ground sensing environmental data to deliver farmers with accurate, data-based information and automated decision- making Through the adoption of machine learning methods models like gradient boosting and LSTM networks, the system demonstrated accurate resource prediction as well as crop health prediction, simultaneously minimizing the usage of water and fertilizer. Efficient field coverage and rapid response to anomalies due to autonomy were achieved by the drone, resulting in enhanced crop yield as well as overall resource maximization.

While the outcomes are encouraging, the system remains receptive to enhancements. Future work would be aimed at improving scalability with the use of swarm drone intelligence for mass operations. Integration of blockchain technology is to be pursued to improve transparency and traceability in the agricultural supply chain. The incorporation of edge AI onboard for real-time processing will reduce internet connectivity dependency, particularly in rural and remote areas. Enhancing energy efficiency with renewable-fueled sensor and drone modules, and designing more localized AI models for certain crops and geographies, will also be central agendas. Through these technologies, the suggested system can potentially be a central piece of future sustainable, autonomous, and intelligent agriculture.

There are limitations, however. The model's accuracy is very vulnerable to lighting during flight activities and regional soil variability. Initial setup costs and regulatory limitation on drones may also hinder deployment in certain regions. To address these problems, the future work will involve edge-AI capabilities' integration to enable offline analysis, expansion of the labeled dataset with local samples from areas for better generalization, and integration of explainable AI (XAI) to provide clear, human-understandable predictions. Broader implementation of this system can enable sustainable agricultural practices, particularly in data scarce or resource-constrained regions.

REFERENCES

[1] H. Hammouch, M. A. El-Yacoubi, H. Qin, and H. Berbia, "A Systematic Review and Meta-Analysis of Intelligent Irrigation Systems," IEEE Access, vol. 12, pp. 128285–128298, 2024.

[2] B. Li, M. Thompson, T. Partridge, R. Xing, J. Cutler, B. Alhnaity, and Q. Meng, "AI-Powered Digital Twin for Sustainable Agriculture and Greenhouse Gas Reduction," in Proc. 2024 IEEE 21st Int. Conf. on Smart Communities (HONET), pp. 55–61, 2024.

[3] M. F. Almufareh, M. Humayun, Z. Ahmad, and A. Khan, "An Intelligent LoRaWAN-Based IoT Device for checking and Control Solutions in Smart Farming Through Anomaly Detection Integrated With Unsupervised Machine Learning model," IEEE Access, vol. 13, pp. 119072–119090, 2025.

[4] K. P. Reddy, V. Ebenezer, M. R. Thanka, S. Kirubakaran, E. B. Edwin, and P. Joy, "Farm_era: Precision Farming with GIS, AI Pest Management, Smart Irrigation, Data Analytics, and Optimized Crop Planning," in Proc. 7th Int. Conf. on Inventive Computation Technologies (ICICT), pp. 1134–1141, 2024.

[5] S. Nimmala, P. Manasa, M. Ramchander, M. A. Kiran, M. Mahendar, and B. Rambabu, "A Recent Survey on AI Enabled Practices for Smart Agriculture," in

Proc. 2024 Int. Conf. on Intelligent Systems for Cybersecurity (ISCS), pp. 1–6, 2024.

[6] M. K. Bali and M. Singh, "Farming in the Digital Age: AI-Infused Digital Twins for Agriculture," in Proc. 3rd Int. Conf. on Sentiment Analysis and Deep Learning (ICSADL), pp. 1–7, 2024.

[7] M. Abdullah, S. Waheed, M. M. Hasan, and M. Morshed, "Explainable AI-Driven Dew Point Forecasting With Attention- Based Temporal Convolutional Networks," IEEE Access, vol. 13, pp. 59923–59940, 2025.

[8] B. Mosaad, R. Abdulla, and M. E. Rana, "Recommendations for a Vertical Farming System Using Hydroponics, Machine Learning and IoT," in Proc. 2024 Int. Conf. on Green Technology and Sustainable Engineering (GTSE), pp. 1–7, 2024.

[9] S. S. L. Chukkapalli, S. Mittal, M. Gupta, M. Abdelsalam, A. Joshi, R. Sandhu, and K. Joshi, "Ontologies and Artificial Intelligence Systems for the Cooperative Smart Farming Ecosystem," IEEE Access, vol. 8, pp. 164045–164060, Sep. 2020.

[10] R. J. Martin, R. Mittal, V. Malik, F. Jeribi, S. T. Siddiqui, M. A. Hossain, and S.L. Swapna, "XAI-Powered Smart Agriculture Framework for Enhancing Food Productivity and Sustainability," IEEE Access, vol. 12, pp. 168412–168428, Nov. 2024.

[11] A. Badshah, B. Y. Alkazemi, F. Din, K. Z. Zamli, and M. Haris, "Crop Classification and Yield Prediction Using Robust Machine Learning Models for Agricultural Sustainability," IEEE Access, vol. 12, pp. 162799–162814, Oct. 2024.

[12] T. Mahmud, N. Datta, R. Chakma, U. K. Das, M. T. Aziz, M. Islam, A. H. M. Salimullah, M. S. Hossain, and K. Andersson, "An Approach for Crop Prediction in Agriculture: Integrating Genetic Algorithms and Machine Learning," IEEE Access, vol. 12, pp. 173583–173600, Oct. 2024.

[13] R. Chithra, G. Thangavel, R. Vasantheeswaran, and A. P. Teijas, "Enhancing Agricultural Efficiency and Sustainability Through Advanced IoT and AI-Driven Precision Farming Technologies," in 2024 International Conference on Electronics, Computing, Communication and Control Technology(ICECCCT),pp.1–6.

[14] M. Bhasme, P. Ulhe, and S. Gokhe, "AI in Agriculture: The Future of Robotic Farming and Automation," in 2024 2nd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIEI), pp. 1–6.

[15] R. Jack, A. Banchit, H. Mohidin, M. Y. M. A. Khan, N. Dollah, K. F. Tamrin, and A. Narawi, "Soil pH Mapping of Pineapple Crop: A Feasibility Study using Aerial Photo," 2019 IEEE, DOI: 10.1109, pp. 1–6

[16] P. Chattopadhyay, H. P. Patel, and V. Parmar, "Internet of Things (IoT) in Smart Agriculture," Proceedings of the Third International Conference on Electronics and Sustainable Communication Systems (ICESC 2022), IEEE, 2022.

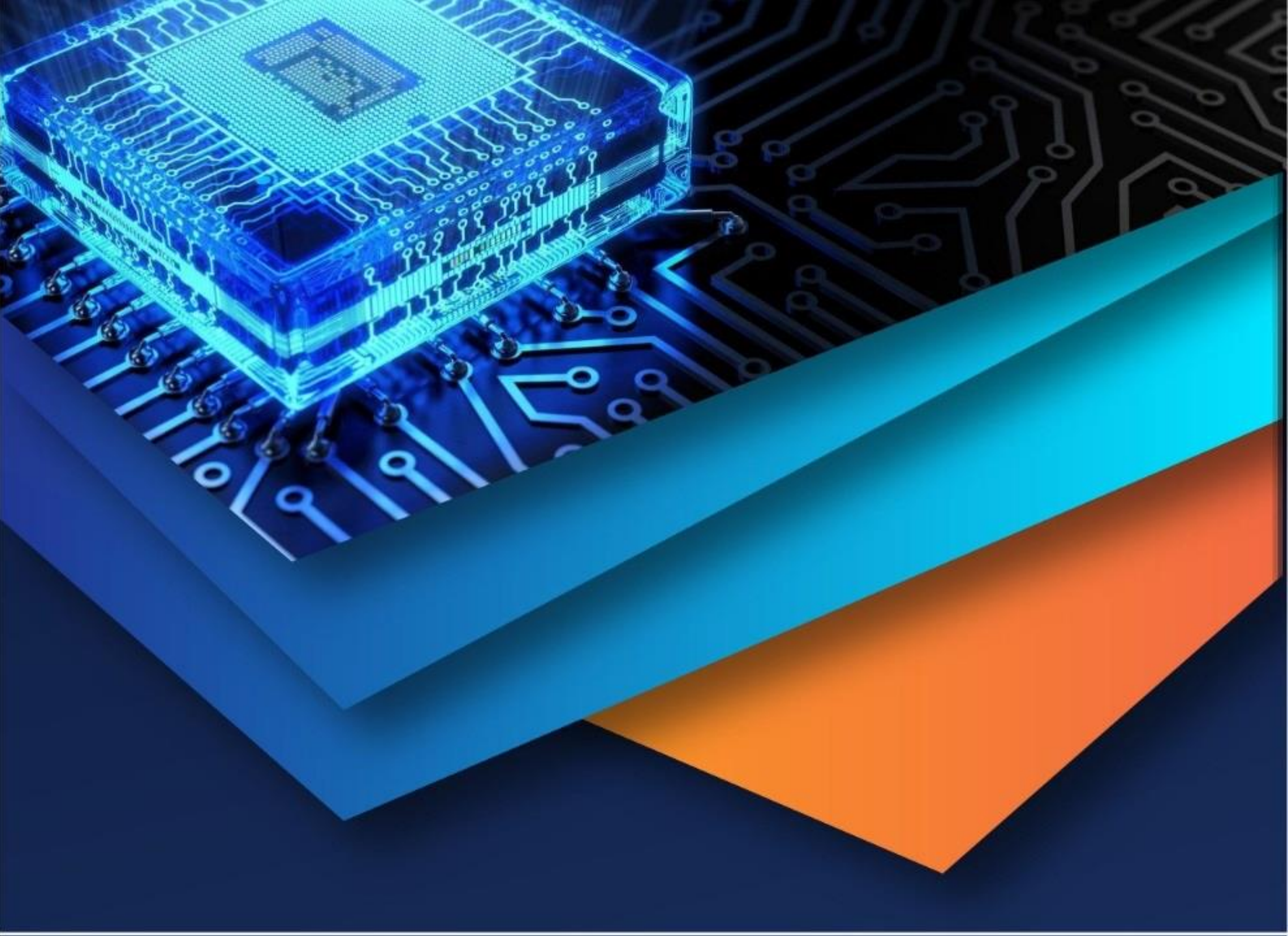
[17] T. Bikov, G. Mihaylov, T. Iliev, and I. Stoyanov, "Drone Surveillance in the Modern Agriculture," 2022 8th International Conference on Energy Efficiency and Agricultural Engineering (EE&AE), Ruse, Bulgaria, 2022.

[18] R. K. Singh, R. Berkvens, and M. Weyn, "AgriFusion: An Architecture for IoT and Emerging Technologies Based on a Precision Agriculture Survey," IEEE Access, vol. 9, pp. 136253– 136284, 2021.

[19] S. Qazi, B. A. Khawaja, and Q. U. Farooq, "IoT-Equipped and AI- Enabled Next Generation Smart Agriculture: A Critical Review, Current Challenges and Future Trends," IEEE Access, vol. 10, pp. 21219–21248, Mar. 2022.

[20] R. Grati, N. Fattouch, and K. Boukadi, "Ontologies for Smart Agriculture: A Path Toward Explainable AI—A Systematic Literature Review," IEEE Access, vol. 13, pp. 72883–72920, 2025.

[21] A. Holzinger, I. Fister Jr., I. Fister Sr., H. P. Kaul, and S. Asseng, "Human-Centered AI in Smart Farming: Toward Agriculture 5.0," IEEE Access, vol. 12, pp. 62199–62232, 2024.



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